UCLA

Recent Work

Title

Common Factors in the Serial Correlation of Stock Returns

Permalink

https://escholarship.org/uc/item/2jf8r7n7

Authors

Fama, Eugene F. French, Kenneth R.

Publication Date

1986-09-01

#30-86

Common Factors in the Serial Correlation of Stock Returns

September 1986 Revised October 1986

Eugene Fama

Anderson Graduate School of Management University of California, Los Angeles Los Angeles, CA 90095-1481

and

Kenneth French

Graduate School of Business University of Chicago Chicago, IL 60637

Finance Working Paper sponsored by



September 1986; revised October 1986 Not for circulation or quotation: comments invited

COMMON FACTORS IN THE SERIAL CORRELATION OF STOCK RETURNS

Eugene F. Fama and Kenneth R. French*

I.INTRODUCTION

Evidence that expected stock returns vary through time is plentiful.

See, for example, Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976),

Fama and Schwert (1977), Fama (1981), Keim and Stambaugh (1986), and French,

Schwert, and Stambaugh (1986). The common conclusion, usually from tests on

monthly data, is that stock returns are predictable, but the implied time
variation of expected returns is a small fraction (usually less than 5%) of

return variances.

Fama and French (1986) find negative serial correlation in stock returns that becomes stronger for return horizons beyond a year and that implies stronger predictability of long-horizon returns. For example, 3-to 5-year returns are more predictable from negative serial correlation than 1-year returns. Returns are also more predictable for small-firm portfolios than for large-firm portfolios. Past returns explain about 25% of 3- to 5-year variances for large-firm portfolios and about 40% for small-firm portfolios.

Our goal is to test whether the negative serial correlation of longhorizon returns, and the substantial time-variation of expected returns it implies, can be attributed to one or more common factors in returns. The question is important. Most equilibrium pricing models, for example, Sharpe (1964), Lintner (1965), Merton (1973), and Ross (1976), assume that the

^{*} Graduate School of Business, University of Chicago, and Graduate School of Management, UCLA (Fama, winter quarters). The support of the National Science Foundation (Fama), the Center for Research in Security Prices (French) and Batterymarch Financial Management (French) are gratefully acknowledged.

factors that explain the cross-section of expected asset returns are a subset of the common factors that generate the correlation matrix of returns. If, period-by period, the cross-section of expected returns is explained by common factors, then the same common factors explain the time variation of expected returns. If, however, the serial correlation of returns has firm-specific components, then neither the variation through time of expected returns nor the cross-section of expected returns can be explained in terms of common factors. If expected returns have important firm-specific components, the study of equilibrium pricing models becomes less interesting.

Tests on size-ranked and industry portfolios that cover all stocks on the New York Stock Exchange (NYSE) show that the negative serial correlation of 3-to 5-year returns is pervasive. Regression tests are consistent with the conclusion that the strong time-variation of expected returns implied by this negative serial correlation is due to a single common factor. Tests on the 82 individual stocks listed on the NYSE for the entire 1926-85 period produce no evidence that firm-specific return factors are serially correlated.

De Bondt and Thaler (1985) find long-horizon reversals which are common only to subsets of stocks. When stocks are allocated to "winner" and "loser" portfolios on the basis of prior 3-year returns, extreme losers have reliably higher subsequent returns than the market, but extreme winner returns are not reliably different from market returns. Our tests indicate that their results are sensitive to technique. When we control for size and use true cumulative returns, we find reversal behavior for extreme winners but not for losers.

Moreover, extreme winners and especially losers are unusual in terms of size and market betas. When we examine loser and winner portfolios that cover the NYSE, cumulative reversals are weak and statistically unreliable. Our results suggest that the De Bondt-Thaler reversals are not pervasive across stocks.

This is in contrast to the pervasive negative serial correlation of longhorizon returns identified by Fama and French (1986), which the evidence here suggests is due to a single common factor.

The tendency toward reversal implied by negative serial correlation of size and industry portfolio returns may reflect time-varying expected returns generated by rational investor behavior and the dynamics of macro-economic driving variables. On the other hand, reversal behavior may reflect waves of over-reaction of stock prices of the kind assumed in models of an inefficient market. We comment on this critical but unresolvable issue, after presenting the results.

II. SERIAL AND CROSS CORRELATIONS FOR SIZE-RANKED PORTFOLIOS A. The Data

Firm size is known to capture differences in cross correlations (Huberman and Kandel 1985) and serial correlations (Fama and French 1986) of returns. If multiple common factors generate the cross and serial correlations of returns, it seems reasonable to presume that loadings on these factors vary as a function of firm size. Thus, we first examine size portfolios. The data are returns for all NYSE stocks for 1926-85 from the Center for Research in Security Prices of the University of Chicago. At the end of each year, stocks are ranked by size (number of shares outstanding times price per share) and allocated to ten (decile) portfolios. One-month simple portfolio returns, with equal-weighting of securities, are calculated and transformed into continuously compounded returns. These returns are summed to get overlapping monthly observations on longer-horizon returns. Unless otherwise noted, the word return implies continuous compounding.

B. Serial Correlations

Table 1 shows first-order serial correlations of returns on the decile portfolios for return horizons (holding periods) from 1 to 10 years. The estimates are slopes in regressions of the return on decile i from t to t+T, $r_i(t,t+T)$, on the lagged T-year return, $r_i(t-T,t)$. These OLS slopes have negative bias that depends on true slopes, sample sizes, and the fact that the estimates use overlapping monthly observations on annual returns. See Marriot and Pope (1954), Kendall (1954), and Huizinga (1984). The bias adjustments relevant when the true slopes are 0.0 are difficult to derive. Fama and French (1986) use simulations, constructed to mimic properties of 1926-85 NYSE returns, to estimate bias adjustments. Their corrections (positive constants that increase with the return horizon and are added to OLS slopes) are used in the bias-adjusted slopes in Table 1 and later.

The Fama-French simulations also show that unadjusted OLS slopes have little bias when true serial correlations are negative and on the order of the estimates for 3- to 5-year returns on size and (later) industry portfolios. We usually show both unadjusted and bias-adjusted serial correlations.

The serial correlations in Table 1 have the U-shaped pattern observed in Fama and French (1986). The serial correlations are negative for 2- to 5-year returns. Minimum values occur in 3-year returns for the larger-firm deciles 7 to 10, and in 4- or 5-year returns for deciles 1 to 6. Minimum values tend to be lower for small-firm portfolios. All bias-adjusted serial correlations less than -0.3 and unadjusted serial correlations less than -0.4, occur in deciles 1 to 6. Serial correlations for all deciles move toward 0.0 for return horizons beyond 5 years. Our goal is to determine whether the U-shaped pattern of serial correlations for increasing return horizons, also observed later for industry portfolios, is generated by one or more common factors.

Small effective sample sizes imply imprecise parameter estimates for long-horizon returns. The standard errors of the serial correlations are large -- between 0.11 and 0.16 for 3- to 5-year returns. Nevertheless, every decile produces an unadjusted first-order serial correlation of 3-, 4-, or 5-year returns more than 2.0 standard errors below 0.0, and deciles 1 to 7 produce bias-adjusted serial correlations more than 2.0 standard errors below 0.0. The fact that the U-shaped pattern of the serial correlations is common to all portfolios increases our confidence in its general reliability.

C. Cross Correlations

Common factors with different serial correlation can cause cross correlations to change with the return horizon. Table 2 shows correlation matrices for 1-, 3-, 5-, and 10-year decile returns. As Huberman and Kandel (1985) show, correlations between 1-year returns are highest for similar size portfolios. For example, decile 10 is most correlated with decile 9 (0.98) and least correlated with decile 1 (0.78).

More interesting, correlations between portfolios that differ much in size decline for increasing return horizons. Pairwise correlations among deciles 8 to 10 are high and similar across horizons (always 0.93 or greater), but their correlations with the first 7 deciles decline for longer horizons. Pairwise correlations among deciles 3 to 7 are high and similar across return horizons (0.93 or greater), but their correlations with the extreme deciles decline for longer horizons. Correlations of decile 1 with other deciles decline most with the return horizon. The correlation between decile 1 and decile 10 drops from 0.78 in 1-year returns to 0.16 in 10-year returns. Thus, there is strong correlation between the smallest and largest deciles at short return horizons but only weak correlation at long horizons.

Given a linear factor model for returns, systematic changes in cross correlations imply that the relative variances of factors change with the return horizon because different factors have different serial correlations. Table 2 is thus evidence on the relevance of a model in which time-series properties differ across common factors.

III. A FACTOR MODEL

Our goal for a factor model is to explain the U-shaped pattern of the first-order serial correlations for increasing return horizons observed for the decile portfolios in Table 1 and (later) for industry portfolios. We show that a model with a single common stationary (and thus mean-reverting) price component can explain the negative serial correlation of 2- to 5-year returns, while random-walk (and thus permanent) price components explain the tendency of the serial correlations to return to 0.0 for longer horizons.

A. The Model

Let $p_i(t)$ be the natural log of the price of stock i at time t. The mutually independent common factors in log prices are a mean-stationary component, S(t), and F random-walks, $W_f(t)$, f=1,...,F. The log price also has an independent firm-specific random-walk, $V_i(t)$. Thus,

(1) $p_{i}(t) = \gamma_{i}S(t) + \Sigma_{f} \phi_{if}W_{f}(t) + V_{i}(t),$

where γ_i and ϕ_{if} are factor loadings and Σ_f is a sum over f=1,...,F. The expected change in the firm-specific random walk is 0.0, and the mean of the common stationary price component is also 0.0. To make expected returns positive, the common random walks are assumed to have positive mean drift.

B. The Implications of a Stationary Price Component

Since $p_i(t)$ is the log of the stock price, the continuously compounded return from t to t+T is

$$r_{i}(t,t+T) = p_{i}(t+T) - p_{i}(t)$$

= $\gamma_{i}s(t,t+T) + \Sigma_{f} \phi_{if}w_{f}(t,t+T) + v_{i}(t,t+T),$

where s(t,t+T), $w_f(t,t+T)$, and $v_i(t,t+T)$ are the changes from t to t+T in S(t), $W_f(t)$, and $V_i(t)$.

