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FADS, MARTINGALES, AND MARKET EFFICIENCY*

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Predictable variation in equity returns might reflect either (1) predictable changes in expected returns or (2) market inefficiency and stock price "overreaction." These explanations can be distinguished by examining returns over short time intervals since systematic changes in fundamental valuation over intervals like a week should not occur in efficient markets. The evidence suggests that the "winners" and "losers" one week experience sizeable return reversals the next week in a way that reflects apparent arbitrage profits which persist after corrections for bid-ask spreads and plausible transactions costs. This probably reflects inefficiency in the market for liquidity around large price changes.

I. INTRODUCTION

Much of the theoretical basis for current monetary and financial theory rests on the efficiency of financial markets. Considerable effort has been expended testing the efficient markets hypothesis, usually in the form of the random walk model for stock prices. Most early studies supported the random walk model, finding that the predictable variation in equity returns was both economically and

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statistically small. However, much recent research has found evidence that equity returns can be predicted with some reliability.[1]

These are two competing explanations of this phenomenon. The first is that required returns vary through time, resulting in predictable, but efficient, mean reversion in stock prices. Alternatively, the predictability of equity returns may reflect the overreaction of stock prices, "fads," or the cognitive misperceptions of investors in an inefficient market as suggested by Shiller [1984], Black [1986], Poterba and Summers [1987], DeBondt and Thaler [1985, 1987], and Shefrin and Statman [1985].

These two explanations can be distinguished by examining asset returns over short time intervals. As Sims [1984] and others have emphasized, asset prices should follow a martingale process over very short time intervals even if there are predictable variations in expected security returns over longer horizons—systematic short-run changes in fundamental values should be negligible in an efficient market with unpredictable information arrival. Fads models, in contrast, predict serial correlation over all time intervals, although most versions emphasize predictability over long time intervals.

While rejection of martingale behavior over short horizons is evidence against market efficiency, such evidence probably reflects inefficiency in the market for liquidity in common stocks. In other words, short-run price movements probably provide little information about the long-term differences between prices and fundamental values typically emphasized in fads models. Pricing fads may be more economically interesting, but potential short-run inefficiencies in financial markets are probably more easily and precisely measured.[2]

Nevertheless, there remain severe econometric problems associated with the construction of powerful tests of this short-run martingale hypothesis. Shiller [1981], Shiller and Perron [1985], and Summers [1986] have emphasized the low power of standard tests for serial correlation when applied to security returns. This problem is particularly severe over short differencing intervals.

1. See Fama [1970] and Singleton [1987] for surveys of the evidence on predictable variation.

2. There is considerable evidence of systematic reversals in stock returns over longer intervals. DeBondt and Thaler [1985], Fama and French [1987], and Poterba and Summers [1987] found evidence for such variation over three-to-ten-year intervals. Rosenberg, Reid, and Lanstein [1985] and Jegadeesh [1987] provided sharp evidence at the monthly frequency. Chan [1988] argued that the evidence in DeBondt and Thaler [1985] is attributable in part to changes in the riskiness of winners and losers, an interpretation contested in DeBondt and Thaler [1987].

Many assets are traded on organized securities markets. It is reasonable to suppose that any stock price overreaction infects many security returns for both security or industry-specific and market-wide reasons. Hence, well-diversified portfolios composed of either "winners" or "losers" might be expected to experience return reversals in these circumstances, suggesting a simple heuristic strategy for testing market efficiency: study the profits of costless (i.e., zero net investment) portfolios which give negative weight to recent winners and positive weight to recent losers. The short-run martingale model predicts that these costless portfolios should tend to earn zero profits. In contrast, these costless portfolios will typically profit from return reversals over some horizon if stock prices "overreact."[3]

The remainder of the paper quantifies this intuition and tests its empirical implications. The next section analyzes the testing procedure and contrasts it with more conventional approaches. The subsequent section discusses implementation issues and addresses some potential problems. The fourth section provides empirical evidence, and the final section contains concluding remarks.

II. The Profits on Return Reversal Portfolio Strategies

Portfolios that involve short positions in securities that experienced recent price increases and long positions in those that suffered recent price declines might earn abnormal profits if asset prices partially reflect overreaction to speculative fads. The employment of this intuition to test the market efficiency hypothesis requires the development of measures of abnormal profits. This section discusses the comparative merits of two such strategies.

To make matters concrete, consider the following portfolio strategies involving a given set of N securities over T time periods. At the beginning of period t, buy w_{it-k} dollars of each security i. This involves going long security i when w_{it-k} is positive and short selling it when this quantity is negative. Each position is closed out at the end of time t. Choose the weights w_{it-k} so that they are negative when security i is a winner and positive when security i is a loser.

