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Further Evidence On Investor Overreaction and Stock Market Seasonality

WERNER F. M. DE BONDT and RICHARD H. THALER*

ABSTRACT

In a previous paper, we found systematic price reversals for stocks that experience extreme long-term gains or losses: Past losers significantly outperform past winners. We interpreted this finding as consistent with the behavioral hypothesis of investor overreaction. In this follow-up paper, additional evidence is reported that supports the overreaction hypothesis and that is inconsistent with two alternative hypotheses based on firm size and differences in risk, as measured by CAPM-betas. The seasonal pattern of returns is also examined. Excess returns in January are related to both short-term and long-term past performance, as well as to the previous year market return.

IN A PREVIOUS PAPER (De Bondt and Thaler [11]), we investigated a simple stock market investment strategy motivated by work in cognitive psychology on intuitive prediction. The strategy is based on the notion that many investors are poor Bayesian decision makers. Experimental and survey evidence indicates that in probability revision problems people show a tendency to "overreact," i.e., they overweight recent information and underweight base rate data. We conjectured that, as a consequence of investor overreaction to earnings, stock prices may also temporarily depart from their underlying fundamental values. With prices initially biased by either excessive optimism or pessimism, prior "losers" would be more attractive investments than prior "winners."

We found considerable evidence consistent with this simple hypothesis.¹ For example, using monthly return data between 1926 and 1982 for stocks listed on the New York Stock Exchange (as compiled by the Center for Research in Security Prices (CRSP) at the University of Chicago), we formed portfolios of the 50 most extreme winners and 50 most extreme losers (as measured by cumulative excess returns over successive five year formation periods). It was reported that over the following five-year test periods the portfolios of losers outperformed the portfolios of winners by an average of 31.9 percent.

However, many issues regarding the "winner-loser" effect were left unresolved. First, there is a pronounced seasonality in the "price correction." Almost all of it occurs in the successive months of January, especially for the losers. Second, the

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¹ Other empirical work reporting evidence (on a firm-by-firm basis) consistent with overreaction includes Brown and Harlow [6] and Howe [17].

correction appears to be asymmetric: after the date of portfolio formation, losers win approximately three times the amount that winners lose. Third, the characteristics of the firms in the extreme portfolios were not fully described. This is important since studies by, e.g., Keim [19] and Reinganum [26] contain results that suggest that the winner-loser effect may simply be another instance of the well-known size and/or turn-of-the-year effects (for a review, see Schwert [31]). Finally, the interpretation of our results as evidence of investor overreaction has been questioned. There are at least two alternative explanations, both involving time-varying equilibrium rates of return. Using methodology similar to our own, Vermaelen and Verstringe replicate the winner-loser anomaly for the Belgian stock market. They argue, however, that "... this 'overreaction' effect is a rational market response to risk changes..." [33, p. 13]. Their "risk-change hypothesis," also presented by Chan [8, 9], states that a decline (increase) in stock prices leads to an increase (decline) in debt-equity ratios and risk as measured by CAPM betas. More recently, Fama and French [13] again report significant negative serial correlation in stock returns, explaining 25 to 45 percent of three- to five-year return variation. While these authors agree that their findings are consistent with our own (as well as with other models in which prices take long swings away from fundamental values, e.g., Keynes [21] or Shiller [32]), they suggest that mean-reverting factor risk premia may be the cause, citing (among other studies) the work of Keim and Stambaugh [20].

In an effort to re-evaluate the overreaction hypothesis, this paper discusses new empirical findings that are relevant to the winner-loser, size, and January effects, as well as to the broader issues of time-varying risk premia and market efficiency. Section I, based on CRSP data, extends our earlier results and further discusses the seasonality in the return behavior of extreme winner and loser portfolios. In addition, we address the issue of whether the winner-loser anomaly can be explained by differences in CAPM-betas. Along with return data, Section II uses accounting numbers drawn from COMPUSTAT to characterize the extreme portfolios and to compare and contrast the small firm and winner-loser effects. This section also matches earnings movements to the observed return performance. Stock prices may be thought of as discounted expected earnings, $p = E(c)/\rho$, where c is the earnings stream and ρ is the discount rate. The primary focus of the time-varying expected return explanations is on ρ . Here, we examine the numerator. It is found that, at least for the extreme portfolios, prior stock price performance predicts subsequent reversals in company earnings. The fact that earnings reversals are accompanied by contemporaneous stock price reversals suggests that the market fails to recognize the tendency towards mean reversion in extreme earnings numbers.

While we stress overreaction, we concede that part of the mean reversion in stock prices may also be due to time-varying equilibrium expected returns, and that the tax code may be linked to the unusual January returns. Indeed, these and other valid arguments are not mutually exclusive with overreaction bias. However, our principal motivation remains a concern with the microfoundations of modern finance. Parallel to George Akerlof's approach to economic theory, we aim "to explore the consequences of new behavioral assumptions" [1, p. 1].

I. The Winner-Loser Effect, Stock Market Seasonality, and Risk

Perhaps the most curious result in our previous paper is the strong seasonality in the test period returns of winners and losers. A large portion of the excess returns occurs in January. Using CRSP monthly return data, we now explore some questions motivated by these earlier findings and other research which links the unusual January returns either to the tax code (e.g., Branch [4], Chan [7], Dyl [12], Reinganum [26], Roll [28] and Rozeff [30]) or to seasonality in the risk-return relationship (e.g., Keim and Stambaugh [20], and Rogalski and Tinic [27]). First, are there any seasonal patterns in returns during the formation period? Next, within the extreme portfolios, do systematic price reversals occur throughout the year, or do they occur only in January? Finally, are the January corrections driven by recent share price movements (say, over the last few months), or by more long-term factors? Using the same data set, we also investigate the hypothesis that the winner-loser effect can be explained by changes in CAPM-betas (see Chan [9], and Vermaelen and Verstringe [33]). Before turning to the results, we briefly describe the empirical methods used in this section.

A. Empirical Methods

1. For every stock j on the CRSP Monthly Return Tape (1926–1982) with at least 61 months of return data (without any missing values in between, and starting in January, 1926), we estimate 120 monthly market-adjusted excess returns, $u_{jt} = R_{jt} - R_{mt}$, covering both a five-year portfolio “formation” and a five-year “test” period.² An equal-weighted average of the monthly returns on all stocks listed on the NYSE is used for R_{mt} . The procedure is repeated 48 times for each of the ten-year periods starting in January 1926, January 1927, . . . , up to January 1973. Over the years, the various samples grow from 381 to 1245 stocks.

2. For every stock in each sample, we find the cumulative excess return CU_j over the five-year formation period. After that, the CU_j 's are ranked and portfolios are formed. The 50 stocks with the highest CU_j 's are assigned to a winner portfolio W ; the 50 stocks with the lowest CU_j 's to a loser portfolio L . In total, there are 48 winner and 48 loser portfolios each containing 50 securities.

3. For some of the descriptive statistics and regression tests below, we combine the 48 winner and 48 loser portfolios into two “master” samples, one of winners and one of losers. These two “master” samples each contain 2400 observations.

For the correlation tests below, new sets of portfolios are formed as follows. For the five sequences of all non-overlapping formation periods that start in January 1926, January 1927, . . . , January 1930, the single most extreme winners from each formation period are combined to form group W_1 . The stocks that

² If some or all of the raw return data beyond month #61 are missing, the excess returns are calculated up to that point. No survivorship bias is introduced with this methodology. Firms which drop out before the formation date are not included. For those which drop out during the test period, we use the last entry on the CRSP file to compute the final return, which can be -1 if the shares have no value. See footnote 4 of our previous paper.

came in second in the formation periods form group W_2 , etc. We thus have, for each of five experiments, 50 of what we call "rank portfolios" for winners, W_1, \dots, W_{50} , and 50 "rank portfolios" of losers formed in the same manner. In total, there are 250 winner and 250 loser rank portfolios. Depending on the number of periods, each rank portfolio contains a maximum of either nine or ten stocks.