Random walks in prices produce white noise in returns, but the mean reversion of the stationary price component S(t) leads to negative serial correlation in returns. The slope in the regression of s(t,t+T) on s(t-T,t), the first-order serial correlation between T-period changes in S(t), is

(3)
$$\alpha(T) = \cos[s(t,t+T),s(t-T,t)]/\sigma^{2}[s(t-T,t)].$$

The numerator covariance is

(2)

(4)
$$cov[s(t,t+T),s(t-T,t)] = -\sigma^{2}(S) + 2cov[S(t),S(t+T)]$$

- $cov[S(t),S(t+2T)],$

where $\sigma^2(S)$ is the variance of S(t). Stationarity of S(t) implies that the covariances on the right of (4) approach 0.0 as T increases, so the covariance on the left approaches $-\sigma^2(S)$. The denominator of (3),

(5)
$$\sigma^2[s(t-T,t)] = 2\sigma^2(S) - 2cov[S(t-T),S(t)],$$

approaches $2\sigma^2(S)$. Thus the slope in the regression of s(t,t+T) on s(t-T,t) approaches -0.5 for large T.

For long horizons, the slope $\alpha(T)$ is also (minus) the proportion of the variance of s(t,t+T) explained by mean reversion. If S(t) is stationary with a zero mean, as T increases the expected change, $E_t[s(t,t+T)]$, approaches -S(t), and the variance of the expected change approaches $\sigma^2(S)$. Thus, the ratio of the long-horizon variance of the expected change in S(t), $\sigma^2(S)$, to the long-horizon variance of the actual change, $2\sigma^2(S)$, is 0.5.

For example, if S(t) is a first-order autoregression (AR1),

(6)
$$S(t) = \delta S(t-1) + e(t), \quad 0 < \delta < 1,$$

the expected change from t to t+T is

(7)
$$E_{t}[s(t,t+T)] - (\delta^{T}-1)S(t),$$

and the covariance in the numerator of $\alpha(T)$ is

(8)
$$\operatorname{cov}[s(t,t+T),s(t-T,t)] = (-1+2\delta^{T}-\delta^{2T})\sigma^{2}(S) = -(1-\delta^{T})^{2}\sigma^{2}(S).$$

With (7) and (8) we can infer that the covariance is minus the variance of the T-period expected change, $-\sigma^2[E_ts(t,t+T)]$. Thus, when S(t) is an AR1, the slope in the regression of s(t,t+T) on s(t-T,t) is (minus) the ratio of the variance of the expected change in S(t) to the variance of the actual change. For other stationary processes, this interpretation of the slope is an approximation which is valid for long return horizons.

Equation (7) shows that when δ is close to 1.0, the expected change in an AR1 slowly approaches -S(t). Likewise, the slope $\alpha(T)$ is close to 0.0 for short return horizons and slowly approaches -0.5. This illustrates that the slow decay of a stationary price component with high positive serial correlation can generate serial correlations that are close to 0.0 at short horizons but substantially negative at longer horizons. This is the pattern observed for 1- to 5-year returns in Table 1. To explain why serial correlations for longer horizons move toward 0.0, we consider the joint effects of stationary and random-walk price components.

C. The Time-Series Properties of Returns

Using (2) and (3), the slope in the regression of $r_i(t,t+T)$ on $r_i(t-T,t)$, the first-order serial correlation between T-period returns, is

(9)
$$\rho_{i}(T) = cov[r_{i}(t,t+T),r_{i}(t-T,t)]/\sigma^{2}[r_{i}(t-T,t)]$$

(9a)
$$= \alpha(T) \gamma_{i}^{2} \sigma^{2}[s(T)] / \{\gamma_{i}^{2} \sigma^{2}[s(T)] + \Sigma_{f} \phi_{if}^{2} \sigma^{2}[w_{f}(T)] + \sigma^{2}[v_{i}(T)] \}.$$

(9b)
$$\approx -\gamma_{i}^{2} \sigma^{2} [E_{t} s(t, t+T)] / \sigma^{2} [r_{i}(t-T, t)],$$

where $\sigma^2[s(T)]$, $\sigma^2[w_f(T)]$, and $\sigma^2[v_i(T)]$ are the variances of the T-period changes, s(t,t+T), $w_f(t,t+T)$, and $v_i(t,t+T)$.

Equation (9a) helps predict the behavior of the slopes as the return horizon T increases. The mean reversion of S(t) tends to push the slopes toward -0.5 for long return horizons. However, the white-noise variances, $\sigma^2[\mathbf{w_f}(T)] \quad \text{and} \quad \sigma^2[\mathbf{v_i}(T)], \quad \text{grow in proportion to T, while } \sigma^2[\mathbf{s}(T)]$ approaches $2\sigma^2(S)$. Since the white-noise variances grow without bound, the slopes in regressions of $\mathbf{r_i}(t,t+T)$ on $\mathbf{r_i}(t-T,t)$ move toward 0.0 for large values of T. In short, the return model (2) offers the hypothesis that the U-shaped pattern of serial correlations for increasing return horizons is due to the interplay of a single common stationary price component S(t), which is relatively more important in the variation of shorter-horizon returns, and random-walk price components, which are relatively more important in the variation of long-horizon returns.

D. The Variation of Expected and Actual Returns Due to S(t)

Expression (9b) highlights the result that, for long return horizons, the slope in the regression of $r_i(t,t+T)$ on $r_i(t-T,t)$ measures the proportion of the variance of T-period returns due to the time-varying expected return generated by the stationary price component S(t). For 3-, 4- and 5-year decile portfolio returns, simple OLS slopes (which are relatively unbiased when the true slopes are negative) average -0.31, -0.39, and -0.37 (Table 1). Slopes for industry portfolios, shown later, are similar. Thus, estimated time-variation of expected returns is around 35% of 3- to 5-year return variances, a conclusion documented with direct tests of predictive power in Fama and French (1986).

Moreover, the limiting argument for the serial correlations says that the variance of the expected change in S(t) approaches half the variance of the long-horizon change in S(t). Thus, serial correlations that average -0.31 or less estimate that 60% or more of 3- to 5-year return variances are due to the

stationary price component S(t). These large proportions of variance motivate our interest in tests of the hypothesis that negative serial correlation is due to a single common factor.

IV. UNIVARIATE REGRESSIONS FOR DECILE PORTFOLIOS

A. Testing Properties of Factors: The Problem

Factor analysis and principal component methods for estimating factor structures extract linear combinations of underlying factors. Since these methods cannot isolate individual factors, they do not allow tests of properties of individual factors. We work around this problem. A portfolio presumed to load heavily on the stationary price component S(t) is used as the explanatory portfolio in univariate regressions. If a single portfolio absorbs the negative serial correlation observed for a range of portfolios presumed to load differently on common factors, then the hypothesis that negative serial correlation is due to a single common factor is consistent with the data.

The univariate regressions are of form,

(10)
$$r_i(t,t+T) = \alpha_i(T) + \beta_i(T)r_s(t,t+T) + \epsilon_i(t,t+T).$$

We assume that the decile portfolio i and the explanatory portfolio s are so diversified their returns have negligible firm-specific variation,

(11)
$$r_i(t,t+T) = \gamma_i s(t,t+T) + \Sigma_f \phi_{if} w_f(t,t+T),$$

(12)
$$r_s(t,t+T) = \gamma_s s(t,t+T) + \Sigma_f \phi_s f^w f^{(t,t+T)}$$
.

With (11) and (12), the slope $\beta_i(T)$ in (10) is

(13)
$$\beta_{i}(T) = \text{cov}[r_{i}(t, t+T), r_{s}(t, t+T)] / \sigma^{2}[r_{s}(t, t+T)]$$

$$= \frac{\gamma_{i}\gamma_{s}\sigma^{2}[s(T)] + \Sigma_{f} \phi_{if}\phi_{sf}\sigma^{2}[w_{f}(T)]}{\gamma_{s}^{2}\sigma^{2}[s(T)] + \Sigma_{f} \phi_{sf}^{2}\sigma^{2}[w_{f}(T)]}.$$

Substituting (12) into (10) and equating the result with (11) gives an expression for the regression residual,

(14) $\varepsilon_i(t,t+T) = [\gamma_i - \gamma_s \beta_i(T)] s(t,t+T) + \Sigma_f [\phi_{if} - \phi_{sf} \beta_i(T)] w_f(t,t+T) - \alpha_i(t,t+T)$ We assume that the factors are independent, so serial correlations of the residuals in (14), like serial correlations of returns, are weighted averages of the serial correlations of the factors. The (bracketed) coefficients for factors in (14), and the factor loadings for returns in (2), are squared in serial correlations. Thus, positively autocorrelated factors increase the autocorrelations of both the residuals and the returns, and negatively autocorrelated factors reduce their autocorrelations.

B. Choosing the Explanatory Portfolio

Our goal is to choose an explanatory portfolio that produces residuals that have little of the serial correlation of s(t,t+T), the common component assumed to generate all negative serial correlation in returns. Equation (14) implies that such a portfolio must produce slopes $\beta_i(T)$ close to γ_i/γ_s in 3- to 5- year returns. If $\beta_i(T)$ is to be close to γ_i/γ_s for a wide range of portfolios i, then (13) says that the explanatory portfolio's loadings on the common random walks, ϕ_{sf} , must be small relative to γ_s , its loading on the common stationary component. Equivalently, variation in returns on the explanatory portfolio must be heavily weighted toward s(t,t+T).

The serial correlations in Table 1, and the limiting arguments for serial correlations in Section III, imply that mean-reversion in prices explains more of the variation of returns for small-firm portfolios. Concretely, serial correlations less than -0.4 for small-firm portfolios suggest that $\sigma^2[s(T)]$ is 80% or more of 3- to 5-year return variances. Thus, univariate regressions should do better extracting negative serial correlation generated by s(t,t+T) -- the negative serial correlation of returns should be less evident in residuals -- when the explanatory portfolio is a small-firm portfolio.

If negative serial correlation of decile (and later, industry) returns is due to multiple factors on which firms load differently, a single explanatory portfolio is unlikely to absorb the serial correlation of returns for all deciles (and industries). Thus, residual serial correlations can reject the hypothesis that negative serial correlation is due to one common factor when the hypothesis is false. Moreover, even if negative serial correlation is due to one common factor, a small-firm explanatory portfolio may not load enough on s(t,t+T) to absorb the serial correlation s(t,t+T) generates in other portfolio returns. Thus, the tests are probably biased toward rejecting the hypothesis that negative serial correlation is due to one common factor when the hypothesis is true.

B. Residual Serial Correlations

Table 3 shows serial correlations of residuals from regressions of deciles 2 to 10 on decile 1 (smallest firms). The bias-adjusted serial correlations are all positive. This finding, that a single portfolio absorbs the negative serial correlation of returns for all deciles, is consistent with the hypothesis that the serial correlation, and the time-variation of expected returns it implies, is due to one common factor.