In particular, set the number of dollars invested in each security proportional to the previous period's return (R_{it-k}) less the

3. This strategy avoids the power difficulties associated with *time series* autocorrelation tests by the *cross-sectional* aggregation of autocorrelation information, an intuition exploited by Jegadeesh [1987] to develop powerful cross-sectional tests of linear asset pricing relations.

return of an equally weighted portfolio of these N assets in that period ($\bar{R}_{t-k}$). Ignoring the factor of proportionality, the weights are given by

$$(1) \qquad w_{it-k} = -[R_{it-k} - \bar{R}_{t-k}]; \qquad \bar{R}_{t-k} = \frac{1}{N}\sum_{i=1}^{N} R_{it-k}.$$

Accounting profits in period $t(\pi_{t,k})$ are[4]

$$(2) \qquad \pi_{t,k} = \sum_{i=1}^{N} w_{it-k}R_{it} = -\sum_{i=1}^{N} [R_{it-k} - \bar{R}_{t-k}][R_{it} - \bar{R}_t],$$

so that the average profit ($\bar{\pi}_k$) on this k period ahead portfolio strategy over T periods is

$$(3) \qquad \bar{\pi}_k = -\frac{1}{T}\sum_{t=1}^{T} \pi_{t,k} = -\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N} [R_{it-k} - \bar{R}_{t-k}][R_{it} - \bar{R}_t].$$

Algebraic manipulation of this expression yields

$$(4) \qquad \bar{\pi}_k = \frac{N}{T}\sum_{t=1}^{T} [\bar{R}_{t-k} - \bar{\bar{R}}][\bar{R}_t - \bar{\bar{R}}] - \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N} [R_{it-k} - \bar{R}_i]\,[R_{it} - \bar{R}_i] - \sum_{i=1}^{N} [\bar{R}_i - \bar{\bar{R}}]^2,$$

where

$$(5) \qquad \bar{\bar{R}} = \frac{1}{T}\sum_{t=1}^{T} \bar{R}_t; \qquad \bar{R}_i = \frac{1}{T}\sum_{t=1}^{T} R_{it}$$

are the average returns of the equally weighted portfolio and of security i over time, respectively.[5] Thus, average portfolio profits depend on the autocovariances of the returns of an equally weighted portfolio, the autocovariances of the returns of the individual securities, and the cross-sectional variation in the unconditional mean returns of the individual securities.

Does the hypothesis of market efficiency place restrictions on either $\bar{\pi}_k$ or $\pi_{t,k}$? The traditional answer to this question reflects Fama's [1970, pp. 413–14] suggestion that the efficient markets hypothesis "only has empirical content, however, within a context of a more specific model of market equilibrium, that is, a model that specifies the nature of market equilibrium when prices 'fully reflect' available information." For example, it is common to assume that security returns are independently distributed (and often identically distributed as well) with constant expected returns in both the filter rule and the monthly return reversal literatures.

4. These are profits because this is a zero net investment strategy, and hence, returns are not defined.

5. Relation (4) holds for population moments as well and is studied in Lo and MacKinlay [1988].

If security returns are independently distributed over time, the population autocovariances of both individual securities and the equally weighted portfolio are zero. Hence, expected average profits on the return reversal portfolio strategies are

$$E\{\overline{\pi}_k\} = -E\left\{\sum_{i=1}^{N} [\overline{R}_i - \overline{\overline{R}}]^2\right\} \tag{6}$$

with two testable implications: expected average profits should be negative and identical for each value of k.[6] This makes intuitive sense—on average, return reversal strategies are long securities with below average expected returns and short those with above average expected returns and thus systematically lose the cross-sectional variation in expected returns in these circumstances.

As with most market efficiency tests, rejection of the hypothesis that average portfolio profits are identical for each value of k might simply indicate that returns are not independently distributed, perhaps because of time-varying expected returns in an efficient market. Put differently, the probability of rejecting the null hypothesis of market efficiency when it is true (i.e., a Type I error) involves both the usual sampling errors and the probability that security returns are not independently distributed. In other words, the conventional approach to testing the hypothesis of market efficiency with return reversal portfolios is not likely to yield a useful test in the absence of a plausible a priori model of temporal variation in expected returns.

An alternative strategy is suggested by the local martingale literature: the variation in short-run expected returns cannot be too pronounced, or else intertemporally well-diversified portfolio strategies will be too profitable. That is, strategies that bet on expected return changes without concentrating investment in any short period will earn arbitrage profits if very short-run security price changes are predictable.[7] If securities experience predictable price reversals, a simple market efficiency test can be based on time-

6. This is a version of a result derived in Jegadeesh [1987] for linear asset pricing relations.

7. The following example illustrates the intertemporal diversification argument. The typical annualized standard deviation of daily returns is 20 percent per year. Let E_t be the conditional expected return of a security in day t. Consider the strategy of buying E_t dollars of the security (which is a short sale when this quantity is negative) at the beginning of day t and closing out the position at the end of the day. If both the variance of squared daily expected returns and the covariance between squared daily expected returns and security volatility make a negligible contribution to portfolio profit variance, the expected annual profit on this strategy is more than 6,000 times its variance. This strategy is virtually riskless, unless daily expected returns and their variance are both very small (i.e., if there are no "near" arbitrage opportunities).

aggregated return reversal portfolio profits, which reflect the payoff to an intertemporally well-diversified strategy.

In particular, consider the J period profits:

$$\pi^J_{t,k} = \sum_{j=t+1}^{t+J} \pi_{j,k}. \tag{7}$$

The return reversal strategies reflect a *measured* arbitrage opportunity if these J period profits are consistently of one sign over the T/J periods covered by the data. This is evidence against the market efficiency hypothesis since these costless portfolios are riskless ex post in these circumstances. Failure to find a measured arbitrage opportunity involves failure to reject the joint hypothesis that the market is efficient and that the J period profits reflect the payoff of an intertemporally well-diversified portfolio strategy.