Average and cumulative average excess returns are found for each rank portfolio. Whenever a return is missing, the average excess return for that portfolio is calculated over the remaining observations. The cumulation periods include the formation period, the test period and various subperiods. The tests involve simple, partial and Spearman rank correlations between relevant pairs of average return performances covering different (sub-)periods.

B. Excess Returns, Seasonality and Taxes

It is immediately apparent from the plots of test period returns in our previous paper ([11], Figures 1, 2 and 3) that they contain an important seasonal component. To examine this seasonality in greater detail, and to see whether the formation period returns also show seasonality, Table I presents average excess returns earned by both the winner and loser "master" portfolios for various subperiods.³ During the test period, losers earn virtually all of their excess returns in January (with the last three months of the year offsetting any gains between February and September). Winner excess returns, though smaller (in absolute terms) than for losers, also occur predominantly in January. In the formation period, the January excess returns for winners are about double that of the abnormal performance in other months. For losers, by the last two years of the formation period, the seasonal pattern starts to resemble that of the test period: positive January returns and the larger than usual negative returns towards the end of the year.

One implication of the overreaction hypothesis is a tendency (which Brown and Harlow [6] call the "magnitude effect") for the most extreme initial winners and losers to exhibit the most extreme subsequent price reversals. Our earlier paper provided supporting evidence by comparing the test period performance of portfolios chosen over formation periods with different durations. The longer the formation period, the greater both the initial price movements and the subsequent reversals. Brown and Harlow's study of the magnitude effect uses a more stringent test. They find that the effect holds even within portfolios of extreme winners and losers. The rank portfolios, described in the empirical methods section above, permit us to investigate this hypothesis as well. In addition, they allow us to focus on the seasonality of the magnitude effect.

We start by calculating Spearman rank correlations between cumulative average excess returns (CAR) for the entire formation period and the first one, two, . . . , five years of the test period. For losers, consistent with overreaction, the average correlations are $-.14, -.28, -.22, -.29$ and $-.30$. A simple bivariate regression (using all 250 loser rank portfolios) of CAR for the formation period on CAR for the test period yields an intercept of $-.205$ (t -statistic: -2.55) and a

³ The average returns in Table I are based on 48 replications with the test periods starting in January of all years between 1931-1978, while our previous paper used the years 1933-1978.

Table I
Average Monthly Excess Returns of Long-term Winners and Losers for Varying Periods

A: Formation Period		Winners				Losers			
Period	All Months	Jan.	Feb.- Sept.	Oct.- Dec.	All Months	Jan.	Feb.- Sept.	Oct.- Dec.	
$t-4, t$	2.7	4.5	2.6	2.3	-2.1	-.5	-2.1	-2.6	
$t-4, t-2$	2.7	5.6	2.6	2.1	-2.0	-1.8	-2.0	-2.2	
$t-1, t$	2.6	3.0	2.6	2.7	-2.1	1.6	-2.1	-3.3	

B: Test Period		Winners				Losers			
Period	All Months	Jan.	Feb.- Sept.	Oct.- Dec.	All Months	Jan.	Feb.- Sept.	Oct.- Dec.	
$t+1, t+5$	-2	-.8	-.3	0.0	.6	5.0	.4	-.4	
$t+1, t+3$	-.3	-1.3	-.3	.1	.7	6.1	.5	-.5	
$t+4, t+5$	-1	-1	-1	-1	.3	3.3	.1	-.3	

Note: All entries in the table are average market-adjusted excess returns (in percent) where the return on the market portfolio is measured by an equally-weighted index of all stocks listed on the NYSE, as provided by CRSP. They are based on 2400 observations. See Section I.A for details. Year t represents the last year of the formation period.

slope of $-.421$ (-6.67). The R -square (adjusted for degrees of freedom) is $.149$. On the other hand, for winners, there is no evidence of a magnitude effect. None of the equivalent Spearman rank correlations are significantly different from zero, and neither is the slope-coefficient of the bivariate regression.

The previous findings conceal the seasonality of the magnitude effect. Further correlation tests indicate that, except in January, winner and loser excess returns are unrelated to formation period CAR.⁴ This raises the question to what extent the exceptional January returns of long-term winners and losers are actually driven by performance over the immediately preceding months, possibly reflecting tax-motivated trading.

Table II shows OLS regressions with the excess return in the first January of the test period as the dependent variable. The predictor variables measure relative performance over, respectively, [1] the prior December, [2] the last five months (July through November) prior to December, and [3] the remaining $4\frac{1}{2}$ years of the formation period.⁵ Equations A.1 and B.1 indicate that the January excess returns of both winners and losers show significant short-term reversals. For losers, these reversals may reflect tax-loss selling pressure (see e.g., Branch [4], Reinganum [26] and Roll [28]). For winners, the short-run reversals are consistent with a capital gains tax "lock-in" effect. While we are not aware of any other study documenting turn-of-the-year return reversals for winners, Dyl [12] and Lakonishok and Smidt [22] report unusually low trading volume for these stocks in December and unusually high volume in January, facts also consistent with a lock-in effect.

Equations A.3 and B.3 further show a statistically significant link between January excess returns and prior long-term performance. For losers, the long-term effect is negative and predicted by investor overreaction. By its mere presence, the long-term effect contradicts rational tax-loss selling as an explanation of the January seasonal (see also Chan [7]). For winners, surprisingly, the long-term effect is positive. This observation is in conflict with the overreaction hypothesis.⁶

⁴ Using five times 100 rank portfolios, we compute Spearman rank, simple and partial correlations (controlling for excess returns during the last December of the formation period) between formation period CAR and subperiod CAR's for January, February through September, and October through December of each test year. Except for January, no correlations are sizable. For losers, the January correlations are significantly negative. For winners, they are positive for the first January of the test period but generally close to zero for later Januaries. Further regression tests (based on the two "master" samples) indicate that, even though the R -squares are small (varying between $.018$ and $.120$), January test period excess returns of both winners and losers are reliably related to return movements in adjacent Januaries.

⁵ For the sake of brevity, Table II shows only results based on the two "master" samples. The securities in each sample are not independently selected since the formation periods are partially overlapping. However, tests using five subsamples that overcome this problem do not affect our conclusions.

⁶ OLS-regressions with loser January excess returns for later test years as the dependent variable yield results similar to Table II. For example, for the 5th January, the coefficient on the excess return for the previous December (i.e., the December of the 4th test year) is $-.462$ (t -statistic: -12.96), while the coefficient on the formation period cumulative residual equals $-.066$ (t -statistic: -6.71)! For winners, the short-term reversals persist (e.g., for the 5th January, the relevant coefficient is $-.169$ (t -statistic: -7.60)) but the (positive) long-term effect disappears beyond the 2nd January of the test period.