Equation (14) implies that when the explanatory portfolio absorbs the negative serial correlation of s(t,t+T), regression residuals have information about the serial correlation of other factors. The bias-adjusted residual serial correlations in Table 3 are all positive and are often large in magnitude and relative to standard errors. Moreover, when true residual serial correlations are positive, the Fama-French (1986) bias adjustments (for models with no serial correlation) are too small and the "bias-adjusted" serial correlations are biased downward. See Kendall (1954) or Marriot and Pope (1954). In short, the residual serial correlations suggest that one or

more of the common "random-walks", $W_f(T)$, f=1,...,F, generate positive serial correlation in returns. Time-variation of expected returns is richer than implied by the model of (1) and (2).

C. Regression Slopes

Table 4 shows the slopes from the regressions of deciles 2 to 10 on decile 1 (smallest firms). For comparison, slopes from the regressions of deciles 1 to 9 on decile 10 (largest firms) are also shown. When the explanatory portfolio is decile 1, deciles 2 to 10 produce slopes that are less than 1.0 and decline with the return horizon. For example, $\beta_{\bf i}({\bf T})$ for decile 10 starts at 0.40 in 1-year returns and drops to 0.09 in 10-year returns. In contrast, when the explanatory portfolio is decile 10, the slopes for deciles 1 to 7 start out greater than 1.0, decline with the return horizon, and decline more for smaller deciles. For example, $\beta_{\bf i}({\bf T})$ drops from 1.48 for 1-year returns on decile 1 to 0.38 for 10-year returns.

Previous work on monthly returns (Banz 1981 and Huberman and Kandel 1985), shows that slopes are higher when small-firm portfolios are regressed on large-firm portfolios and correlations are higher for portfolios of firms similar in size. The new evidence in Tables 2 and 4 is that correlations and slopes for portfolios of firms that differ much in size decline with the return horizon. This behavior is consistent with the following view of (2):

(a) larger short-horizon correlations and slopes for firms that differ a lot in size are due to the mean-reverting price component S(t), which becomes less important in the variation of long-horizon returns, and (b) other common factors in returns for the largest and smallest firms are largely independent.

IV. TESTS ON INDUSTRY PORTFOLIOS

If firms in each industry are distributed across deciles, industry factors that generate negative serial correlation may look like a single market factor in decile portfolios. Tests on industry portfolios may overturn the conclusion that negative serial correlation is due to one common factor.

A. Properties of Industry Portfolios

We form 17 industry portfolios using Standard Industrial Classification codes. One (necessarily vague) criterion in defining an industry is that it contains firms in similar activities. The other criterion is that the industry produces diversified portfolios during the 1926-85 period. Table 5 shows the number of firms and the average of the deciles of firms in each industry at 10-year intervals. Each industry has at least 7 firms (15 after 1929), and the number of firms per industry is usually greater than 30.

The average of the deciles of firms in an industry ranges from 3.8 to 8.3; most are between 4.0 and 7.0. The detailed distribution of firms across deciles at the end of 1985 in Table 5 (distributions for other years are similar) confirms that within industries there is little concentration of firms in specific deciles. Size and industry are not proxies. Thus industry portfolios can provide additional evidence on the hypothesis that negative serial correlation is due to one common factor.

B. Serial Correlation of Returns

Table 6 shows first-order serial correlations for the industry portfolios for return horizons from 1 to 10 years. The U-shaped pattern of serial correlations for increasing return horizons observed for the decile portfolios (Table 1) is clear in industry portfolios. As for the deciles, bias-adjusted

serial correlations of 3- to 5-year industry returns are negative and usually large in magnitude and relative to standard errors.

If true serial correlations are negative and on the order of the estimates for 3- to 5-year industry returns, unadjusted serial correlations are relatively unbiased. (See Fama and French 1986.) Using the analysis in Section III, the average serial correlations of 3-, 4-, and 5-year industry returns, -.35, -.45, and -.46, suggest that around 80% of the variances of 3-to 5-year returns are due to stationary (and thus mean-reverting) price components, and time-varying expected returns generated by stationary price components account for about 40% of 3-to 5-year return variances.

C. Serial Correlation of Residuals

If negative serial correlation of returns is due to a single stationary price component S(t), an explanatory portfolio, decile 1, that loads heavily on S(t) is again a candidate to absorb the serial correlation. The evidence from regressions of industry returns against decile 1 is similar to that for the deciles. The bias-adjusted residual serial correlations for the industries (Table 7) are mostly positive. Again, these results are consistent with the hypothesis that negative serial correlation of portfolio returns is due to one (and the same) stationary component of prices.

As for the deciles, residual serial correlations for industry portfolios are mostly positive, and some are large in magnitude and relative to their standard errors. There is again the suggestion that when the common factor that generates negative serial correlation is removed, other factors on balance generate positive serial correlation in returns. Time variation of expected returns seems to be a multi-factor phenomenon.

V. TESTS ON 82 STOCKS LISTED FOR 1926-85

Since the decile and industry portfolios are diversified, firm-specific factors contribute little to the variation of their returns. The evidence that negative serial correlation of 3- to 5-year portfolio returns is due to one common factor does not rule out serial correlation in individual stock returns due to firm-specific factors. If the serial correlation of returns has important firm-specific components, then neither the variation through time of expected returns nor the period-by-period cross-sections of expected returns can be explained in terms of common factors. Evidence of important firm-specific serial correlation would substantially diminish the general enthusiasm for parsimonious equilibrium pricing models.

Reliable inferences about the serial correlations of long-horizon returns require long sample periods, but the population of NYSE stocks changes through time. Our solution to this problem is to study the 82 stocks listed for the entire 1926-85 period. Table 8 summarizes first order serial correlations on the 82 stocks, and on an equal-weighted portfolio of the stocks, for return horizons from 1 to 10 years.

Since more of the variation of individual stock returns is due to firmspecific factors, serial correlations for individual stocks need not replicate
the pattern observed for portfolios. If firm-specific factors have positive
or no serial correlation, negative serial correlation of long-horizon returns
is weaker for individual stocks than for portfolios. On the other hand,
stationary components of individual stock prices due to over-reaction to firmspecific information (market inefficiency) can mean that long-horizon returns
on individual stocks have more negative serial correlation than portfolios.

The portfolio of the 82 stocks produces a U-shaped pattern of serial correlations similar to those observed for decile and industry portfolios.

The bias-adjusted serial correlations of 3-, 4-, and 5-year returns on this portfolio (Table 8) are -0.38, -0.38, and -0.29, and they are at least 2.4 standard errors below 0.0. The serial correlation of returns on the 82 individual stocks is weaker. The averages of the (82) 3-, 4-, and 5-year bias-adjusted serial correlations are -0.16, -0.14, and -0.07, and the serial correlations are on average -1.12, -1.10, and -0.62 standard errors from 0.0.

Table 8 also summarizes serial correlations of residuals from regressions of the 82 stocks, and the portfolio of the 82, on decile 1. Again, decile 1 absorbs the strong negative serial correlation of the 3- to 5-year portfolio returns; the regression residuals for the portfolio of the 82 stocks show no evidence of negative serial correlation. More interesting, even the hint of negative serial correlation of the individual stock returns disappears in the regression residuals. The average residual serial correlations for the 82 stocks are close to 0.0 for all return horizons, and the distributions of the serial correlations are roughly symmetric about 0.0. Thus, the residuals for the 82 stocks also do not show the positive residual serial correlation observed for decile and industry portfolios.

Heavy-handed conclusions from this rather special sample of stocks are inappropriate, but the results are consistent with the hypothesis that the firm-specific components of stock returns have no serial correlation. This evidence is heartening for proponents of parsimonious pricing models.

VI. TESTS ON "WINNER" AND "LOSER" PORTFOLIOS

Negative serial correlation indicates a tendency toward reversal. When long-horizon returns are low relative to their means, future returns tend to be high, and vice versa. The tests are consistent with the hypothesis that the reversal tendency in decile and industry returns is market-wide and due to

a single factor. The tests that follow look for contemporaneous reversals that have opposite signs for different portfolios and so are not market-wide.

A. The Extreme 35

The first tests are similar to De Bondt and Thaler's (1985). At the end of each of 19 non-overlapping 3-year periods, 1926-28,..,1980-82, the 35 stocks with the highest returns for the period are put in a winner portfolio; the 35 with the lowest returns are a loser portfolio. Portfolio formation periods end in November. Returns for the following 3 years, beginning in January, are examined for reversals. We skip a month to avoid spurious reversals due to any tendency for loser (winner) portfolios to choose stocks that happen to trade at bid (ask) prices at the end of formation periods.

The average 3-year continuously compounded return (Table 9) for the loser portfolio for the 19 portfolio formation periods is -1.11, a loss in value of 67%. The average return for the winner portfolio is 1.34, a gain in value of 380%. As such wealth changes suggest, firms in the loser portfolio tend to be smaller when portfolios are formed than firms in the winner portfolio. The average of the vitile ranks (1/20th of the NYSE in ascending order of size) of stocks in the loser portfolio at the end of the portfolio formation periods is 5.25, versus 11.77 for the winners (and 10.5 for all stocks on the NYSE).

Since average returns are inversely related to size (Banz 1981), comparison of post-formation returns on loser and winner portfolios might suggest reversals (the losers do better than the winners) because the losers tend to be smaller. We compare post-formation returns on the winner or loser portfolio to returns on matching portfolios of firms similar in size when portfolios are formed. The control portfolio for the losers matches each with the firm smaller but closest in size. If there is no smaller firm (the 35 losers often include several of the 10 smallest firms), the larger firm

closest in size is chosen. The control portfolio for the winners matches each with the firm larger but closest in size.

The matching portfolios have average firm sizes and market betas similar to the winner and loser portfolios. Average values of winners or losers are usually within 2% of average values of firms in the matching portfolios (Table 9). Betas for the winner portfolio and its matching portfolio, calculated by regressing monthly post-formation returns for 1929-85 against the NYSE value-weighted market portfolio, are 1.22 and 1.24. Betas for the loser portfolio and its matching portfolio are 1.51 and 1.45.

Part A of Table 10 shows average returns on the winner and loser portfolios, net of size-matched portfolio returns, for the 3 Januaries following portfolio formation. Like De Bondt and Thaler (1985), we find January reversals. The differences between size-adjusted January returns on the loser and winner portfolios are greater than 4.3% and more than 2.3 standard errors from 0.0. Relative to control portfolios similar in size and market beta, there are reversals in winner and loser returns for at least three Januaries after portfolio formation.

Since securities are held throughout the year, we are more interested in reversals in cumulative returns. Post-formation cumulative size-adjusted returns on the loser portfolio (Part B of Table 10) are always positive.

After the first January, however, cumulative loser returns (those shown and not shown) are never close to 2.0 standard errors from 0.0. After 3 years, the cumulative size-adjusted return on the loser portfolio is 5.18% and 0.64 standard errors from 0.0. In contrast, the 3-year size-adjusted return on the winner portfolio is -14.81% and 2.42 standard errors from 0.0. Cumulative size-adjusted return reversals are larger and more reliable for the winner portfolio. The difference between the 3-year size-adjusted returns on the

loser and winner portfolios is 19.99% and 1.70 standard errors from 0.0 -- suggestive but not overwhelming evidence of a reliable difference.