There is a major difference between the test based on measured arbitrage opportunities and that predicted on a model of market equilibrium. This test has a small Type I error rate, although it can easily result in failure to reject the market efficiency hypothesis when it is false (i.e., a Type II error).[8] This stands in sharp contrast to the conventional approach where Type I errors result from both the usual sampling problems and failure of the underlying model of market equilibrium.[9]

This test avoids the problems associated with specifying a model for expected return variation at the cost of requiring measured arbitrage opportunities to reject the hypothesis of market efficiency, a very stringent test that makes false rejection of the market efficiency hypothesis difficult. In addition, these portfolio strategies can, at best, only detect sources of market inefficiency that give rise to particular short-term arbitrage opportunities. For example, it is possible to construct models in which prices deviate from fundamental values because of fads or noise trading without giving rise to riskless arbitrage opportunities as in Campbell and

8. A Type I error occurs when an investigator concludes that an ex ante costless portfolio that was self-financing (i.e., earned strictly positive profits) ex post by chance was riskless ex ante.

9. There is another way to see this distinction. Average return reversal profits converge to zero in the limit of continuous trading. The assumption that J period profits reflect the payoff of an intertemporally well-diversified strategy involves the assumption that trading over discrete time intervals closely approximates continuous trading. A test of the null hypothesis that average return reversal portfolio profits are zero encounters the same conceptual difficulty as that based on the independence of security returns. The probability of rejecting this null hypothesis when it is true depends on the sampling errors in average return reversal portfolio profits as well as the probability that discrete trading well approximates continuous trading.

Kyle [1987] and De Long, Shleifer, Summers, and Waldmann [1987]. Alternatively, speculative fads may be market-wide, giving rise to long-term swings in stock prices such as bull and bear markets. In other words, speculative fads may have an important influence on asset prices but need not be reflected in short-run return reversal portfolio profits.

III. Empirical Methods, Potential Problems, and Safeguards

While the discussion of the previous section pointed to a general strategy for testing market efficiency, it left several choices open: (1) the appropriate set of securities; (2) the lag length k; (3) the horizon over which to aggregate portfolio profits (i.e., J); and (4) the time interval t over which the local martingale model applies under the efficient markets hypothesis. Moreover, the discussion neglected taxes, transactions costs, and other impediments to trade and presumed that prices could be measured without error.

Each of these issues requires careful a priori consideration. While this is a truism about empirical work in general, it has special force here since the strategy involves the search for unexploited arbitrage opportunities. It is obviously trivial to generate portfolio strategies that were profitable ex post but that need not have been profitable ex ante.

The empirical work that follows reflects one plausible set of a priori choices.[10] The asset menu was restricted to equity securities listed on the New York and American Stock Exchanges because the Center for Research in Security Prices (CRSP) returns file contains daily observations on all such securities from 1962 to present. Portfolio weights were taken to be proportional to the difference between the return of security i and the return on an equally weighted portfolio at different lags. Finally, a week was taken to be a sufficiently short period for the local martingale model to apply

10. This is also the only strategy that I have studied, and hence, the results reflect no obvious retrospective biases with one major exception: the fact that I read papers in the monthly and longer horizon return reversal literature prior to embarking on this study (particularly Jegadeesh [1987]). However, note that there is one ex ante forecast implicit here: the 1986 results were obtained after the first draft of this paper was circulated. Note also that most reasonable alterations of the analysis would probably increase measured portfolio profits. For example, all securities listed on the NYSE and the AMEX were included, even though a reasonable ex ante expectation is that small winners and losers contribute primarily to transactions costs and not to portfolio profitability.

while the horizon of the portfolio strategy was set to twenty-six weeks.[11]

The empirical work proceeded as follows. Every week, all securities that were listed on the New York and American Stock Exchanges in that week and k weeks previously were selected for inclusion in the portfolio strategy.[12] The number of dollars invested in each security was proportional to the return in week k less the return of the equally weighted portfolio of the included securities.[13] The factor of proportionality was the inverse of the sum of the positive deviations of individual security returns from this mean, making the portfolios long and short one dollar of equity securities. Hence, the number of dollars invested in security i in week t was

$$w_{it-k} = -[R_{it-k} - \bar{R}_{t-k}] \Big/ \sum_{\{R_{it-k} - \bar{R}_{t-k} > 0\}} R_{it-k} - \bar{R}_{t-k}. \tag{8}$$

These portfolio weights yield profits that are the difference in the returns on two dollar portfolios and, hence, are measured in units of percent per week.[14] The weights were then multiplied by the return on the corresponding security k weeks hence, and these returns were summed to arrive at portfolio profits for the week as in (2). Finally, this process was repeated for J weeks to generate the total profits on the strategy for the portfolio horizon J as in (7).[15]

11. Shorter intervals such as days were deemed inappropriate for reasons discussed below and other strategy horizons are reported below. A week was taken to begin on Wednesday and end on Tuesday to mimimize the number of days that exchanges were closed over the sample.

12. There is some room for selection bias since an investor would not know now that a firm would still exist in k weeks. Fortunately, the amount of delisting on the **CRSP** tapes is sufficiently small (especially over a few weeks) that this bias probably has little impact on the results. In addition, delisting alone overstates any upward bias in portfolio profits since firms typically leave the **CRSP** tapes for many reasons including name changes and takeovers.