Table II
 OLS-Regressions of Winner and Loser Excess Returns for the First January of the Test Period on
 Selected Variables

Regression #	Independent variables					Adj. R-square
	Intercept	D1 (intercept)	Dec. Excess Return (Year t)	D2 (slope)	July-Nov. Cumulative Excess Return (Year t)	
A: Winners						
A.1	-.011 (-3.37)		-.235 (-9.76)			.038
A.2	-.038 (-6.95)	.043 (6.21)	-.340 (-7.10)	.135 (2.44)		.058
A.3	-.046 (-6.47)		-.214 (-8.88)		-.006 (-.58)	.054
A.4	-.072 (-8.66)	.044 (6.45)	-.285 (-5.91)	.088 (1.59)	-.009 (-.94)	.073
B: Losers						
B.1	.051 (11.45)		-.704 (-18.92)			.130
B.2	.065 (8.41)	-.026 (-2.79)	-1.082 (-20.27)	.813 (11.09)		.190
B.3	-.022 (-1.68)		-.727 (-19.68)		-.144 (-6.85)	.148
B.4	.005 (0.36)	-.023 (-2.43)	-1.080 (-20.37)	.771 (10.52)	-.108 (-5.25)	.200
					-.051 (-4.86)	
					-.041 (-4.00)	

Note: T -statistics are shown in parentheses. All regressions are based on 2400 observations. See Section I.A for details. Dummy variable $D1$ equals one if the equal-weighted return of all NYSE stocks is positive in the last year of the formation period (year t). It is zero otherwise. Predictor variable $D2$ equals the excess return in December of year t multiplied by $D1$.

The economic significance of the long-term effects is substantial. In order to compare it with the economic weight of the short-term effects, we compute the "component contribution" of each predictor variable, i.e., the product of its estimated coefficient and its sample mean. For losers (equation B.3), the average January excess return of 7.9 percent can be decomposed into an unexplained intercept (-2.2 percent), 2.9 percent that is due to a short-term reversal from the previous December, 1.7 percent due to reversals from the previous July through November, and 5.5 percent due to long-term reversals. For winners (equation A.3), the average January excess return equals -1.8 percent and the long-term component is a positive 3.5 percent.

Earlier work (e.g., Rozeff [30]) suggests that the size of the January excess returns depends on the performance of the market as a whole over the previous year (or previous six months). In order to see whether this applies to our portfolios, intercept and slope dummy variables are added to the OLS-regressions in Table II. The intercept dummy equals one if R_{mt} , annually compounded, is positive during the last year of the formation period. It is zero otherwise. The slope dummy is defined as the intercept dummy multiplied by the excess return for December. Equations A.2, A.4, B.2 and B.4 show that, on average, following down years, long-term winners perform worse and long-term losers better than they do following years in which the market has risen. For losers, the slope dummy indicates that also the December-January reversals are significantly more pronounced following years of market declines. Again, these findings are consistent with tax explanations of the unusual January returns.

C. Excess Returns and Changing Risk

In our previous paper, we investigated whether the excess returns to winner and loser portfolios could be explained by differences in CAPM-betas. The betas were estimated over the formation period. Regardless of the length of the formation period (varying between one to five years), the beta for the loser portfolio was always lower than the beta for the winner portfolio. We therefore concluded that, within the CAPM framework, the reported market-adjusted excess returns were conservative estimates of the "true" risk-adjusted excess returns. However, Chan [8, 9] and Vermaelen and Verstringe [33] argue that the usual procedure of estimating betas over a prior period is inappropriate if betas vary with changes in market value. For winners and losers, a negative correlation between risk and market value is plausible because of changes in financial leverage that accompany extreme movements of the value of equity. The implication is that the winner-loser effect may disappear if the risk estimates are obtained during the test period.

To test this hypothesis, we construct "arbitrage" portfolios that finance the purchase of losers by selling winners short, and we regress (using OLS) the annual test period returns $R_{At} = R_{Lt} - R_{Wt}$, on the market risk premium, $R_{mt} - R_{ft}$, i.e., $R_{At} = \alpha_A + \beta_A(R_{mt} - R_{ft}) + \epsilon_{At}$. As before, R_{mt} is the (annually compounded) monthly return on an equal-weighted index of NYSE stocks. R_{ft} is taken from Ibbotson and Sinquefeld [18], and it is measured as the (annually compounded) one-month holding period return on U.S. Treasury bills. The constant term α_A

is the well-known Jensen performance index; β_A is an estimate of the difference in Sharpe-Lintner CAPM-betas between the loser and winner portfolios. The equation is also estimated separately for the winners and losers with, respectively, $R_{wt} - R_{ft}$ and $R_{Lt} - R_{ft}$ as the dependent variable. Additional regressions include dummy variables that control for the year of the test period. Finally, all the previous regressions are repeated with January and February through December returns as the dependent variables.

The results appear in Table III. Regression A.1 indicates that, during the test period, the estimated beta for the loser portfolio is indeed .220 greater than the winner-beta. However, this difference in risk is insufficient to explain the return on the arbitrage portfolio since α_A , at 5.9 percent, is significantly positive. Thus, this simple test of the risk-change hypothesis fails to explain the winner-loser effect. Regression B.1 is also of interest because, unlike our previous results, it indicates that, on a CAPM risk-adjusted basis, the winner portfolio has significantly negative excess returns. The coefficients on the dummy variables reveal the familiar pattern of declining excess returns through the test period.

Using alternative methods which allow for time-varying betas, Chan [9] finds a test period beta of about 0.1 for the arbitrage portfolio, but obtains an alpha insignificantly different from zero. The alpha and beta are average coefficients obtained from separate equations estimated (using monthly data) for each of 18 non-overlapping three-year experiments. Chan readily admits that the small difference in betas "would appear to have no chance to explain the average monthly return of 0.586 percent" ([9], p. 12). Instead, he explains the combined observations of a small alpha, a small beta, and a large return by positive correlation between the time-varying betas and the market risk premium. The argument is that both the betas and the expected market risk premium may be responding to common state variables.

To further investigate this issue, we recalculate the regressions in Table III in a way that permits two betas to be estimated, one for periods when the stock market is rising, and another for when it is falling. Define a dummy variable D which equals one if $R_{mt} > 0$ and zero if $R_{mt} < 0$. The estimated equation for the arbitrage portfolio is now $R_{At} = \alpha_A + \beta_{Au}(R_{mt} - R_{ft})D + \beta_{Ad}(R_{mt} - R_{ft})(1 - D) + \epsilon_{At}$, with similar equations for the winner and loser portfolios.

As shown in Table IV, once betas are allowed to vary with the market, the alphas are no longer significantly positive. These results, which confirm Chan's findings, require careful interpretation. We see in equation A.1 that, while the average CAPM-beta of the arbitrage portfolio was earlier estimated to be .220, the portfolio actually has a positive beta when the market goes up, and a negative beta when it falls. In other words, the arbitrage portfolio does well in both up and down markets. Equations B.1 and C.1 indicate how this happens. For the winner portfolio, the up-beta is .993 while the down-beta is 1.198. For the loser portfolio, the betas are 1.388 and .875. In rising markets, the losers have a tendency to gain more than the winners, while in falling markets, the winners tend to lose more than the losers. Equations A.2, B.2 and C.2 reveal a similar but magnified pattern of returns in January. In contrast, during the rest of the year, the results are muted and the loser alpha is significantly negative.