Our results differ some from those of De Bondt and Thaler (1985). For example, they find reliable reversals for losers but not for winners. The differences have many sources. Our sample is larger (19 versus 16 3-year periods). They use average simple returns, and we use compound returns, which are more relevant for hypotheses about long-term price reversals. We control for size; they use market-adjusted (equal-weighted NYSE) returns. When we market-adjust (Part B of Table 10), 3-year return reversals are similar for losers (14.1%) and winners (-16.8%), and the difference (30.8%) is 2.2 standard errors from 0.0 -- results more similar to theirs, and subject to criticism for failure to control for differences in winner and loser firm sizes. The fact that results are sensitive to technique means that even for extreme winners and losers, evidence of return reversals is not strong.

B. Winners and Losers within Deciles

The winner and loser portfolios focus on the outliers of the two groups. In contrast, the decile and industry tests identify common reversal behavior for portfolios that cover all stocks. We test next for a general tendency toward reversals among winners and losers. At the end of non-overlapping 3-year periods, the stocks in each decile are placed in three portfolios, based on returns for the 3-year period. The 25% with the highest returns are the winner portfolio for the decile. The 25% with the lowest returns are the loser portfolio. The remaining 50% are the control portfolio for the decile.

Table 11 shows means and their t's for differences between the January return on the winner or loser portfolio of each decile and the return on the decile control portfolio. For the three Januaries after portfolio formation, size-adjusted returns on loser portfolios are positive and usually large

relative to their standard errors, even for large-firm deciles. For winner portfolios, size-adjusted returns are negative and typically large relative to their standard errors for the first two Januaries after portfolio formation. Thus, as in Chan (1985) and Grier (1985), January returns suggest reversal behavior that is pervasive across deciles and persists for several years.

Again, since stocks are held throughout the year, we are more interested in cumulative reversals. Table 12 shows average 3-year returns for the winner and loser portfolios of the deciles. There is no evidence of reversals in size-adjusted returns on loser portfolios; the returns split evenly (5 deciles each) between positive and negative. All size-adjusted 3-year returns on the winner portfolios are negative, but only two (deciles 2 and 10) are more than 2.0 standard errors from 0.0. Returns (not shown) for horizons less than 3 years are similar. Unlike the curious January returns, cumulative returns for winner and loser portfolios of the deciles show little evidence of reversals.

To put the results in perspective, when 3-year returns are averaged across deciles (last column of Table 12), the difference between postformation returns on loser and winner portfolios is 5.27% (1.08 standard errors from 0.0). The difference between average 3-year returns on the winner (78.5%) and loser portfolios (-40.2%) during portfolio formation periods is 118.7%. Thus post-formation returns on average reverse less than 5% of the difference between formation period returns on winners and losers. This is much weaker and statistically less reliable than the 25-40% average return reversals implied by the negative serial correlation of 3- to 5-year decile and industry returns.

De Bondt and Thaler (1986) interpret their reversal results in terms of market over-reaction (inefficiency). Even putting aside the issues raised above about the robustness and pervasiveness of the evidence, market

inefficiency is not the only possibility. Higher returns on losers than on winners may imply the discovery of dimensions of risk and rational timevarying expected returns not captured by market betas or firm size.

Moreover, the evidence does not lean clearly toward inefficiency. For example, reversals are always measured using market-adjusted returns (theirs) or size-adjusted returns (ours). Negative adjusted returns on the winner portfolios do not imply negative raw returns. Even for January (Tables 10 and 11), unadjusted average winner returns are almost always positive. Cumulative unadjusted returns (Tables 10 and 12) are always substantial and positive.

VI. CONCLUSIONS

There is a U-shaped pattern in first-order serial correlations of portfolio returns for increasing return horizons. Serial correlations become negative for 2-year returns, reach minimum values in 3- to 5- year returns, and then move back toward 0.0 for longer return horizons. This pattern is interpreted with a model in which stock prices are a mix of random walks and a slowly decaying, highly autocorrelated, stationary component. The negative serial correlation of returns generated by a slowly decaying price component is weak at the short return horizons common in empirical work, but it becomes substantial as the return horizon increases. Eventually, random-walk price components dominate the variation of returns, and long-horizon serial correlations move back toward 0.0.

The point estimates of the serial correlations, and the tests of forecast power in Fama and French (1986), suggest that the stationary price component generates a substantial fraction of return variation. Serial correlations in the neighborhood of -0.25 to -0.40 suggest that 25-40% of the variances of 3-to 5-year returns is due to time-varying expected returns generated by the

mean reversion of the stationary price component, and the stationary price component generates 50-80% of the variances of 3- to 5-year returns.

In regression tests, a single explanatory portfolio, decile 1 (smallest firms), presumed to load heavily on the stationary price component, absorbs the negative serial correlation of all decile and industry portfolio returns. This evidence is consistent with the hypothesis that the pervasive negative serial correlation of returns is due to a single common factor. Positive serial correlation of regression residuals then suggests that other factors on balance generate positive serial correlation in returns. Time-variation of expected returns is a multi-factor phenomenon.

The equal-weighted portfolio of the 82 stocks listed on the NYSE for the entire 1926-85 period produces a U-shaped pattern of serial correlations much like the decile and industry portfolios. For the 82 individual stocks, the pattern is weak, at best. Moreover, residuals from regressions of the 82 individual stocks on decile 1 show no evidence of serial correlation, positive or negative. These results are consistent with the hypothesis that the serial correlation of portfolio returns (both the negative serial correlation of raw portfolio returns and the positive serial correlation of regression residuals) is due to common factors. Since evidence to the contrary would imply firmspecific variation in expected returns, these results are heartening for enthusiasts of equilibrium pricing models.

The tendency toward reversal implied by the negative serial correlation of decile and industry portfolio returns may reflect time-varying expected returns generated by rational investor behavior and the dynamics of common macro-economic driving variables. On the other hand, reversals generated by a stationary component of prices may reflect market-wide waves of over-reaction of the kind assumed in models of an inefficient market. The fact that tests

of market efficiency are not possible without arbitrary restrictions on the behavior of equilibrium expected returns means that the issue is not resolvable. See Fama (1970).

In short, Fama and French (1986), and the results presented here are evidence of predictable variation in long-horizon returns stronger than measured in previous studies that concentrate on short-horizon (daily or monthly) returns. Whether predictability reflects market inefficiency or time-varying expected returns generated by rational investor behavior is, and will remain, an open issue.

REFERENCES

- Banz, Rolf W., 1981, "The Relationship between the Return and the Market Value of Common Stocks", <u>Journal of Financial Economics</u> 9 (?): 3-18.
- Bodie, Zvi, 1976, "Common Stocks as a Hedge Against Inflation", <u>Journal of Finance</u> 31 (May): 459-70.
- Chan, K. C., 1985, "Can Tax Loss Selling Explain the January Seasonals in Stock Returns?", working paper, Ohio State University, forthcoming in the Journal of Finance.
- De Bondt, Werner F. M., and Richard Thaler, 1985, "Does the Stock Market Overreact?", <u>Journal of Finance</u> 40 (July): 793-805.
- Fama, Eugene F.,1970, "Efficient Capital Markets: A Review of Theory and Empirical Work", <u>Journal of Finance</u> 25 (May): 383-417.
- Fama, Eugene F., 1981, "Stock Returns, Real Activity, Inflation, and Money", American Economic Review 71 (September): 545-65.
- Fama, Eugene F., and Kenneth R. French, 1986, "Permanent and Temporary Components of Stock Prices", Working Paper No. ?, Center for Research in Security Prices, University of Chicago, May, revised July.
- Fama, Eugene F., and G. William Schwert, 1977, "Asset Returns and Inflation", Journal of Financial Economics 5 (November): 115-46.
- French, Kenneth R., Robert Stambaugh, and G. William Schwert, 1986, "Expected Stock Returns and Volatility", manuscript, Graduate School of Business, University of Chicago (April).
- Grier, John, 1985, "The Relationship between Past Price Declines and Stock Returns", Honors Paper, Graduate School of Business, University of Chicago, April.
- Hansen, Lars P., and Robert J. Hodrick, 1980, "Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis", <u>Journal of Political Economy</u> 88 (October): 829-53.
- Huberman, Gur, and Shmuel Kandel, 1985, "A Size Based Stock Returns Model", Working Paper No. 148, Center for Research in Security Prices, Graduate School of Business, University of Chicago (October).
- Huizinga, John, 1984, "Tests of Market Efficiency in Models with Multiperiod Forecasts", manuscript, Graduate School of Business, University of Chicago (February).
- Jaffe, Jeffrey, and Gershon Mandelker, 1976, "The 'Fisher Effect' for Risky Assets: An Empirical Investigation", <u>Journal of Finance</u> 31 (May): 447-58.
- Keim, Donald B., and Robert F. Stambaugh, 1986, "Predicting Returns in the Stock and Bond Markets", <u>Journal of Financial Economics</u>, forthcoming.

- Kendall, M. G., 1954, "Note on Bias in the Estimation of Autocorrelation", <u>Biometrica</u> 41 (?): 403-4.
- Lintner, John, 1965, "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets," Review of Economics and Statistics ? (February): 13-37.
- Marriot, F. H. C., and J. A. Pope, 1954, "Bias in the Estimation of Autocorrelations", <u>Biometrica</u> 41 (?): 390-402.
- Merton, Robert C., 1973, "An Intertemporal Capital Asset Pricing Model", <u>Econometrica</u> 41 (September): 867-87.
- Nelson, Charles R., 1976, "Inflation and Rates of Return on Common Stocks", <u>Journal of Finance</u> 31 (May): 471-83.
- Ross, Stephen A., 1976, "The Arbitrage Theory of Capital Asset Pricing", Journal of Economic Theory 13 (?): 341-60.
- Sharpe, William F., 1964, "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk," <u>Journal of Finance</u> 19 (September): 425-442.