13. Investors do not have full use of the proceeds of short sales in equity markets and, hence, cannot finance long positions with short sales. This is probably not cause for concern for three reasons. First, costless portfolios can be thought of as either an arbitrage strategy or as a marginal change in an existing portfolio that is long all of the securities that meet the criterion for inclusion. The restriction on the use of the proceeds from short sales has no force under the latter interpretation. Second, existing margin requirements require putting up margin for half of the market value of the long position, and large investors (such as broker-dealers) can costlessly use available marginable securities as collateral. Finally, borrowing costs are very small (less than 0.2 percent per week).

14. This is not necessarily innocuous since the scaling factor changes from week to week. The results change little when this scaling factor is omitted. The scaling factor can be thought of as a measure of the cross-sectional variation in returns in a given week.

15. Note that the profits for horizon J are the unweighted sum of the profits for each of the J weeks. This ignores the interest that could be earned (or the interest expense that could be incurred) on these profits within the J weeks. This is analogous to the treatment of dividends and coupon payments in the computation of bond and stock returns.

There is a major empirical problem with using weekly security returns to detect market inefficiency in this fashion: there are predictable fluctuations in *measured* security returns that have nothing to do with market inefficiency. Eighty percent of the price movements over successive transactions are between the bid and asked prices, giving the appearance of pronounced negative serial correlation even in daily returns. The **CRSP** data files list only closing prices without regard for whether the last transaction was executed at the bid price, the offer price, or within the bid-ask spread. Stocks will tend to look like winners (losers) if the last transaction on Tuesday was at the bid (offer) price. This will make the one-week strategy look more profitable than it is—stocks that appeared to be winners (losers) because the last transaction on Tuesday was at the bid (ask) price will move to the offer (bid) price next Tuesday roughly half of the time, yielding an apparent profit on the short (long) position in that stock.

This problem is mitigated by a few simple precautions. First, these biases are only a serious issue for portfolio strategies linking this week's return to that of next week (i.e., when $k = 1$). In addition, the use of weekly data reduces the severity of bid-ask spread bias. As an added precaution, the portfolio weights (but not the profits) for this strategy were also computed using four-day returns (i.e., from Wednesday through Monday). The absence of the security returns for the intervening Tuesday substantially reduces this bias by reducing the correlation between the portfolio weights and the measurement error in subsequent returns. Note that this is a conservative procedure—it eliminates the useful Tuesday returns (i.e., those that moved from bid to bid or ask to ask) as well as the corrupted ones (i.e., those that moved from bid to ask or ask to bid) and, hence, is likely to overstate the contribution of bid-ask spread bias to portfolio profits.

Most investigators think the fact that a security traded at the bid or the ask price on Monday is typically unrelated to the state at the close of trade on Tuesday. This presumption is false if the market is not sufficiently liquid to accommodate the needs of traders in the day or two after large price movements. Suppose that a random price increase occurs which is not expected to persist. Investors might be expected to sell some of their stock to rebalance their portfolios and market makers might be expected to buy to replenish their inventories to the extent that they were selling during the initial price increase. If investor portfolio adjustment and market maker inventory adjustment took several days following a large price movement, the price at the close of trade on

Monday could systematically be at the bid (ask), while that at the close of trade on Tuesday could systematically be at the ask (bid). My interpretation of the four-day return calculation requires that the market be sufficiently liquid to accommodate such trading needs in a day or two.

Another important issue is transactions costs. These portfolio strategies involve extreme portfolio turnover, typically requiring more than 2,000 transactions each week. Of course, the strategy could be modified to reduce the frequency of trading. Furthermore, it is not clear what transactions costs are relevant since costs are smaller for an investor treating this as a marginal change in an existing active trading strategy. Instead of searching for low transactions costs versions of these strategies (and risking the potentially serious retrospective bias that could then arise), portfolio profits were computed under different transactions cost assumptions.

Transactions cost per security per week was computed as $tc^*|w_{it} - w_{it-1}|$, where tc is the assumed one-way transactions cost per dollar transaction and w_{it} is the number of dollars invested in security i in week t. The profits are reported for several values of tc: 0.05 percent, 0.10 percent, 0.20 percent, 0.30 percent, 0.40 percent, and 1.0 percent. These numbers treat this portfolio strategy as if it generates *typical* trades in *typical* stocks. For large traders using market orders, one-way transactions costs are the clearing house costs of 0.05 percent plus one half the bid-ask spread (which ranges from 0.5 to 4.5 percent) times the fraction of trades in which specialists participate (approximately 10 to 15 percent of trades on the NYSE), suggesting one-way transactions costs of less than 0.20 percent for such investors.[16]

These numbers might be too low. The trades generated by this portfolio strategy are not in *typical* stocks. They are tilted toward smaller market capitalization firms that have larger bid-ask spreads and a greater proportion of trades taking place at the bid or offer price. If the strategy requires typical trades in these stocks, one-way transactions costs are probably closer to 1 percent.