The risk-change hypothesis claims that during the test period the losers are

Table III
OLS-Regressions of Annual, January, and February through December Portfolio Risk Premia for the
Test Period on Selected Variables

Regression #	Independent Variables							Adj. R-sq.
	Intercept	$R_m - R_f$	Test Year Dummy Variables					
			D2	D3	D4	D5		
A: Arbitrage Portfolio								
			Annual Returns					
A.1	.059 (3.72)	.220 (4.72)						.082
A.2	.121 (3.72)		.021 (.46)	-.020 (-.43)	-.063 (-1.36)		-.081 (-1.77)	.012
A.3	.068 (2.75)	.216 (4.65)	.018 (.40)	-.023 (-.53)	-.060 (-1.36)		-.078 (-1.78)	.092
			January Returns					
A.4	.032 (4.40)	.538 (6.94)						.168
			February-December Returns					
A.5	.014 (1.08)	.215 (4.78)						.085
B: Winner Portfolio								
			Annual Returns					
B.1	-.033 (-4.47)	1.043 (47.91)						.906
B.2	.130 (2.69)		-.013 (-.19)	.009 (.13)	-.011 (-.15)		.002 (.03)	.000
B.3	-.030 (-1.99)	1.045 (48.06)	-.028 (-1.38)	-.008 (-.39)	.004 (.18)		.016 (.79)	.906

	January Returns		February-December Returns		
B.4	-.004 (-1.37)	.931 (26.78)			.754
B.5	-.024 (-3.76)	1.054 (47.20)			.905
C: Loser Portfolio					
	Annual Returns		Annual Returns		
C.1	.026 (2.30)	1.263 (38.20)			.859
C.2	.251 (4.20)		.008 (.10)	-.011 (-.87)	.000 (-.94)
C.3	.058 (2.55)	1.260 (38.24)	-.011 (-.34)	-.031 (-1.00)	.860 (-1.98)
	January Returns		February-December Returns		
C.4	.027 (5.11)	1.469 (25.55)			.736
C.5	-.010 (-1.18)	1.269 (42.38)			.885

Note: *T*-statistics are shown in parentheses. In panel A, the dependent variable is, for each of five test years, the return on the loser portfolio minus the return on the winner portfolio. In panel B (panel C), it is the return on the winner (loser) portfolio minus the return on U.S. Treasury Bills. Since our basic experiment is replicated 48 times (covering ten year periods between 1926-1935, 1927-1936, . . ., through 1973-1982), there are 240 observations. *D2*, *D3*, . . ., *D5* are dummy variables that equal one for the 2nd, 3rd, . . ., 5th test year, respectively. They are zero otherwise. The return on the market portfolio is measured using an equally-weighted index of NYSE stocks provided by CRSP. Because we do not have monthly returns for U.S. Treasury Bills beyond December 1961, the regressions with January and February through December returns contain only 235 observations. The last replication of our basic experiment (covering the ten year period between 1973 and 1982) is dropped.

Table IV
OLS-Regressions of Annual, January, and February through December
Portfolio Risk Premia on the Market Risk Premium in Up and Down Markets

Regression #	Independent Variables			Adj. R-sq.
	Intercept	$(R_m - R_f)D$	$(R_m - R_f)(1 - D)$	
A: Arbitrage Portfolio				
	Annual Returns			
A.1	-.005 (-.24)	.395 (6.43)	-.323 (-2.36)	.142
	January Returns			
A.2	.008 (.83)	.748 (8.08)	-.848 (-2.33)	.215
	February-December Returns			
A.3	-.032 (-1.85)	.376 (6.24)	-.176 (-1.60)	.138
B: Winner Portfolio				
	Annual Returns			
B.1	-.015 (-1.43)	.993 (33.77)	1.198 (18.25)	.908
	January Returns			
B.2	.004 (1.04)	.854 (20.39)	1.439 (8.73)	.763
	February-December Returns			
B.3	-.011 (-1.24)	1.007 (32.87)	1.168 (20.97)	.906
C: Loser Portfolio				
	Annual Returns			
C.1	-.020 (-1.29)	1.388 (31.80)	.875 (8.98)	.868
	January Returns			
C.2	.012 (1.73)	1.602 (23.15)	.591 (2.17)	.746
	February-December Returns			
C.3	-.043 (-3.73)	1.384 (34.54)	.992 (13.63)	.892

Note: See Table III. D is a dummy variable which equals one if the return on the market portfolio (as measured by an equally-weighted index of NYSE stocks) is positive. It is zero otherwise.

riskier than the winners, and that this difference in risk is responsible for the apparent excess returns. The above results do not support this view. When risk is measured by CAPM-betas, the risk disparity is insufficient to account for the return gap. Only when the betas are allowed to vary with the level of the market is the alpha of the arbitrage portfolio no longer positive. Furthermore, these time-varying "split" betas are questionable measures of risk. In January, for example, the CAPM-betas are higher for the losers than for the winners (1.469 vs. .931). Yet, it seems odd to say that a portfolio with a beta of 1.602 in up markets and .591 in down markets is riskier than one with up and down betas of .854 and 1.439.⁷

II. The Winner-Loser Effect, the Size Effect, and Overreaction to Earnings

The results so far have utilized only return data. Many questions remain that require additional information. One important issue is whether the winner-loser effect is qualitatively different from the size effect. Are losing firms particularly small? Are small firms for the most part losers? To the extent that the small firm effect (where size is measured by market value of equity) is a losing firm effect, are there any additional excess returns genuinely attributable to company size when size is measured in a way that is independent of short-term price movements? Can we use accounting data to distinguish the overreaction hypothesis from other explanations of the winner-loser effect? To answer these and other questions we turn to the COMPUSTAT tape. Again, we begin by describing our empirical methods.

A. Empirical Methods

1. Six samples are chosen from the main and delisted (research) files of the Annual Industrial COMPUSTAT tapes for the period between 1965 and 1984. In order to be selected, a company needs complete five-year records prior to (and including) the portfolio formation years 1969, 1971, 1973, 1975, 1977 and 1979 for the following annual data items: #6 (Total Assets; Liabilities and Shareholders' Equity), #12 (Sales), #18 (Income Before Extraordinary Items and Discontinued Operations), #24 (Closing Price for the Calendar Year), #25 (Common Shares Outstanding), #26 (Dividends Per Share by Ex-Date), #27 (Cumulative Adjustment Factor), #58 (Primary Earnings Per Share, Excluding Extraordinary Items and Discounted Operations) and #60 (Common Equity). Also, for each of the five years prior to and including the formation year, the company must have a December fiscal-year end. In addition, it must be listed either on the NYSE or the AMEX. Finally, firms that are part of the S&P 40 Financial Index are excluded. For the six samples listed by formation date, the number of companies

⁷ Rogalski and Tinic use arguments similar to Chan's to explain the January size effect. They show that the CAPM-betas of small firms are higher in January than in other months and that, therefore, "the 'abnormal' returns on these stocks may not, after all, be abnormal" ([27], p. 63) if proper risk adjustments are made. However, given that so many small firms are losers, we speculate that small firms also have high January betas in up markets and low betas in down markets, a result which would leave the abnormal returns abnormal.

(and the number of companies listed on the NYSE) are: 1969: 1015 (789); 1971: 1106 (842); 1973: 1262 (931); 1975: 1336 (996); 1977: 1339 (975); and 1979: 1263 (939).

2. For each firm j , annual raw returns R_{jt} and excess returns u_{jt} are computed from COMPUSTAT data (with appropriate adjustments made for stock splits, etc.) for all years between $t - 3$ and $t + 4$, with t representing the final year of the formation period. The excess returns are market-adjusted, $u_{jt} = R_{jt} - R_{mt}$, where the market return R_{mt} is estimated by compounding (over 12 months) a monthly equal-weighted NYSE index taken from CRSP.

3. Every sample is ordered by each of the following four ranking variables: (a) cumulative excess return (CU_j) over a four-year formation period between the end of year $t - 4$ and the end of year t ; (b) market value of equity (MV) at (the end of year) t ; (c) market value of equity divided by book value of equity (MV/BV) at t ; (d) company assets at t (COMPUSTAT item #6).