Table 1 - OLS and Bias-Adjusted First-Order Serial Correlations for Deciles

					Return	Horizon	1	······································	***
Decile		lYr.	2Yr.	3Yr.			6Yr.	8Yr.	10Yr.
							relation		
Small	1	.00	17	33	51	51	29	.02	.09
	2	.02	11	29	51	58	44	34	32
	3	02	12	26	41	42	30	29	31
	4	.00	16	31	46	49	37	31	25
	5	03	19	29	39	42	30	25	25
	6	02	17	33	40	39	26	20	22
	7	05	24	36	37	33	18	12	20
	8	02	17	27	25	21	05	02	10
	9	01	20	32	28	18	01	.03	11
Large	10	03	22	34	27	15	.02	.10	07
Mean		02	18	31	39	37	22	14	17
			Part	B: Bias	-Adjuste	d Serial	Correla	tions	
Small	1	.02	12	25	41	39	13	.23	.36
	2	. 04	06	21	41	45	29	13	06
	3	.00	08	19	30	30	15	08	05
	4	.02	11	24	35	36	22	10	.02
	5	02	14	22	29	29	15	04	.02
	6	.00	12	25	30	26	10	.01	.05
	7	03	19	28	27	20	03	.09	.07
	8	.00	13	20	15	08	.10	.19	.17
	9	.01	16	24	18	06	.15	. 24	.15
Large	10	01	17	26	17	02	.18	.31	19
Mean		.00	13	23	28	24	06	.07	.10
				Par	t C: Sta	ndard Er	rors		
Smal1	1	.11	.15	.16	.15	.16	.19	. 26	. 24
	2	.11	.15	.16	.12	.12	.16	.22	.23
	3	.11	.15	.15	.12	.13	.16	. 20	.21
	4	.11	.15	.15	.11	.12	.15	.19	. 20
	5	.11	.15	.15	.12	.13	.16	.21	. 24
	6	.11	.15	.16	.12	.13	.17	.21	. 24
	7	.11	. 14	.15	.11	.13	.16	. 21	. 24
	8	.11	.15	.15	.12	.13	.15	.19	. 20
	9	.11	.15	.15	.13	.16	.19	. 27	.31
Large	10	.11	. 14	.15	.12	.14	.17	. 25	. 29

Note: OLS serial correlations in Part A are slopes in regressions of the return, $r_i(t,t+T)$, on the lagged T-year return, $r_i(t-T,t)$. The serial correlations in Part B use the bias adjustments (positive constants that increase with the return horizon and are added to the OLS slopes) of Fama and French (1985). The bias adjustments are relevant when true serial correlations are 0.0. Standard errors in Part C are adjusted for the overlap of monthly observations on T-year returns with the method of Hansen and Hodrick (1980). Since the bias adjustment is a constant for any given return horizon, standard errors apply to both OLS and bias-adjusted slopes.

Table 2 - Cross Correlations of Decile Portfolio Returns

		Cor	relati	lons of	- 1-Ye	ar Reti	ırns		
Decile	1	2	3	4	5	6	7	8	9
2	. 96								
3	.94	.98							
4	.93	.98	.99						
5	.91	.97	.98	.99					
					0.0				
6	.89	.95	.97	.98	. 98	00			
7	.89	. 94	.97	.98	. 98	. 99			
8	. 85	. 92	. 95	.96	. 97	.97	. 99		
9	. 84	. 90	.93	. 94	. 96	. 97	. 98	. 99	
10	.78	.85	.88	. 90	. 92	. 94	. 95	. 96	.98
		Co	orrelat	ions o	of 3-Ye	ear Ret	turns		
Decile	1	2	3	4	5	6	7	8	9
2	. 93	_	•	-	-	•	•	•	-
3		0.0							
	.87	.98	00						
4	. 87	.98	.99	0.0					
5	.85	. 96	.99	.99					
6	.81	.93	.96	. 98	. 98				
7	.81	.92	.96			.99			
8	. 74	.88	.95	.95		.97	.99		
9	.74	. 85	.91	.92	. 94	.97	. 98	. 98	
10	.62	. 75	.82	.85	.87	.91	. 93	. 94	.97
		Co	rralat	ione c	of 5-∀4	ear Ret	-11 r n e		
Decile	1	2	3	4	5	6	7	8	9
2		2.	5	4	,	U	′ =	O	
	.90	0.0							
3	. 80	. 96	0.0						
4	.81	. 97	.99						
5	.79	. 96	.99	.99					
6	.74	.93	.98	.98	.99				
7	. 73	.91	.98	.97	.98	.99			
8	.61	.85	.95	.94	. 95	. 97	.98		
9	.62	.83	.92	.91	.93	.96	. 97	.97	
10	.48	.72	.82		.86	.90	.92	. 94	.97
		0.			£ 10 1	Year Re			
D41-	1							8	9
Decile	1	2	3	4	5	6	7	0	7
2	.80								
3	. 47	.87							
4	.57	. 92	.97						
5	.52	.88	.97	.97					
6	.47	.84	.97	.96	.98				
7	. 39	.77	.96	.93	.97	.99			
8	.15	.63	.92	.86	.90	.93	.96		
9	.27	.64	.87	.83	.89	.94	.96	. 94	
10	.16	.53	.81	.77	.83	.89	.93	.93	.98
10									. , ,

Table 3 - Serial Correlations of Residuals from Regressions of Decile Portfolios on Decile 1

				Return	Horizon			
Decile	1Yr.	2Yr.	3Yr.	4Yr.	5Yr.	6Yr.	8Yr.	10Yr.
				Serial C	orrelati	on.		
Small 2	.30	.40	.32	.15	.03	05	09	19
3	.35	.48	.46	.41	.31	.21	.03	09
4	.33	. 32	. 27	.17	.07	02	07	03
5	.24	.21	.16	.18	.11	.04	03	15
6	.32	.18	.10	.13	.12	.10	.02	09
7	.23	.13	.10	.21	. 20	.17	.07	11
8	.23	. 25	. 20	. 28	. 25	.22	.07	06
9	.25	.15	.09	.17	.22	.23	.11	09
Large 10	.25	.12	04	.00	.07	.13	.13	07
			Rias-Ad	ljusted S	erial Co	rrelatio	n	
Small 2	.32	.45	.39	.25	.16	.10	.12	.07
3	.37	.52	. 54	.51	.44	.37	. 24	.18
4	.35	.37	. 35	.27	.19	.14	.14	.23
5	.25	.25	. 24	.28	. 24	.20	.18	.12
6	.34	. 23	.17	. 23	. 25	.26	.23	.18
7	. 25	.17	.18	. 31	.33	.32	.28	.16
8	.25	.29	. 28	. 38	.38	.38	.28	.21
9	. 27	.20	.16	. 27	. 34	.38	.32	.18
Large 10	. 27	.17	. 04	.10	.20	. 29	. 34	. 20
				Standa	rd Error			
Small 2	.11	.14	17	.17	.18	.19	.22	. 24
3	.11	.14	.15	.13	.15	.17	.20	.19
4	.11	.16	.18	.16	.16	.17	.19	.19
5	.11	.17	.18	.16	.17	.20	.23	. 24
6	.11	.17	. 20	.17	.16	.18	.22	. 24
7	.11	.17	.19	.15	.15	.17	.22	.23
8	.11	.17	.18	.14	.14	.16	.19	. 20
9	.11	.17	. 20	.17	.18	.21	.28	.31
Large 10	.11	.17	.20	.17	.16	.19	.26	.30

Note: The bias adjustments of the serial correlations (positive constants that increase with the return horizon and are added to the OLS serial correlations) are from Fama and French (1985). They are the proper bias adjustments when the true serial correlations are 0.0. When the true serial correlations are positive, the bias adjustments are too small and the "bias-adjusted" serial correlations are still biased downward. See Kendall (1954) or Marriott and Pope (1954). The standard errors of the serial correlations are adjusted for the overlap of monthly observations on T-year returns with the method of Hansen and Hodrick (1980).

Table 4 - Slopes in Regressions of Decile Portfolios on Decile 1 or 10

					Return Hori:	zon			
<u>Decile</u>	e	lYr.	2Yr	. 3Yr	. 4Yr.	5Yr.	6Yr.	8Yr.	10Yr
			OLS	Slope:	Explanatory	Variable	is De	ecile 1	
Small	2	.81	. 80	.80	-	.78	.74	.61	.56
	3	.75	.72	.70	.67	.63	. 57	. 38	. 33
	4	. 69	.67	.65	.62	.58	. 52	.37	.34
	5	. 64	.61	. 58		.53	.48	. 36	.33
	6	.61	.57	.55		.48	.42	. 30	.29
	7	. 59	. 55	.52		.44	.38	. 26	. 24
	8	. 53	.49	.46		. 36	. 28	.13	.10
	9	.49	.46	.42		. 34	. 28	.18	.18
Large	10	.40	.36	.31		.22	.17	.08	.09
			OLS S	Slope: E	xplanatory \	Variable	is Dec	ile 10	
Smal1	1	1.48	1.38	1.19		1.00	.74	. 32	.38
	2	1.37	1.32	1.26		1.29	1.17	.79	.71
	3	1.36	1.31	1.28		1.36	1.32	1.10	1.04
	4	1.29	1.28	1.24		1.27	1.20	.95	.87
	5	1.24	1.20	1.16		1.18	1.14	.98	.91
	6	1.24	1.22	1.20		1.23	1.20	1.09	1.04
	7	1.21	1.19	1.15		1.15	1.12	1.03	1.01
	8	1.15	1.14	1.13		1.16	1.16	1.10	1.05
Large	9	1.10	1.10	1.10		1.11	1.11	1.12	1.13
		Stan	dard En	ror of	Slope: Expla	natory V	ariabl	e is Dec	ile 1
Small	2	.03	.04	.06	.07	. 07	.09	.10	.09
	3 =	.03	. 05	.07	.08	.09	.11	.15	.15
	4	.03	.05	.07	.08	.09	.10	.12	.11
	5	.03	.05	.07	.07	.08	.09	.12	.12
	6	. 04	.05	.07	.08	.09	.10	.13	.14
	7	. 04	.05	.07	.07	.08	.09	.13	.14
	8	. 04	.06	.08	.08	.09	.11	.14	.15
	9	.04	.05	.07	.08	.08	.10	.14	.17
Large	10	.04	.05	. 07	.08	.08	.09	.13	.15
		Stan	dard Er	ror of S	Slope: Expla	natory V	ariabl	e is Dec:	ile 10
Small	1	.14	.21	.27	.33	. 38	.42	. 54	.60
	2	.10	.15	.20	. 24	. 26	. 28	. 30	.30
	3	.08	.12	.16	.19	.19	. 20	. 20	.18
	4	.07	.11	.14	.16	.18	.19	.19	.18
	5	.06	.09	.12	. 14	.15	.16	.18	.17
	6	.05	.07	.09	.11	.12	.13	. 14	.13
	7	.05	.07	.08	.10	.11	.11	.11	.10
	8	.04	.06	.07	.08	.09	.09	. 11	.11
Large	9	.03	.04	.05	.05	.06	.06	.06	.05

Note: The standard errors of the OLS slopes are adjusted for residual serial correlation induced by the overlap of monthly observations on T-year returns with the method of Hansen and Hodrick (1980).