These numbers might be too high because the strategy does not

16. Any price pressure generated by this trading strategy is ignored in these computations. For a given value of tc, transactions costs are probably overstated because the strategies, especially those based on four-day returns and on the returns in previous weeks, would afford investors the time to shop around for the best execution prices. The computations also ignore strategies for reducing transactions costs—trading at the open (at which time there is no bid-ask spread) and employing limit orders. Neither strategy can be simulated on CRSP data, which contain only closing prices.

generate *typical* trades. If a security is a big winner (loser), the market maker is typically a net seller to (buyer from) the public. Market makers want to rebalance their inventories in these circumstances so that patient traders like portfolio rebalancers and investors following reversal strategies can typically trade on favorable terms since they are providing needed liquidity. Hence, this strategy will typically be trading when bid-ask spreads are relatively low and when trades are executed within the bid-ask spread more frequently than usual. Baesel, Shows, and Thorp [1983] argued that Beebower and Priest [1979] found approximately zero net transactions costs in a sample of actual trades for this reason.[17]

There are several minor empirical problems which are not accounted for here but which are probably unimportant. The analysis presumes that it is possible to buy at the close of trade on one Tuesday and sell at the close of trade on the subsequent Tuesday. Although it may not have been possible to execute these transactions at these prices, the four-day return computation largely eliminates any bias that might arise.[18] In addition, SEC regulations require that short sales take place only on upticks. This probably has a small impact on the results since most of the profits come from the long and not the short positions. Finally, the portfolio profit computations ignore any price pressure generated by this trading strategy—a serious problem only if large positions are taken in illiquid securities. Typical position sizes will be reported below.

17. See Sweeney [1986] for a detailed discussion of these issues. This view is also supported by the experience of price-sensitive value-based portfolio managers, like Batterymarch Financial Management, and proprietary trading operations, such as those at Morgan, Stanley, & Co. and Bear, Stearns, & Co. They typically confront out-of-pocket costs of less than 0.10 percent and total transactions costs inclusive of price pressure of less than 0.20 percent one-way on similar trading strategies. I am grateful to Dean LeBaron of Batterymarch Financial Management and Greg Kipnis of Morgan, Stanley, & Co. for helpful discussions.

18. The direct effect of the bid-ask spread is accounted for in the transactions cost calculation. The bias arises because the closing price on the **CRSP** tapes is either at the bid or the offer, so that half the time the profit calculation assumes that one is buying (selling) at too low (high) a price since one buys (sells) at the asked (bid) price. Of course, this also means that the profit calculation assumes that one subsequently closes out the position at too low (high) a price for exactly the same reasons, leaving only a Jensen's inequality bias. From Blume and Stambaugh [1983], the bias (relative to true returns) is approximately

$$E\{\pi_{t,k}\} = \pi_{t,k}^{\text{true}} + \sum_{i-1}^{N} w_{it}\delta_i^2,$$

where δ_i is the percentage bid-ask spread. The bias is trivial even if the bid-ask spread is 2 or 3 percent and is made even smaller by the observation that the portfolio weights sum to zero.

IV. Empirical Results

This section evaluates the profitability of the costless portfolio strategies described in the previous section. The strategies were applied to virtually all securities listed on the New York and American Stock Exchanges between July 1962 and December 1986.[19] The portfolio weights were based on the following: the previous full week's returns, previous four-day returns (to mitigate bid-ask spread bias), and on the returns two, three, four, thirteen, twenty-six, and fifty-two weeks ago.

Table I presents the main results of the paper. The table reports the profits for five horizons (i.e., values of J): one, four, thirteen, twenty-six, and fifty-two weeks. Six summary statistics are provided: the mean profit and its t statistic, the standard deviation of profits, the maximum and minimum profit, and fraction of periods for which profits were positive. All of these computations ignore transactions costs, which will be dealt with below.

The results in Table I sharply reject the efficient markets hypothesis ignoring market frictions. The two one-week portfolio strategies earned positive profits for each of the 49 twenty-six-week periods (and for all 98 quarterly and 24 annual observations as well).[20] Table I also reveals little persistence in the return reversal effect. The portfolio strategy based on returns two weeks previously did earn positive profits in each of the six-month periods, but this observation does not survive the inclusion of transactions costs (in Table V). None of the other strategies earned strictly positive profits for any portfolio horizon.

Table II provides a more detailed description of the anatomy of the return reversal effect. It reports the same summary statistics for the dollar portfolios of winners and losers as Table I, including the sample correlation between the winner and loser portfolio returns as well.[21] The weekly mean returns of the two one-week portfolio

19. I calculated all of the results presented in the tables for 1987 except those found in Tables III and IV. The results for 1962–1986 persist in 1987. In particular, the two one-week strategies proved as profitable net and gross of transactions costs in 1987 as they were in the sample described here.

20. It is interesting to consider why such return reversals were not found in the early market efficiency tests. As summarized in Fama [1970], these investigations found evidence of slight negative serial correlation in individual security return autocorrelations and of slight positive autocorrelation in individual security return runs tests with weekly data. The values were so small that it seemed implausible that they reflected anything like an unexploited arbitrage opportunity. This analysis differs by using information on many securities (i.e., winners and losers) as opposed to the "weak form" tests based on only lagged individual security prices.