4. For each sample and for each ranking variable, with minor adjustments, quintile, decile, and "ventile" (20) portfolios are formed. Average and cumulative average excess returns (CAR) are calculated for the four years between $t - 3$ and t , and for the four years between $t + 1$ and $t + 4$. Subsequently, the (cumulative) average excess returns are averaged once again, either across the six samples, or across two times three samples (formation years 1969, 1973 and 1977, vs. formation years 1971, 1975 and 1979). With CU_j as ranking variable, these two times three samples represent truly independent observations since the formation periods are non-overlapping.

For the sake of brevity, the tables below report our findings primarily for the quintile portfolios. However, the statistical tests are done on the basis of ventile or decile portfolios.

5. For each ranking method, portfolio averages and medians are also computed for other variables of interest, most importantly, company income and earnings per share (EPS). The EPS-numbers for different years are adjusted for stock splits, stock dividends, etc.; as a result, they remain strictly comparable through time. In order to improve their cross-sectional comparability, they are scaled by the closing stock price at the end of year $t - 4$.⁸

6. In order to make portfolio comparisons of time-series movements in any given variable X easier, the portfolio averages X_p are indexed by setting them equal to 1.0 in a base year (either t or $t - 4$). Thus, the observations may be represented by $X_{pt}^* = (X_{pt}/X_{pb})$ where X_{pb} is the portfolio average in the base year. A simple method to detrend X_{pt}^* (or, in other words, to remove the market-wide component in its movement through time) starts by repeating the above indexation procedure for the whole sample population. Then, if X_{st} stands for the total sample average at t , $X_{st}^* = (X_{st}/X_{sb})$. The next step is to find the detrended X_{pt}^d by dividing X_{pt}^* by X_{st}^* for all t . Tables VII and VIII below list X_{pt}^d multiplied by 100.

⁸ Whenever there are missing data, the portfolio averages and medians are computed over the remaining observations. There are three sources of missing data: [1] fiscal year changes; [2] removal of the company from the COMPUSTAT research files; [3] missing observations in otherwise complete data records. Except in case [3], the stock is removed from all portfolio averages at the same point in time.

7. Friedman's [15] two-way analysis of variance by ranks is used to test nonparametrically whether, for any ranking method, there is a tendency for the annual excess returns of one portfolio to exceed or to be smaller than the same-year returns of other portfolios. A multiple comparison procedure specifically checks for differences between the extreme decile portfolios. The data are average excess returns during the formation and test periods for twenty portfolios of equal size. The tests are run twice: once for the average excess returns computed with 1969, 1973 and 1977 as the formation years, and again with 1971, 1975 and 1979 as the formation years. We have two times four (years $t - 3 \dots t$; $t + 1 \dots t + 4$) independent samples and twenty "treatments" (portfolios). The test statistic is distributed approximately chi-square with nineteen degrees of freedom.

In some cases, Page's [25] nonparametric test for ordered alternatives provides a more meaningful alternative hypothesis. It checks whether, for any ranking method, the k "treatment" effects are ordered in the following way: $t_1 \leq t_2 \leq \dots \leq t_k$. If the alternative hypothesis is changed to $t_1 \geq t_2 \geq \dots \geq t_k$, the test statistic only changes its sign. For large samples, the statistic is distributed approximately as the standard normal. The exact computational formulas for both the Friedman and Page tests can be found in, e.g., Daniel [10].

B. Results Comparing the Size and Winner-Loser Effects

Table V.A shows a replication of our original winner-loser experiment using both NYSE and AMEX firms listed on COMPUSTAT for the years 1966-1983. The table shows that even for quintile portfolios (which are less extreme than the deciles or groups of 50 stocks used in our previous study) the losers have positive excess returns and the winners have negative excess returns. Indeed, the Page test does not allow us to reject the hypothesis that the ranking of excess returns in the test period is the inverse of the (forced) ranking during the formation period (see Table VI).

Table V.A also shows the average and median market values for each quintile. It is informative to compare these figures with those in panel B where market value of equity (the usual measure of firm size) is the ranking method, and also with panel D, where the ranking criterion is company assets. The firms in both extreme CAR quintiles are smaller than those in the middle portfolios, but they are not unusually small. In fact, the mean for both quintiles is comparable to the 4th quintile of the MV and company assets rankings. (Similar results obtain for the average MV of the extreme deciles and ventiles.) The average market value for the smallest quintile ranked by MV is about 30 times smaller than the average market value for the loser quintile. A comparison of the relevant averages and medians indicates that, while there is some skewness in the distributions, it affects the quintile portfolios more or less evenly. Thus, the winner-loser anomaly cannot be accurately described as primarily a small firm phenomenon.⁹

⁹ Fama and French [14] also examine the size issue. Using the CRSP monthly return file of NYSE firms, they study winner and loser portfolios containing 35 stocks for 19 non-overlapping three-year formation and test periods starting in 1926 and ending in 1982. The market value of the loser portfolio is on average in the 26th percentile, while the market value of the winners is in the 58th percentile. Thus, the most extreme NYSE losers tend to be somewhat smaller than average, but not extremely small. There is also considerable variation from one experiment to another and, on occasion, the

Table V
Descriptive Statistics for Quintile Portfolios Ranked by Cumulative Average Residual, Market Value, Market Value divided by Book Value of Equity, and Assets

Portfolio #	CAR		Sales	Assets	Market Value	Fin. Lev.	MV/BV	Earnings Yield
	Formation Period	Test Period						
A: Ranking Criterion: Cumulative Average Residual (Years $t - 3, t$)								
Averages								
1	-.807	.246	n.a.	700	304	n.a.	.962	.023
2	-.323	.122	n.a.	1197	479	n.a.	1.001	.091
3	.003	-.004	n.a.	1335	557	n.a.	1.145	.127
4	.321	-.015	n.a.	1087	561	n.a.	1.455	.180
5	1.264	-.117	n.a.	689	582	n.a.	2.426	.325
Medians								
1	n.a.	n.a.	200	240	73	.314	.877	.033
2	n.a.	n.a.	204	276	101	.365	.890	.091
3	n.a.	n.a.	215	286	109	.399	.976	.125
4	n.a.	n.a.	216	275	133	.521	1.162	.167
5	n.a.	n.a.	173	174	161	.889	1.848	.245
B: Ranking Criterion: Market Value of Equity (Year t)								
Averages								
1	-.111	.299	n.a.	n.a.	9	n.a.	.888	.121
2	.182	.132	n.a.	n.a.	32	n.a.	1.098	.173
3	.180	.116	n.a.	n.a.	96	n.a.	1.325	.166
4	.131	-.090	n.a.	n.a.	288	n.a.	1.592	.156
5	.028	-.209	n.a.	n.a.	2076	n.a.	2.073	.126
Medians								
1	n.a.	n.a.	35	24	9	.351	.756	.107
2	n.a.	n.a.	93	79	31	.402	.889	.130
3	n.a.	n.a.	177	212	90	.429	1.060	.135
4	n.a.	n.a.	406	558	272	.477	1.194	.117
5	n.a.	n.a.	1470	1769	945	.659	1.437	.102

C: Ranking Criterion: Market Value/Book Value of Equity (Year t)