Table 5 - Number of Firms and Average Decile for Industry Portfolios

							71	- 4	/\1-·	- Ft : #							
Year	1	2	3	4	5	6	Indu 7	stry 8	(Name		ow) 11	19	13	14	15	16	17
<u>lear</u>																10	
								ms in									
1925	43	24	23	33	16	30	11	16	29	19	91	35	12	8	46	22	43
1935	61	30	35	63	27	37	32	37	54	23	99	60	20	15	57	31	40
1945	72	38	38	66	36	47	39	38	69	35	111	82	29	18	69	32	37
1955	83	46	36	73	56	44	52	47	87	96	119	102	40	18	78	32	47
1965	83	60	52	83	84	33	71	80	107	115	96	168	46	31	62	35	46
1975	81	61	49	111	102	37	92	224	153	147	79	179	42	33	5 3	33	56
1985	51	40	45	88	91	27	76	264	186	142	68	179	41	30	45	33	66
				Avera	ige of	Deci	les	for F	irms	in In	dustr	y Port	folic)			
1925	5.2	3.4	5.9	4.9	5.1	5.4	5.5			7.8		-	5.3		5.6	4.5	6.5
1935	6.4	5.0	6.9	3.9	5.2	6.7	6.2		6.0	5.3			4.7	7.8	4.9	5.7	4.3
1945	6.0	3.8	6.2	5.5	5.4	5.1	5.6		4.8	7.1			6.4	4.5	5.0	4.9	7.6
1955	4.9	3.4	5.3	4.5	4.9	4.2	5.7		5.1	7.6			6.7	4.9	6.0	4.9	8.3
1965	5.3	4.0	6.8	4.7	5.0	5.3	4.9		5.6	7.5			6.3	4.1	5.7	5.0	7.6
1975	5.9	3.9	7.5	5.2	4.9	5.8	4.9		5.3	7.0			7.0	4.6	5.5	6.3	7.5
1985	6.4	3.8	7.5	5.7	5.2	5.8	4.7		5.8	6.7	5.8		6.7	4.8	4.3	5.1	5.6
Decil		10	^		mber 12	or F1 2	rms :		en inc 12		у ру 5	Decile 19		4	7	1.	
1 2	6 2	4	0	9 8	7	3	2	38	20	1 6	3 4		3 2	3	7	4 2	6 6
3	2	5	3	8	10	2	14	31	11	11	5		1	4	7	3	11
4	3	7	4	7	10	4	11	22	21	8	7		3	3	3	3	10
5	3	3	4	10	12	4	6	22	19	19	12		3	3	6	5	10
6	8	4	0	10	9	2	5	21	26	18	9		2	4	2	6	5
7	6	4	3	6	9	0	10		19	19	4		7	5	10	3	4
8	4	1	4	11	9	1	5	28	17	22	7		7	2	0	6	5
9	8	2	8	9	í	3	8	27	22	25	9		8	1	1	Ö	5
10	9	ō	16	10	12	6	1	21	19	13	6	12	5	ī	2	1	13
														_	_	_	
	lustry	7		1.0								on Cod					
	ood					•		•		•	2180-	5189,	2191				
_	parel	-			200-23						,						
	ugs				.00-21		830-	2849,	2122	, 5194	4						
	etail urable	. ~			30-59		000	2000	2170	2626	266	9, 386	0.304	0 30	60 30	60	
טע כ	irabre	:5		23				3099, 40-504					0-394	,, ,,	00-39	09,	
6 Au	toc			27	3020 10-37		-		•	,,,,	3094-	3033					
		ction	1							2850	295	2, 320	n_329	0 3/	20-3/	30	
, 60	7115 CT 0	CCLOI	•	1.5				70-507				2, 320	0-323	, J4	20-34	.JJ,	
8 Fi	nance			60	00-69		, 50	,0-301	, , ,	., .	7211						
		.aneou	c				990-	2999	3110.	3119	319	0-3199	398	0-399	9 48	00-48	99
J 111	.50011	ancou	.5	20		•		•			•	-8999,	-			00 40	,,
10 11+	iliti	es		49	00-49	•	٠, ٥.		, -	,	. 555	,		,	-		
		rtati	on		20-37		790	3799	4000	-4790	9						
	-	s Equ										0-3959	. 506	0-506	9. 50	78 - 50	89
13 Ch		-	-pmci		00-28	•		•			, 5,5,		, 500	- 500	.,	. 5 50	-,
14 Me			ts		10-34	-											
15 Me					00-33	•	, , , ,	,	2000	2007							
16 Mi		.iuus t			00-33		400 - 1	499	5050-	5059							
17 Oi	_				00-12	•											
1/ 01				1.7	20-T2	, Z	J 1 U - Z	-/ 4/,	J = 1 0 -	J = 1 J							

Table 6 - OLS and Bias-Adjusted Serial Correlations for Industries

				Return I		(33	037	1.00
Industry	lYr.	2Yr.	3Yr.	4Yr.	5Yr.	6Yr.	8Yr.	10Yr.
			Part A:	OLS Sea	rial Corı	relation		
Food	01	23	38*	50*	53*	40*	40	40
Apparel	08	15	22	36*	44*	41*	55*	65*
Drugs	02	13	26	33*	39*	34	34	35
Retail	.01	14	31	40*	45*	36*	39	43
Durables	.04	13	29	41*	41*	24	20	16
Autos	04	20	37*	48*	43*	26	25	28
Construction	.01	12	31	51*	54*	38*	10	17
Finance	.01	15	29	34*	27	11	10	16
Miscellaneous	01	11	26	43*	47*	34*	27	28
Utilities	03	14	28	28	13	.08	13	27
Transportation	08	17	25	36*	36*	25	31	30
Bus. Equipment	.03	23	46*	54*	52*	40*	23	18
Chemicals	04	36*	52*	56*	57*	44*	27*	18
Metal Products	.01	23	- ,47 *	64*	70*	59*	46*	28
Metal Industries		30*	45*	51*	51*	37*	07	12
Mining	09	31*	46*	59*	65*	50*	26	17
Oil	.01	21	30*	44*	43*	27	07	20
	04	20	35	45	46	33	- , 26	27
Averages	04	20	-,55	.43	. 40		, _ ,	
		Par				1 Correla	ation	
Food	.01	18	31*	40*	40*	24	19	13
Apparel	06	11	14	26	31	25	34	38
Drugs	.00	08	18	23	26	19	13	08
Retail	.03	10	23	30*	32*	20	18	17
Durables	.06	08	21	31*	28*	09	.01	.11
Autos	02	16	30*	38*	30*	10	04	01
Construction	.03	07	23	41*	41*	23	.11	.09
Finance	.03	11	21	24	14	.05	.11	.11
Miscellaneous	.01	06	19	33*	34*	19	06	01
Utilities	01	09	21	18	.00	.23	.08	.00
Transportation	07	12	17	26*	23	10	10	03
	.04	18	38*	44*	39*	24	02	.09
Chemicals	02	32*	45*	46*	44*	28*	06	.09
Metal Products	.03	18	40*	54*	57*		25	01
Metal Industries		25	37*	41*	39*	22	.14	.15
Mining	07	26*	38*	49*	53*	35*	06	.09
Oil	.03	16	22	34*	31*	12	.14	.07
	00	15	27	35	33	17	05	00

Note: Serial correlations in Part A are slopes in regressions of the return on portfolio i from t to t+T, $r_i(t,t+T)$, on the lagged T-period return, $r_i(t-T,t)$. Serial correlations in Part B use the bias adjustments of Fama and French (1986), which are relevant when true serial correlations are 0.0. Starred (*) serial correlations are two standard errors from 0.0. Standard errors in these comparisons are adjusted for overlap of monthly observations on T-year returns with the method of Hansen and Hodrick (1980).

Table 7 - OLS and Bias-Adjusted First-Order Serial Correlations of Residuals from Regressions of Industry Portfolios on Decile 1

	Return Horizon										
Industry	lYr.	2Yr.	3Yr.	4Yr.	5Yr.	6Yr.	8Yr.	10Yr			
		Pai	rt A: OLS	Serial	Correlat	tion	··				
Food	03	.02	02	.12	.21	.08	07	29			
Apparel	.06	.00	.09	. 25	. 30	.13	12	38			
Drugs	.12	.16	.21	.19	.10	01	14	29			
Retail	.11	.05	01	.03	01	04	.01	21			
Durables	.32*	.35*	.29	.21	.10	.03	02	.00			
Autos	. 14	.11	.22	.31*	. 29*	.22*	.07	01			
Construction	.13	. 23	. 29	.15	.06	.00	.05	18			
Finance	.26*	.19	.10	.10	.17	. 20	.08	10			
Miscellaneous	.23*	.31*	. 32	.23	.14	.08	.02	12			
Utilities	.19	.04	14	14	.05	.21	01	22			
Transportation	.21	.29	. 30	.23	.16	.10	04	06			
Bus. Equipment	.22	02	18	16	15	16	12	12			
Chemicals	.14	17	24	16	23	33	28	20			
Metal Products	.05	.03	.00	.01	05	12	32	22			
Metal Industries	.20	.02	19	22	28	28	14	26			
Mining	.07	20	32	17	18	15	11	.03			
011	.19	01	04	07	07	03	01	14			
			B: Bias			L Correla					
Food	01	.07	.05	.22	. 34	. 24	. 14	02			
Apparel	.08	. 04	.17	. 35	.43	.28	.09	12			
Drugs	. 14	.21	. 28	.29	. 22	.14	.07	02			
Retail	.13	.09	.07	.13	.12	.12	. 22	.06			
Durables	.34*	.39*	.36*	.31*	. 23	.19	.18	.27			
Autos	.16	.15	.29	.42*	.42*	. 38*	.28*	. 26			
Construction	.15	.28	.36*	. 25	.19	.16	. 26	.09			
Finance	.28*	. 24	.17	. 20	.30	. 35	. 29	.16			
Miscellaneous	.24*	.36*	.40*	.33	.27	. 24	. 23	.15			
Utilities	.21	.09	06	03	.18	. 37	. 20	.05			
Transportation	.23	.34*	.38	. 33	. 29	.26	.17	.21			
Bus. Equipment	.24*	.03	11	06	02	.00	.09	.15			
Chemicals	.16	13	16	06	10	17	07	.07			
Metal Products	.07	.08	.08	.11	.08	.03	11	.05			
Metal Industries	.21	.06	11	11	15	13	.07	.01			
Mining	.09	16	25	07	05	.01	.10	. 30			
Oil	.21	.03	.03	.03	.06	.13	. 20	.12			

Note: Serial correlations in Part B use the bias adjustments of Fama and French (1986), relevant when true serial correlations are 0.0. Starred (*) serial correlations are two standard errors from 0.0. Standard errors in these comparisons are adjusted for overlap of monthly observations on T-year returns with the method of Hansen and Hodrick (1980).