21. Since these are portfolio returns, the statistics for the winners portfolio are the opposite of those implicit in the profits reported in Table I (i.e., winners are sold short in the costless portfolios).

strategies were of opposite sign, and the mean return of the winners portfolio was on the order of one half the magnitude of the mean return of the losers portfolio. The sample variances of the weekly returns of the two one-week portfolio strategies were comparable. The sample correlations of the weekly returns of the two one-week portfolio strategies were large and positive—0.851 for the full-week strategy and 0.873 for the four-day strategy. A short position in the winners portfolio had a large negative correlation with a long position in the losers portfolio, greatly reducing the variance of the resulting costless portfolio (by approximately 60 percent of the standard deviation of the losers portfolio) and increasing its average profit (by approximately 40 percent over the mean of the losers portfolio).

Put differently, the winners and losers portfolios had weekly mean returns within an order of magnitude of their standard deviations. This implies that the weekly mean returns were much larger than the corresponding sample variances—by a factor of six to nine for the winners portfolio and of nine to fourteen for the losers portfolio. The resulting costless portfolios had mean profits approximately equal to their standard deviations (and between 50 and 75 times their variances) because of the large negative correlations between the long and short positions in the losers and winners portfolios. As a consequence, the mean profits on these strategies over twenty-six-week periods were more than three times their standard deviations, and the profits were positive in each six-month period.[22]

It is worth emphasizing the role of the short position in the winners portfolio in these profits. It is not the case that the returns on the losers portfolio were nearly always positive; they were positive in 65 to 70 percent of the weeks. Similarly, the short position in the winners portfolio typically had positive returns in more than half of the weeks. The short position in the winners portfolio had a large negative correlation with the losers portfolio, rendering the costless portfolio profits positive in between 85 and 94 percent of the weeks. The integral nature of the short position in the winners portfolio in the costless portfolios' profits stands in sharp contrast to the role of short positions in the filter rule

22. Recall that the instantaneous mean and variance of individual asset and portfolio returns must be of the same order of magnitude to prevent the occurrence of riskless arbitrage opportunities in the continuous time asset pricing literature. While the relevance of this observation for weekly returns is open to question, the semiannual time aggregation of weekly return reversal portfolio profits has the same kind of effect as intertemporal portfolio diversification in continuous time.

TABLE I

PROFITS ON COSTLESS RETURN REVERSAL PORTFOLIO STRATEGIES BY PORTFOLIO HORIZON, 1962–1986

Portfolio horizon (weeks)	Mean	Standard deviation	t statistic	Maximum	Minimum	Fraction positive	Number of observations
Panel A: Portfolio weights based on previous week's return							
One	0.0179	0.0156	41.07	0.2294	−0.0539	0.934	1276
Four	0.0717	0.0355	36.06	0.2709	−0.0219	0.991	319
Thirteen	0.2329	0.0803	28.71	0.5029	0.0845	1.000	98
Twenty-six	0.4657	0.1449	22.50	0.9446	0.2555	1.000	49
Fifty-two	0.9289	0.2709	16.80	1.7277	0.5850	1.000	24
Panel B: Portfolio weights based on first four days of previous week's return							
One	0.0121	0.0144	30.02	0.2132	−0.0629	0.867	1276
Four	0.0484	0.0298	28.98	0.2380	−0.0301	0.972	319
Thirteen	0.1573	0.0571	27.27	0.4032	0.0526	1.000	98
Twenty-six	0.3146	0.0923	23.87	0.5947	0.1515	1.000	49
Fifty-two	0.6281	0.1699	18.11	1.1281	0.4115	1.000	24
Panel C: Portfolio weights based on one-week return two weeks ago							
One	0.0050	0.0118	15.15	0.1064	−0.0497	0.695	1275
Four	0.0200	0.0257	13.87	0.1241	−0.0599	0.802	318
Thirteen	0.0651	0.0460	14.02	0.2727	−0.0451	0.929	98
Twenty-six	0.1302	0.0658	13.86	0.3936	0.0242	1.000	49
Fifty-two	0.2590	0.1129	11.24	0.5830	0.0719	1.000	24
Panel D: Portfolio weights based on one-week return three weeks ago							
One	0.0018	0.0112	5.77	0.1085	−0.0556	0.575	1274
Four	0.0073	0.0246	5.31	0.1242	−0.0909	0.638	318
Thirteen	0.0236	0.0442	5.28	0.1708	−0.1104	0.694	98
Twenty-six	0.0472	0.0702	4.71	0.2812	−0.1186	0.776	49
Fifty-two	0.0993	0.1075	4.53	0.3682	−0.1115	0.833	24