		Averages						
1	-.258	.407	n.a.	658	106	n.a.	.361	.100
2	-.030	.226	n.a.	1219	330	n.a.	.766	.149
3	.163	.095	n.a.	1260	424	n.a.	1.022	.169
4	.376	.050	n.a.	1176	594	n.a.	1.427	.180
5	.762	-.013	n.a.	670	1030	n.a.	3.417	.147
		Medians						
1	n.a.	n.a.	136	115	23	.223	.512	.101
2	n.a.	n.a.	173	234	70	.339	.789	.124
3	n.a.	n.a.	193	266	103	.439	1.036	.128
4	n.a.	n.a.	247	295	165	.651	1.437	.128
5	n.a.	n.a.	187	184	270	1.499	2.766	.103

D: Ranking Criterion: Company Assets (Year t)

		Averages						
1	.217	.237	n.a.	22	17	n.a.	1.370	.147
2	.228	.143	n.a.	76	54	n.a.	1.446	.169
3	.146	.091	n.a.	211	148	n.a.	1.424	.161
4	-.030	-.075	n.a.	661	431	n.a.	1.463	.136
5	-.110	-.150	n.a.	4063	1815	n.a.	1.278	.129
		Medians						
1	n.a.	n.a.	28	21	10	.526	.958	.121
2	n.a.	n.a.	95	72	32	.461	1.008	.131
3	n.a.	n.a.	216	192	93	.462	1.057	.126
4	n.a.	n.a.	530	592	268	.437	1.136	.109
5	n.a.	n.a.	1609	2203	755	.350	1.032	.113

Note: Year t represents the last year of the formation period. Sales, assets and market value are measured in \$ millions. Financial leverage is measured as market value divided by balance sheet total. Earnings yield is defined as earnings-per-share in year t divided by share price at the end of year $t - 4$ (with appropriate adjustments made for stock splits, etc.). The reported grand averages (grand average medians) are calculated by first, [1] averaging (or finding the average median of) the replications with 1969, 1973 and 1977 as the last formation year; then, [2] averaging (or finding the average median of) the replications with 1971, 1975 and 1979 as the last formation year; and, finally, [3] averaging the averages (or average medians) from steps [1] and [2].

Table VI
Friedman Two-Way Analysis Of Variance By Ranks and Page's
Test For Ordered Alternatives

Ranking Variable	Friedman chi-square	Friedman multiple comparison procedure	Page z-statistic
A: Formation Period			
CAR($t - 3, t$)	*	*	*
	*	*	*
MV	8.30	-8.0	-1.08
	29.16	-17.0	-2.39 (-)
MV/BV	67.60 (x)	-32.0 (+)	-8.06 (-)
	65.97 (x)	-30.0 (+)	-8.01 (-)
Assets	8.90	3.0	1.21
	11.91	-1.0	.79
B: Test Period			
CAR($t - 3, t$)	41.31 (x)	23.0	5.63 (-)
	15.67	10.0	3.41 (-)
MV	46.76 (x)	33.0 (+)	6.01 (-)
	62.46 (x)	34.0 (+)	7.67 (-)
MV/BV	34.10 (x)	26.0 (+)	5.04 (-)
	37.86 (x)	29.0 (+)	5.48 (-)
Assets	31.66 (x)	22.0	4.79 (-)
	46.50 (x)	29.0 (+)	6.25 (-)

Notes: [1] The test-statistics in the top (bottom) rows are based on the replications with formation years 1969, 1973 and 1977 (1971, 1975 and 1979). Entries that are significant by construction (the formation period returns for portfolios ranked by cumulative average residuals) are marked with an asterisk. [2] Friedman's test-statistic is distributed chi-square with $k - 1$ degrees of freedom where k , the number of portfolios, equals 20. The null hypothesis can be rejected at the 5 (10) percent level of significance if the test-statistic is greater than or equal to 30.14 (27.20). Entries significant at the 5 percent level are marked with x. [3] The tests using Friedman's multiple comparison procedure are based on decile portfolios, comparing the returns on portfolios 1 and 10. The critical values for this test are 25.3 ($p = .05$), 23.6 ($p = .10$), 22.7 ($p = .15$) and 21.9 ($p = .20$). Entries significant at the 5 percent level are marked with +. [4] The Page z-statistic is distributed approximately as the standard normal. The computations are based on 20 portfolios. Entries larger than 2.0 are marked with -.

In contrast, it seems more apt to characterize the winner-loser effect as an overvalued-undervalued effect. One traditional measure of under- (or over-) valuation (similar to Tobin's Q) is the ratio of market value to book value of equity (MV/BV). From the MV/BV column in Table V.A, one sees that the ranking by CAR coincides with the ranking of MV/BV. The similarity of the two

losers are bigger than the winners. Our COMPUSTAT sample differs in several respects. It includes AMEX firms, covers only the period 1965-84, and the numbers we report in Table V.A are for quintile portfolios (rather than 35 stocks). Even so, the size estimates are roughly comparable. For the subset of periods studied by Fama and French which overlap with our COMPUSTAT sample (1965-1982), the average market value of their losers is \$164 million which is larger than the median firm on COMPUSTAT. The number may be usefully compared with the average market value, \$234 million, of our most extreme loser ventile (containing, on average, 61 stocks).

ranking methods can also be judged by comparing panels A and C where MV/BV is the ranking criterion. Notice that the CAR's for the extreme MV/BV portfolios show the familiar winner-loser reversal pattern. The Page test in Table VI does not allow us to reject such return reversals. Excess returns for portfolios formed on a "book/price" strategy have been reported earlier by Rosenberg, Reid, and Lanstein [29].

While the losing firm effect cannot be characterized as a small firm effect, one may still ask: To what extent is the small firm effect a losing firm effect?¹⁰ Table VII provides indexed, detrended measures of MV for portfolios formed on the same criteria used in Table V. Notice that the companies in the smallest quintile (ranked by MV) have recently shrunk in size relative to other firms in the sample.¹¹ In fact the V-shaped pattern is similar to that seen for the extreme portfolios ranked by CAR and by MV/BV. It is instructive to compare the MV results with those of Assets. For Assets there is no trend in market value during the formation period. In this sense, Assets is a more permanent measure of firm size than MV.¹²

Since the size effect, as measured by MV, is partly a losing firm effect, it is interesting to see whether there are still excess returns to small firms if another measure of size such as Assets (or Sales) is used. In Tables V (panel D) and VI, we show that, in fact, excess returns are still significantly related to size. (Similar results, not reported here, are obtained if Sales (COMPUSTAT item #12) is used as the ranking criterion).

C. Excess Returns and Overreaction to Earnings

In contrast to the risk-change and time-varying discount rate explanations of the winner-loser effect, one interpretation of the overreaction hypothesis stresses misperceptions of future cash flows for extreme winners and losers.¹³ The hypothesis entails that investors, on average, have an excessively short-term orientation: They focus on the recent past and do not look beyond the immediate future. An implication of the hypothesis is that there should be a close correspondence between stock returns and short-term changes in the earnings outlook. Of course, if earnings were to follow a random walk (even in the tails of the cross section of firms), then myopic forecasts could coincide with rational expectations (in the absence of other information). However, if earnings are mean-reverting in the tails, as suggested by e.g., Brooks and Buckmaster [5], then stock prices

¹⁰ Previous research by Reinganum [26, Table 1] indicates that the smallest MV decile has a disproportionate number of prior short-term losers, and that among the small firms, the losers do particularly well in January. See also Chan [8, Table 1].

¹¹ Note that (as explained in Section II.A above) we are detrending relative to the whole sample population, while the CAR's shown in Table V were calculated with respect to a NYSE equal-weighted index. That index is likely to underestimate the annual returns to our COMPUSTAT samples since they include about 26% AMEX firms. Thus the moderate fall in returns seen in the second column of Table V.B is not inconsistent with Table VII.