Table 8 - OLS and Bias-Adjusted First-Order Serial Correlations of (A) Returns and (B) Residuals from Regressions of Returns on Decile 1 for 82 Individual Stocks Listed over the Entire 1926-85 Sample Period and for an Equally Weighted Portfolio of These Stocks

	4	0.00	0	Return		6.77	0.77	1.0**
	1Yr.	2Yr.	3Yr.	4Yr.	5Yr.	6Yr.	8Yr.	10Yr.
			Part A:	Returns				
		OLS	Serial	Correlat:	ions			
Portfolio	06	28	46	48	42	20		13
Average of 82	.01	13	24	24	20	14	16	23
	I	Bias-Adi	usted Se	rial Cor	relations	3		
Portfolio	04	23		38		04	.16	.14
Average of 82	.03	08	16	14	07	.01	.05	.03
Fractile: .05	14	29	38	39	37	35	31	30
.25	03		30				09	11
.50	.03	07		16			.08	.05
.75	.07	.00	04	02	.04	.20	. 21	.19
. 95	.20	.17	.22	.29	.38	.42	.41	.40
•	t-Statist	ics for	Rias-Adi	lusted Se	rial Cor	relation	s	
Portfolio	41	-1.68			-2.40	29	.72	. 53
Average of 82	. 24	61	-1.12		62	02	.17	.12
Fractile: .05	-1.31	-2.17	-2.74	-3.46	-3.16	-2.63	-1.50	-1.32
.25	31		-1.99				29	47
.50	.29	51			34		.26	.17
.75	.65	02		10	.21	.92	.87	. 69
.95	1.91	1.09	1.16	1.70	1.78	1.98	1.95	1.97
					_			
Part B:	Residual	ls from	Regressi	ons of Re	eturns ag	gainst De	ecile 1	
Part B:	Residual		-	ons of Ro		gainst De	ecile 1	
Part B: Portfolio	Residua:		Serial			.11	ecile 1 .08	09
		OLS	Serial	Correlat:	ions .08			
Portfolio	.19 .10	OLS .09 .02	Serial 02 04	.04 03	ions .08 04	.11	. 08	
Portfolio	.19 .10	OLS . 09 . 02 Bias-Adj	Serial 02 04	.04 03	ions .08 04 relations	.11	. 08	26
Portfolio Average of 82	.19 .10	OLS .09 .02	Serial 02 04 usted Se	Correlat: .04 03	ions .08 04 relations .21	.11 07	.08 16	26 .18
Portfolio Average of 82 Portfolio Average of 82	.19 .10	OLS .09 .02 Bias-Adj .14 .07	Serial 02 04 usted Se .05 .03	Correlat: .04 03 rial Cor: .14 .07	ions .08 04 relations .21 .09	.11 07 3 .27	.08 16 .29 .05	26 .18 .01
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05	.19 .10 .21 .12 08	OLS .09 .02 Bias-Adj .14 .07	Serial 02 04 usted Se .05 .03 25	.04 03 rial Cor: .14 .07	ions .08 04 relations .21 .09 25	.11 07 3 .27 .09	.08 16 .29 .05	26 .18 .01 32
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05 .25	.19 .10 .21 .12 08 .05	OLS .09 .02 Bias-Adj .14 .07 26 04	Serial 02 04 usted Se .05 .03 25 13	Correlat: .0403 rial Cor: .14 .072809	ions .08 04 relations .21 .09 25 07	.11 07 3 .27 .09 34 11	.08 16 .29 .05 31 08	26 .18 .01 32 12
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05 .25 .50	.19 .10 .21 .12 08 .05 .13	OLS .09 .02 Bias-Adj .14 .07 26 04 .09	Serial 02 04 usted Se .05 .03 25 13 .04	Correlat: .0403 rial Cor: .14 .072809 .06	.08 04 relations .21 .09 25 07	.11 07 3 .27 .09 34 11	.08 16 .29 .05 31 08 .08	26 .18 .01 32 12
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05 .25 .50 .75	.19 .10 .21 .12 08 .05 .13 .21	OLS .09 .02 Bias-Adj .14 .07 26 04 .09 .19	Serial 02 04 usted Se .05 .03 25 13 .04 .21	.04 03 rial Cor: .14 .07 28 09 .06 .20	.08 04 relations .21 .09 25 07 .08 .25	.11 07 3 .27 .09 34 11 .10	.08 16 .29 .05 31 08 .08	26 .18 .01 32 12 .03
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05 .25 .50	.19 .10 .21 .12 08 .05 .13	OLS .09 .02 Bias-Adj .14 .07 26 04 .09	Serial 02 04 usted Se .05 .03 25 13 .04	Correlat: .0403 rial Cor: .14 .072809 .06	.08 04 relations .21 .09 25 07	.11 07 3 .27 .09 34 11	.08 16 .29 .05 31 08 .08	26 .18 .01 32 12 .03
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05	.19 .10 .21 .12 08 .05 .13 .21 .31	OLS .09 .02 Bias-Adjo .14 .07 26 04 .09 .19 .44	Serial 02 04 usted Se .05 .03 25 13 .04 .21 .41	Correlat: .0403 rial Cor: .14 .072809 .06 .20 .53	ions .0804 relations .21 .092507 .08 .25 .54	.11 07 s .27 .09 34 11 .10 .27 .49	.0816 .29 .053108 .08 .21 .44	26 .18 .01 32 12 .03 .15
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05 .25 .50 .75 .95	.19 .10 .21 .12 08 .05 .13 .21 .31	OLS .09 .02 Bias-Adj .14 .07 26 04 .09 .19 .44 ics for .84	Serial 02 04 usted Se .05 .03 25 13 .04 .21 .41 Bias-Adj	Correlat: .0403 rial Cor: .14 .072809 .06 .20 .53 usted Se .83	ions .0804 relations .21 .092507 .08 .25 .54 rial Corr	.11 07 3 .27 .09 34 11 .10 .27 .49 relation 1.34	.0816 .29 .053108 .08 .21 .44	26 .18 .01 32 12 .03 .15 .36
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05	.19 .10 .21 .12 08 .05 .13 .21 .31	OLS .09 .02 Bias-Adjo .14 .07 26 04 .09 .19 .44	Serial 02 04 usted Se .05 .03 25 13 .04 .21 .41	Correlat: .0403 rial Cor: .14 .072809 .06 .20 .53	ions .0804 relations .21 .092507 .08 .25 .54	.11 07 s .27 .09 34 11 .10 .27 .49	.0816 .29 .053108 .08 .21 .44	26 .18 .01 32 12 .03 .15 .36
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05 .25 .50 .75 .95	.19 .10 .21 .12 08 .05 .13 .21 .31	OLS .09 .02 Bias-Adj .14 .07 26 04 .09 .19 .44 ics for .84	Serial 02 04 usted Se .05 .03 25 13 .04 .21 .41 Bias-Adj	Correlat: .0403 rial Cor: .14 .072809 .06 .20 .53 usted Se .83	ions .0804 relations .21 .092507 .08 .25 .54 rial Corr	.11 07 3 .27 .09 34 11 .10 .27 .49 relation 1.34	.0816 .29 .053108 .08 .21 .44	26 .18 .01 32 12 .03 .15 .36
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05	.19 .10 .21 .12 08 .05 .13 .21 .31 t-Statist 1.90 1.07	OLS .09 .02 Bias-Adj .14 .07 26 04 .09 .19 .44 ics for .84 .40	Serial 02 04 usted Se .05 .03 25 13 .04 .21 .41 Bias-Adj .29 .13	.04 03 rial Cor: .14 .07 28 09 .06 .20 .53	ions .0804 relations .21 .092507 .08 .25 .54 rial Cor: 1.14 .43	.11 07 s .27 .09 34 11 .10 .27 .49 relation 1.34 .38	.0816 .29 .053108 .08 .21 .44 s 1.11 .14	26 .18 .01 32 12 .03 .15 .36
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05	.19 .10 .21 .12 08 .05 .13 .21 .31 t-Statist 1.90 1.07 74	OLS .09 .02 Bias-Adj .14 .07 26 04 .09 .19 .44 ics for .84 .40	Serial0204 usted Se .05 .032513 .04 .21 .41 Bias-Adj .29 .13 -1.56	Correlat: .0403 rial Cor: .14 .072809 .06 .20 .53 iusted Se .83 .30 -1.72	ions .0804 relations .21 .092507 .08 .25 .54 rial Cor: 1.14 .43 -1.71	.11 07 s .27 .09 34 11 .10 .27 .49 relation 1.34 .38 -2.03	.0816 .29 .053108 .08 .21 .44 s 1.11 .14 -2.02	26 .18 .013212 .03 .15 .36 .62 .03 -1.31
Portfolio Average of 82 Portfolio Average of 82 Fractile: .05	.19 .10 .21 .12 08 .05 .13 .21 .31 t-Statist 1.90 1.07 74 .40	OLS .09 .02 Bias-Adj .14 .07 26 04 .09 .19 .44 ics for .84 .40 -2.07 23	Serial0204 usted Se .05 .032513 .04 .21 .41 Bias-Adj .29 .13 -1.5668	Correlat: .0403 rial Cor: .14 .072809 .06 .20 .53 usted Se .83 .30 -1.7254	ions .08 .04 relations .21 .092507 .08 .25 .54 rial Cor: 1.14 .43 -1.7146	.11 07 .27 .09 34 11 .10 .27 .49 relation 1.34 .38 -2.03 44	.0816 .29 .053108 .08 .21 .44 s 1.11 .14 -2.0231	.03 -1.31 51

Note: Estimates for firms 4, 20, 41, 62, and 79 are reported for fractiles.