¹² In addition, using Assets to measure firm size avoids any confounding effect introduced by changes in the financial structure of a firm (such as a corporation repurchasing its shares and issuing debt).

¹³ Overreaction behavior could be manifest in other ways as well. Investors might be overly sensitive to perceived risks, producing normatively excessive risk premia. Alternatively, some investors' decisions might be influenced by temporary fads, as proposed by Shiller [32].

Table VII
Average Market Value of Equity for Top and Bottom Quintiles, Indexed and Detrended
($MV_{t-4} = 100$)

Ranking Variable	Quintile #	Years										
		$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$		
CAR($t-3, t$)	1	100	85	77	71	59	61	65	74	73		
	5	100	118	137	146	170	159	162	154	153		
MV	1	100	89	80	72	58	60	69	78	89		
	5	100	100	101	101	102	99	96	94	91		
MV/BV	1	100	96	90	84	66	67	73	77	85		
	5	100	101	107	105	113	110	107	103	99		
Assets	1	100	97	95	98	101	104	118	133	134		
	5	100	100	99	99	98	96	93	91	89		

Note: Year t represents the last year of the formation period. All entries are indexed and detrended averages for six replications with 1969, 1971, 1973, 1975, 1977 and 1979 as the last formation year. See Section II.A for details.

influenced by myopic forecasts will show mean reversion as earnings realizations systematically diverge from earlier expectations. Therefore, paradoxically, extreme stock price increases and decreases should be predictive of subsequent earnings reversals. If this pattern is not observed, then at least this simple form of the overreaction hypothesis can be rejected.

Table VIII shows average and median earnings per share, normalized by share price at the end of year $t - 4$, detrended, and indexed to be equal to 100 at the beginning of the test period. The results for the portfolios formed by CAR are consistent with the overreaction hypothesis. Both winners and losers show the predicted reversal pattern.^{14,15} The same pattern is observed for the MV/BV ranking criterion, which is another proxy for market price deviations from fundamental value. One intriguing aspect of these results is that the reversal of earnings is much larger for the losers than for the winners. This offers one possible explanation of the similar asymmetry in excess returns. If the anomalous price behavior is driven by earnings surprises, then the returns pattern should be similar to the earnings pattern.¹⁶

In contrast, both size measures, MV and Assets, show distinctly different patterns. Small firms, by either measure, show faster earnings growth than large firms throughout both the formation and test periods. This suggests that one possible explanation for the size effect is a failure by the market to recognize the small firms' higher growth potential. This and other related hypotheses are investigated by Givoly and Lakonishok [16], but are not pursued any further here.

III. Summary and Conclusions

The principal findings of this study are:

1. Excess returns for losers in the test period (and particularly in January) are

¹⁴ A comparison of the average and median EPS makes it clear that the averages are somewhat affected by outliers. Preliminary work suggests that there is similar cross-sectional skewness in the test period returns of securities that make up the extreme portfolios. Simple binomial tests further indicate that, for a majority of test periods starting each year between 1970 and 1980, the percentage of firms in the loser decile portfolio that experience above-average earnings growth is significantly larger than the equivalent percentage in the winner decile.

¹⁵ Since the samples are selected from both the main and delisted (research) files of COMPUSTAT, they do not suffer from "ex post selection" (survivorship) bias as it is normally understood in the literature (see, e.g., Banz and Breen [2]). However, for our purposes, the earnings pattern of companies after they leave the research file is still relevant. If there were unusual attrition in the extreme quintile portfolios, the earnings trends documented in Table VII would be biased in a direction that unduly favors the overreaction hypothesis. We doubt that this is actually happening in an important way. Summed over the six samples, each quintile portfolio contains 1452 companies in the formation year. With CAR as the ranking criterion, the loser portfolio still contains 1349 (92.9%) companies at the end of year $t + 3$. For the other quintiles, the relevant percentages are 93.9, 94.9, 95.2, and 93.3 (with the extreme winner portfolio last). While the reasons for delisting may differ, it is also important to note at this point that the number of firms removed from COMPUSTAT because of financial difficulty is "substantially smaller than the number delisted because of merger or limited distribution" (McElreath and Wiggins [23, p. 74]).

¹⁶ For a sample of COMPUSTAT firms, Beaver, Lambert and Morse also study the relationship between price changes and earnings changes. They conclude that prices behave "as if earnings are perceived to be dramatically different from a simple random walk process" ([3], p. 3). In particular, the market expects events that cause positive or negative earnings surprises to induce additional earnings changes later on. These findings are consistent with overreaction.

Table VIII
Average and Median Earnings Per Share, Indexed and Detrended

Ranking Variable	Years									
	$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$	
Decile Portfolios: $[\text{EPS}(t-4)/\text{P}(t-4)] = 100$										
	Average Earnings-Per-Share									
CAR($t-3, t$)	1	100.0	55.1	15.3	-2.6	0.1	17.6	35.4	41.9	52.4
	2	100.0	80.8	73.6	34.8	43.6	57.1	63.3	71.0	79.0
	3	100.0	81.6	73.5	68.1	57.4	56.6	61.8	66.4	66.1
	8	100.0	99.3	98.6	100.9	101.6	97.9	93.4	88.7	90.6
	9	100.0	149.2	164.8	186.6	185.3	185.0	176.8	177.3	175.1
	10	100.0	164.2	216.4	262.3	277.5	266.8	250.4	239.5	239.0
Quintile Portfolios: $[\text{EPS}(t)/\text{P}(t-4)] = 100$										
	Median Earnings-Per-Share									
CAR($t-3, t$)	1	n.a.	197.0	151.9	114.1	100.0	106.3	118.0	137.2	126.6
	5	n.a.	83.3	91.5	99.2	100.0	97.3	94.0	92.7	94.6
	Average Earnings-Per-Share									
CAR($t-3, t$)	1	n.a.	361.1	257.8	66.3	100.0	185.9	248.7	284.7	334.5
	5	n.a.	66.8	82.1	96.5	100.0	96.7	89.7	87.9	87.7
MV	1	n.a.	83.3	94.9	88.0	100.0	101.5	120.9	115.3	125.6
	5	n.a.	114.5	106.7	100.2	100.0	100.0	98.2	100.7	95.0
MV/BV	1	n.a.	142.1	128.0	104.3	100.0	104.4	119.2	112.8	124.4
	5	n.a.	69.8	83.5	89.3	100.0	110.1	111.4	111.4	108.2
Assets	1	n.a.	72.5	89.6	89.1	100.0	102.9	110.4	114.7	118.2
	5	n.a.	125.9	117.0	109.7	100.0	102.2	96.2	100.1	97.7

Note: See Table VII. The earnings-per-share data are adjusted for stock splits and stock dividends. Before portfolio averaging, they are scaled by the closing stock price on the last trading day of year $t-4$.

negatively related to both long-term and short-term formation period performance. For winners, January excess returns are negatively related to the excess returns for the prior December, possibly reflecting a capital gains tax "lock-in" effect.

2. The winner-loser effect cannot be attributed to changes in risk as measured by CAPM-betas. While the (zero-investment) arbitrage portfolio has a positive beta of .220, this is insufficient to explain its average annual (test period) return of 9.2 percent. Further analysis shows that the arbitrage portfolio has a positive beta in up markets and a negative beta in down markets, a combination that would not generally be considered particularly risky.

3. The winner-loser effect is not primarily a size effect.

4. The small firm effect is partly a losing firm effect, but even if the losing firm effect is removed (by using a more permanent measure of size, such as assets) there are still excess returns to small firms.

5. The earnings of winning and losing firms show reversal patterns that are consistent with overreaction.

What conclusions seem warranted at this time? Many puzzles remain, especially regarding the seasonality in excess returns. We have no satisfactory explanation for the January effects, rational or otherwise.

On the more positive side, the reversal pattern documented by our earlier paper has now been replicated by many other researchers (Brown and Harlow [6], Chan [9], Fama and French [13, 14], Howe [17]), and there is plenty of evidence that stock returns vary over time in a manner that can be predicted by variables that reflect levels of asset prices (Keim and Stambaugh [20]).

According to Fama and French [14, p. 24], "Whether predictability reflects market inefficiency or time-varying expected returns generated by rational investor behavior is, and will remain, an open issue." In fact, they conclude that the issue is not resolvable. How then can progress be made? In our view, students of financial markets have little choice but to broadly examine the evidence on return predictability and make a judgment regarding which type of model offers the most parsimonious explanation of the facts.

This paper has made contributions to this task in two different directions. First, two plausible explanations of the winner-loser effect, namely those based on the size or risk characteristics of the winning and losing firms, have been examined. The data do not support either of these explanations. Second, the paper provides new evidence consistent with the simple behavioral view that investors overreact to short-term (i.e., a few years) earnings movements. Certainly, within the framework of the efficient market hypothesis, it is distinctly puzzling that a dramatic fall (rise) in stock prices is predictive of a subsequent rise (fall) in company-specific earnings.

As to time-varying discount rates, we certainly agree that they may play a role in explaining the observed price reversals. However, even if time-varying discount rates can be shown to offer a coherent explanation of the winner-loser effect and other anomalies, for the "market rationality hypothesis" (Merton [24]) to be accepted, it will also be necessary to demonstrate that these fluctuations in discount rates can be characterized as rational responses to economic conditions rather than emotional shifts in the mood of market participants.

REFERENCES

1. George A. Akerlof. *An Economic Theorist's Book of Tales*. London: Cambridge University Press, 1984.
2. Rolf W. Banz and William J. Breen. "Sample-Dependent Results Using Accounting and Market Data: Some Evidence." *Journal of Finance* (September 1986), pp. 779-793.
3. William Beaver, Richard Lambert, and Dale Morse. "The Information Content of Security Prices." *Journal of Accounting and Economics* (2:1980), pp. 3-28.
4. Ben Branch. "A Tax Loss Trading Rule." *Journal of Business* (April 1977), pp. 198-207.
5. LeRoy D. Brooks and Dale A. Buckmaster. "Further Evidence of the Time Series Properties of Accounting Income." *Journal of Finance* (December 1976), pp. 1359-1373.
6. Keith C. Brown and W. V. Harlow. "Assessing the Magnitude and Intensity of Stock Market Overreaction." *Journal of Portfolio Management* (forthcoming).
7. K. C. Chan. "Can Tax-Loss Selling Explain the January Seasonal in Stock Returns?" *Journal of Finance* (December 1986), pp. 1115-1128.
8. K. C. Chan. "The Use of Information in Market Values for Estimating Time-Varying Stock Betas." Working Paper, Faculty of Finance, Ohio State University, June 1986.
9. K. C. Chan. "On the Return of the Contrarian Investment Strategy." Working Paper, Faculty of Finance, Ohio State University, January 1987.
10. Wayne W. Daniel. *Applied Nonparametric Statistics*. Boston: Houghton Mifflin Company, 1978.
11. Werner F. M. De Bondt and Richard H. Thaler. "Does the Stock Market Overreact?" *Journal of Finance* (July 1985), pp. 793-805.
12. Edward A. Dyl. "Capital Gains Taxation and Year-End Stock Market Behavior." *Journal of Finance* (March 1977), pp. 165-175.
13. Eugene F. Fama and Kenneth R. French. "Permanent and Temporary Components of Stock Prices." Working Paper No. 178, Graduate School of Business, University of Chicago, July 1986.
14. Eugene F. Fama and Kenneth R. French. "Common Factors in the Serial Correlation of Stock Returns." Working Paper, Graduate School of Business, University of Chicago, October 1986.
15. Milton Friedman. "The Use of Ranks to Avoid the Assumption of Normality Implicit in the Analysis of Variance." *Journal of the American Statistical Association* (32:1937), pp. 675-701.
16. Dan Givoly and Josef Lakonishok. "Earnings Growth and the Firm-Size Anomaly." Working Paper No. 832/84, The Leon Recanati Graduate School of Business Administration, Tel Aviv University, November 1984.
17. John S. Howe. "Evidence on Stock Market Overreaction." *Financial Analysts Journal* (July/August 1986), pp. 74-77.
18. R. G. Ibbotson and R. A. Sinquefeld. *Stocks, Bonds, Bills, and Inflation: The Past and the Future*. Charlottesville: The Financial Analysts Research Foundation, University of Virginia, 1982.
19. Donald B. Keim. "Size Related Anomalies and Stock Return Seasonality." *Journal of Financial Economics* (June 1983), pp. 13-32.
20. Donald B. Keim and Robert F. Stambaugh. "Predicting Returns in the Stock and Bond Markets." *Journal of Financial Economics* (1986), pp. 357-390.
21. John Maynard Keynes. *The General Theory of Employment, Interest and Money*. London: Harcourt Brace Jovanovich, 1964 (reprint of 1936 edition).
22. Josef Lakonishok and Seymour Smidt. "Volume for Winners and Losers: Taxation and Other Motives for Stock Trading." *Journal of Finance* (September 1986), pp. 951-974.
23. Robert B. McElreath, Jr. and C. Donald Wiggins. "Using the COMPUSTAT Tapes in Financial Research: Problems and Solutions." *Financial Analysts Journal* (January/February 1984), pp. 71-76.
24. Robert C. Merton. "On the Current State of the Market Rationality Hypothesis." Working Paper No. 1717-85, Massachusetts Institute of Technology, October 1985.
25. E. B. Page. "Ordered Hypothesis for Multiple Treatments: A Significance Test for Linear Ranks." *Journal of the American Statistical Association* (58:1963), pp. 316-230.
26. Marc R. Reinganum. "The Anomalous Stock Market Behavior of Small Firms in January: Empirical Tests for Tax-Loss Selling Effects." *Journal of Financial Economics* (June 1983), pp. 89-104.

27. Richard J. Rogalski and Seha M. Tinic. "The January Size Effect: Anomaly or Risk Measurement?" *Financial Analysts Journal* (November/December 1986), pp. 63-70.
28. Richard Roll. "Was ist Das? The Turn-of-the-Year Effect and the Return Premia of Small Firms." *Journal of Portfolio Management* (Winter 1983), pp. 18-28.
29. Barr Rosenberg, Kenneth Reid and Ronald Lanstein. "Persuasive Evidence of Market Inefficiency." *Journal of Portfolio Management* (Spring 1985), pp. 9-16.
30. Michael S. Rozeff. "The December Effect in Stock Returns and the Tax-Loss Selling Hypothesis." Working Paper No. 85-18, College of Business Administration, University of Iowa, May 1985.
31. William Schwert. "Size and Stock Returns, and Other Empirical Regularities." *Journal of Financial Economics* (June 1983), pp. 3-12.
32. Robert J. Shiller. "Stock Prices and Social Dynamics." *Brookings Papers on Economic Activity* (2:1984), pp. 457-510.
33. Theo Vermaelen and Marc Verstringe. "Do Belgians Overreact?" Working Paper, Catholic University of Louvain, Belgium, November 1986.