Table 9 - Characteristics of Portfolios of 35 Highest (Win) and Lowest (Lose)
Return Stocks and Their Size-Matched Control Portfolios
for 3-year Portfolio Formation Periods

Period		3 Yr.	Averso	e Vitile	Eguit	y Value	_	Portfolio y Ratio
Formed	Loser	Winner	Loser	Winner	Loser			Winner
1926-28	85	1.67	3.14	12.91	5.1	237.0	1.02	1.13
1929-31	-3.63	.00	2.60	16.23	. 6	134.5	1.02	1.32
1932-34	-1.52	1.76	6.63	10.60	6.1	22.3	1.01	. 98
1935-37	-1.10	1.35	4.77	11.57	3.4	51.5	1.01	. 98
1938-40	-1.70	1.08	3.06	11.40	2.0	21.1	1.00	.99
1941-43	44	1.48	8.31	7.40	14.5	16.2	1.01	.99
1944-46	04	1.63	11.03	7.83	62.4	26.6	1.08	.99
1947-49	-1.10	.91	3.51	12.03	5.5	40.2	1.01	.99
1950-52	41	1.41	4.20	11.66	22.2	86.3	1.00	.99
1953-55	39	1.48	4.43	12.49	18.2	210.1	1.01	.97
1956-58	58	1.22	5.46	12.54	42.1	321.4	1.00	.93
1959-61	69	1.42	4.06	12.71	35.0	339.3	1.00	. 96
1962-64	-1.03	1.22	5.66	10.69	43.6	263.6	1.01	.98
1965-67	47	1.80	8.80	11.86	385.6	348.1	1.05	.98
1968-70	-1.62	.94	6.34	14,26	81.7	473.8	1.00	.99
1971-73	-1.75	1.13	3.97	16.37	29.8	1231.9	1.00	.98
1974-76	-1.96	1.47	2.17	10.69	24.1	215.8	.98	.99
1977-79	69	1.74	7.77	9.46	392.8	218.0	1.01	1.00
1980-82	-1.03	1.79	3.91	10.94	69.7	621.0	1.00	1.00
Average	-1.11	1.34	5.25	11.77	65.5	256.8	1.01	1.01

Note: 3-year return is the total continuously compounded return on the portfolio for the 3-year portfolio formation period. Vitiles are decile size groups, split in half, and numbered from 1 (smallest firms) to 20 (largest firms). Average vitile is the average of the vitiles for stocks in a portfolio at the end of the portfolio formation period. Equity value is the average of the market values (millions of dollars) of the stocks in a portfolio. The matching portfolio equity ratios in the last two columns of the table are equity values of loser or winner portfolios relative to the equity values of their size-matched portfolios. The matching winner-portfolio equity ratio is 1.32 for 1929-31 because the largest stock (AT&T) on the NYSE is in the winner portfolio. The equity value for AT&T is 2.2 times the value of its matching firm (General Motors) and more than seven times the value of any other firm in the winner or matching portfolio. This is the only period when the largest stock is in the winner portfolio. In contrast, the smallest stock is in the loser portfolio six times.

Table 10 - Average and Cumulative Average Post-Formation Returns (Size-Adjusted, Market-Adjusted, and Unadjusted)
for Portfolios of 35 Stocks with
Highest (Winner) or Lowest (Loser) Formation Period Returns

_	Size	-Adjusted	Returns	Marke	t-Adjuste	d Returns	Unadjuste	d Returns
Month	Loser	Winner	Difference	Loser	Winner	Difference	Loser	Winner
·			Part A:	Average Jar	nuary Ret	urns		
1 Jan	4.65	-1.96	6.61	7.58	-3.03	10.60	10.91	.30
	(2.44)	(2.30)	(2.75)	(3.44)	(2.95)	(3.46)	(4.14)	(.25)
13 Jan	4.00	-3.50	7.50	7.14	-3.77	10.91	11.56	.65
	(1.68)	(3.03)	(2.43)	(2.62)	(2.85)	(3.02)	(3.06)	(.47)
25 Jan	3.17	-1.19	4.36	6.01	-1.79	7.80	12.94	5.14
	(1.90)	(1.14)	(2.39)	(3.04)	(1.37)	(3.06)	(3.75)	(2.67)
			Part B	: Cumulati	ve Return	<u>18</u>		
1 Jan	4.65	-1.96	6.61	7.58	-3.03	10.60	10.91	.30
	(2.44)	(2.30)	(2.75)	(3.44)	(2.95)	(3.46)	(4.14)	(.25)
12 Dec	2.71	50	3.21	3.73	-1.97	5.69	15.12	9.42
	(1.08)	= (.14)	(.89)	(1.06)	(.66)	(1.31)	(1.99)	(1.37)
13 Jan	6.72	-4.00	10.72	10.87	-5.73	16.60	26.68	10.08
	(1.71)	(-1.11)	(2.24)	(2.29)	(-1.75)	(2.79)	(3.34)	(1.58)
24 Dec	4.81	-8.11	12.91	9.76	-9.40	19.16	35.29	16.13
	(.89)	(-1.53)	(1.71)	(1.40)	(-1.80)	(2.01)	(2.47)	(1.46)
25 Jan	7.98	-9.30	17.28	15.77	-11.19	26.96	48.23	21.27
	(1.21)	(-1.65)	(1.96)	(1.87)	(-1.84)	(2.29)	(3.05)	(1.93)
36 Dec	5.18	-14.81	19.99	14.08	-16.75	30.83	49.45	18.62
	(.64)	(-2.42)	(1.70)	(1.33)	(-2.85)	(2.20)	(2.56)	(1.33)

Note: Month is the number of the month in the 3-year period following portfolio formation. A size-adjusted return is the difference between the continuously compounded return on a winner or loser portfolio and the continuously compounded return on its size-matched control portfolio. A market-adjusted return is the difference between the continuously compounded return on a winner or loser portfolio and the continuously compounded return on the NYSE equal-weighted market portfolio. The average and cumulative average returns, and the standard deviations used to calculate their t's, are for the 19 3-year post-formation periods, 1929-31,..,1983-85. The "difference" columns of the table for size-adjusted returns are based on the differences between size-adjusted loser and winner continuously compounded portfolio returns.

Table 11 - Average Size-Adjusted and Unadjusted January Returns for 25% Loser and 25% Winner Portfolios from Each Decile

						ecile	_	_			
Month	1	2	3	4	5	6	7	8	9	10	Mear
		P	art A:	Size-Ad	justed	Average	Januar	y Retur	ns		
					Los	ers					
1	5.05	1.60	2.71	1.23	1.69	2.50	1.27	1.60	1.04	1.22	1.99
13	4.42	3.45	2.63	1.89	2.07	2.56	3.46	. 86	1.51	1.78	2.46
25	2.76	3.26	2.75	1.67	2.11	2.29	2.40	1.69	1.39	1.36	2.17
					Win						
1	-2.66	-3.55	-1.60	74	-1.98	- , 40	-1.74				-1.67
13	-1.91	-1.21	20	77	-1.33	85	-1.69	-1.70		-1.04	-1.33
25	-1.90	-1.22	27	.06	.21	38	58	. 07	96	12	51
						Losers		_			
1	1.88	1.59	3.32	1.42	2.07		1.68	1.76	1.58	1.68	2.82
13	1.70	2.79	1.33	4.27	3.74		3.66	1.71	2.02	2.53	3.47
25	1.47	2.61	2.49	1.85	3.16	2.41	2.85	2.59	2.97	3.10	3.70
						Winners					
1	-2.70	-2.87	-2.40	-1.45	-2.78	77	-2.47				-3.58
13	-2.18	81	21	-1.21	-1.52		-1.89	-2.15		-1.64	-2.49
25	-1.89	-1.77	45	.06	.46	28	86	.11	-1.44	25	-1.04
			Part B	: Unadju	sted A	verage J	anuary	Returns	;		
					Los	ers					
1	13.12	8.38	7.36	5.08	5.10		2.90	2.65	1.96	1.28	5.20
13	13.82	10.11	8.02	6.30	5.79	5.82	5.89	3.34	3.45	1.98	6.45
25	14.52	12.64	11.09	9.22	8.33	8.11	7.34	5.71	5.38	4.52	8.69
					Win	ners					
1	5.40	3.23	3.05	3.11	1.44	1.25	1.25	30	66	-1.09	1.53
13	7.49	5.46	5.19	3.63	2.39	2.41	2.41	.77	62	84	2.66
25	9.87	8.16	8.07	7.60	6.43	5.44	5.44	4.10	3.03	3.04	6.01
					t's for	Losers					
1	4.07	4.86	4.74	3.67	3.60	3.84	2.40	2.36	2.31	1.57	4.29
13				3.46						1.51	
25	4.09	3.92	3.63	3.54	3.68	3.23	3.36	3.18	3.94	3.72	3.84
						Winners					
						1.15				83	
13						1.41					1.64
25	4.36	3.91	3.38	3.51	3.17	3.21	2.82	2.57	2.12	2.11	3.43

Note: Month is the number of the month in the 3-year period following portfolio formation. A size-adjusted return is the difference between the continuously compounded return on a winner or loser portfolio and the continuously compounded return on its size-matched control portfolio. The average returns, and the standard deviations used to calculate their t's, are for the 19 3-year postformation periods, 1929-31,..,1983-85.

Table 12 - Average Size-Adjusted and Unadjusted Cumulative Returns for 25% Loser and 25% Winner Portfolios for Each Decile for 3-Year Post-Formation Period

				De	cile					
1	2	3	4	5	6	7	8	9	10	Mean
		Part	A: Aver	age Size	-Adjuste	d Cumula	tive Ret	urns		
					Losers					
07	-3.72	75	-7.02	1.32	5.29	2.38	85	2.91	1.85	.14
(.01)	(.68)	(.14)	(1.66)	(.29)	(1.12)	(.51)	(.19)	(.57)	(.67)	(.04)
					Winners					
-9.62	-8.84	-1.39	-5.86	-1.03	-3.20	-2.32	-7.86	-2.27	-8.99	-5.14
(1.82)	(2.66)	(.46)	(1.45)	(.23)	(.62)	(.50)	(1.34)	(.64)	(2.17)	(1.80)
•				Los	ers-Winn	ers				
9.56	5.12	. 64	-1.16	2.35	8.50	4.70	7.01	5.18	10.84	5.27
(.93)	(.66)	(.12)	(.21)	(.36)	(1.19)	(.83)	(1.15)	(.76)	(2.10)	(1.08)
		Par	t B: Ave	rage Cun	mulative	Unadjust	ed Retur	ns		
					Losers					
51.88	42.37	37.64	32,52	34.40	37.37	31.38	31.45	31.13	25.12	35.53
(2.38)	(2.42)	(2.61)	(2.13)	(3.14)		(2.77)	(2.70)	(2.65)	(3.17)	(2.74)
					Winners					
42.32	37.25	37.00	33.68	32.05	28.87	26.68	24.44	25.95	14.28	30.25
(2.61)	(3.01)	(2.54)	(2.30)	(2.51)	(2.02)	(2.29)	(1.97)	(3.34)	(1.37)	(2.48)
	•	•								

Note: A size-adjusted return is the difference between the continuously compounded return on a winner or loser portfolio and the continuously compounded return on its size-matched control portfolio. The average and cumulative average returns, and the standard deviations used to calculate their t's, are for the 19 3-year post-formation periods, 1929-31,..,1983-85. The "losers-winners" estimates for size-adjusted returns are based on the differences between size-adjusted loser and winner continuously compounded portfolio returns. t-statistics are in parentheses. The means and their t-statistics are estimated by first averaging across deciles for each 3-year post-formation period.