			Panel E: Portfolio weights based on one-week return four weeks ago				
One	0.0011	0.0111	3.56	0.1273	−0.0515	0.521	1273
Four	0.0043	0.0235	3.31	0.1324	−0.0638	0.569	318
Thirteen	0.0136	0.0379	3.53	0.1370	−0.0655	0.649	97
Twenty-six	0.0279	0.0581	3.32	0.1887	−0.0880	0.646	48
Fifty-two	0.0557	0.0921	2.96	0.3106	−0.0900	0.750	24
			Panel F: Portfolio weights based on one-week return thirteen weeks ago				
One	−0.0009	0.0088	−3.47	0.0400	−0.0465	0.438	1264
Four	−0.0034	0.0182	−3.35	0.0617	−0.0599	0.415	316
Thirteen	−0.0112	0.0351	−3.15	0.0770	−0.1494	0.371	97
Twenty-six	−0.0210	0.0432	−3.37	0.0546	−0.1179	0.354	48
Fifty-two	−0.0421	0.0566	−3.64	0.0584	−0.1540	0.167	24
			Panel G: Portfolio weights based on one-week return twenty-six weeks ago				
One	−0.0004	0.0086	−1.71	0.0511	−0.0415	0.473	1251
Four	−0.0017	0.0177	−1.70	0.0759	−0.0530	0.455	312
Thirteen	−0.0055	0.0335	−1.62	0.0944	−0.0969	0.458	96
Twenty-six	−0.0111	0.0359	−2.14	0.0773	−0.1204	0.396	48
Fifty-two	−0.0222	0.0478	−2.27	0.0459	−0.1588	0.375	24
			Panel H: Portfolio weights based on one-week return fifty-two weeks ago				
One	−0.0016	0.0092	−6.18	0.0284	−0.1170	0.424	1225
Four	−0.0065	0.0220	−5.14	0.0490	−0.1555	0.366	306
Thirteen	−0.0210	0.0417	−4.87	0.0807	−0.1762	0.298	94
Twenty-six	−0.0419	0.0589	−4.91	0.0740	−0.2009	0.234	47
Fifty-two	−0.0831	0.0976	−4.09	0.0873	−0.3801	0.130	23

TABLE II

WEEKLY RETURNS ON DOLLAR PORTFOLIOS OF WINNERS AND LOSERS, 1962–1986

Portfolio	Mean	Standard deviation	t statistic	Maximum	Minimum	Fraction positive	Pairwise correlation
		Panel A: Portfolio weights based on previous week's return					
Winners	−0.0055	0.0248	−7.96	0.1296	−0.1264	0.413	0.851
Losers	0.0124	0.0297	14.92	0.3321	−0.1338	0.714	0.851
		Panel B: Portfolio weights based on first four days of previous week's return					
Winners	−0.0035	0.0247	−5.05	0.1171	−0.1311	0.460	0.873
Losers	0.0086	0.0295	10.43	0.3211	−0.1354	0.665	0.873
		Panel C: Portfolio weights based on one-week return two weeks ago					
Winners	0.0003	0.0253	0.41	0.1638	−0.1458	0.579	0.911
Losers	0.0053	0.0286	6.63	0.2702	−0.1344	0.620	0.911
		Panel D: Portfolio weights based on one-week return three weeks ago					
Winners	0.0022	0.0261	3.07	0.2154	−0.1406	0.711	0.917
Losers	0.0041	0.0282	5.14	0.2254	−0.1340	0.598	0.917

	Panel E: Portfolio weights based on one-week return four weeks ago						
Winners	0.0025	0.0262	3.42	0.2041	−0.1129	0.736	0.920
Losers	0.0036	0.0283	4.56	0.2320	−0.1569	0.590	0.920
	Panel F: Portfolio weights based on one-week return thirteen weeks ago						
Winners	0.0039	0.0268	5.17	0.2006	−0.1286	0.816	0.947
Losers	0.0030	0.0271	3.97	0.2174	−0.1376	0.578	0.947
	Panel G: Portfolio weights based on one-week return twenty-six weeks ago						
Winners	0.0038	0.0268	4.98	0.2191	−0.1288	0.821	0.949
Losers	0.0034	0.0268	4.43	0.2140	−0.1499	0.592	0.949
	Panel H: Portfolio weights based on one-week return fifty-two weeks ago						
Winners	0.0045	0.0280	5.59	0.2326	−0.1410	0.842	0.944
Losers	0.0028	0.0261	3.82	0.2124	−0.1355	0.585	0.944

literature—as Sweeney [1986] has emphasized, short positions contribute primarily transactions costs (and not profits) to filter rule profits.

It is difficult to interpret the behavior of these portfolios as reflecting time-varying expected returns even if one rejects the market inefficiency interpretation of this evidence. Suppose that market prices were determined by the consumption-based capital asset pricing model with time-varying consumption betas and risk premiums. If firms with consumption betas above the market average one week typically had consumption betas above the market average next week as well, the consumption risk premium would have to be highly negatively serially correlated from week to week to explain these results. It is certainly difficult to rationalize such a short-run relation.[23]

Table II also accounts for the failure to find pronounced persistence in the return reversal effect. On averge, the winners portfolio only had negative mean returns in the subsequent week and had positive and increasing mean returns over the next month. Similarly, the losers portfolio had large positive mean returns in the subsequent week which diminished over the next month. This measured mean reversion in stock returns is studied further in Lehmann [1988].

Tables III and IV provide a detailed description of the characteristics of the winners and losers portfolios, respectively, for the two one-week strategies and those based on one-week returns two and three weeks ago. Eight statistics are given for each of the five quintiles of the winners and losers portfolios (running from largest to smallest). As before, the tables report the mean return and its t statistic, the standard deviation of returns, and the maximum and minimum return for each quintile (i.e., for each 20 cents of the dollar invested in the winners or losers portfolio). In addition, the tables provide three summary measures of quintile characteristics:

23. To make matters concrete, let the excess return of security i be given by

$$R_{it} - R_{ft} = \beta_{ict} [R_{ct} - R_{ft}] + \epsilon_{ict},$$

where β_{ict} is the consumption beta of security i at time t, R_{ct} is the return on the portfolio of these N assets that has the largest correlation with aggregate consumption, R_{ft} is the return on the riskless asset, and ϵ_{ict} is the portion of the return on security i conditionally uncorrelated with aggregate consumption. If the unconditional covariances cov $\{\beta_{ict}\beta_{ict+1}, [R_{ct} - R_{ft}][R_{ct+1} - R_{ft+1}]\}$ and cov $\{\epsilon_{ict}\beta_{ict+1} [R_{ct+1} - R_{ft+1}]\}$ are both zero (ignoring, for example, the small effect of weekly leverage changes on consumption betas), then $E\{[R_{ct} - R_{ft}][R_{ct+1} - R_{ft+1}]\} < 0$ if cov $\{\beta_{ict}, \beta_{ict+1}\} > 0$ to account for the observed positive average portfolio profits. It is hard to rationalize pronounced negative serial correlation in either $[R_{ct} - R_{ft}]$ or β_{ict}, especially in weekly data.

average turnover, average investment per firm, and weighted average market capitalization. The portfolio turnover calculation is the average sum across securities within each quintile of the transactions cost base $|w_{it} - w_{it-1}|$. Average investment per firm in each quintile is the average value of 20 cents divided by the number of firms in each quintile in each week. The market value calculation is the sample average of the portfolio weighted market capitalization of the firms in each quintile of those firms for which price and share data existed at the beginning of the week.

The measured arbitrage profits on the two one-week strategies reflect returns on reasonably well-diversified portfolios (with weights typically ranging from 0.03 to 0.53 percent), not the reward to investing in a few big winners and losers. To be sure, the largest winners and losers experienced the largest subsequent reversals. However, the top three quintiles of winners and all five quintiles of losers typically experienced large reversals in the next week. Moreover, the average market capitalizations of the quintile portfolios were in size deciles six through nine, mitigating concern about price pressure and liquidity. Note also the extraordinary volume of transactions generated by the strategies: approximately three dollars a week per dollar long in the return reversal portfolio strategy. In other words, the two one-week strategies profited from the exploitation of many relatively small predictable price reversals each week and, hence, probably would not have required large positions in illiquid stocks.

Of course, there are legitimate concerns about the economic relevance of the profits documented in Table I. In particular, the costless portfolio strategies typically generate more than 2,000 round-trip transactions per week, and hence, the resulting transactions costs might be expected to wipe out the profits reported in Table I. Table V reports the semiannual profits for the two one-week strategies and those based on one-week returns two and three weeks ago under assumed one-way transactions costs ranging from 0.05 to 1.0 percent.

The results in Table V differ somewhat from those in Table I without altering the main conclusions, as long as the one-way transactions costs confronting large traders are less than 0.20 percent. The two one-week portfolio strategies still yielded measured arbitrage profits at this level of transactions costs. The strategy based on returns two weeks ago did not yield positive profits in each of the 49 six-month periods at any level of transactions costs, and hence, its profits do not constitute a true arbitrage

TABLE III
WEEKLY RETURNS AND CHARACTERISTICS OF SELECTED DOLLAR PORTFOLIOS OF WINNERS BY QUINTILE, 1962–1986

						Average portfolio characteristics		
Portfolio quintile	Mean	Standard deviation	t statistic	Maximum	Minimum	Portfolio turnover (cents)	Investment per firm (cents)	Market value in millions of dollars
Panel A: Portfolio weights based on previous week's return								
One	−0.0041	0.0076	−19.02	0.0396	−0.0529	22.57	0.49	77.7
Two	−0.0014	0.0055	−9.10	0.0424	−0.0255	23.09	0.25	171.8
Three	−0.0005	0.0050	−3.35	0.0259	−0.0213	24.23	0.16	284.3
Four	0.0001	0.0046	0.46	0.0219	−0.0226	27.07	0.10	393.5
Five	0.0003	0.0044	2.78	0.0269	−0.0237	52.07	0.03	497.8
Panel B: Portfolio weights based on first four days of previous week's return								
One	−0.0030	0.0075	−14.32	0.0415	−0.0810	22.00	0.53	71.9
Two	−0.0008	0.0054	−5.11	0.0284	−0.0277	22.52	0.26	165.8
Three	−0.0003	0.0049	−2.04	0.0237	−0.0275	23.84	0.16	274.0
Four	0.0002	0.0047	1.15	0.0213	−0.0223	26.88	0.10	380.8
Five	0.0004	0.0044	3.60	0.0296	−0.0237	52.39	0.03	493.8
Panel C: Portfolio weights based on one-week return two weeks ago								
One	−0.0007	0.0070	−3.42	0.0430	−0.0320	21.21	0.49	77.3
Two	−0.0000	0.0056	−0.16	0.0378	−0.0313	21.85	0.25	171.7
Three	0.0002	0.0051	1.44	0.0277	−0.0283	23.41	0.16	285.1
Four	0.0003	0.0047	2.35	0.0292	−0.0285	26.60	0.10	393.7
Five	0.0005	0.0044	3.81	0.0300	−0.0257	52.16	0.03	497.8
Panel D: Portfolio weights based on one-week return three weeks ago								
One	0.0002	0.0070	0.94	0.0461	−0.0314	20.89	0.49	77.8
Two	0.0004	0.0058	2.41	0.0463	−0.0313	21.53	0.25	172.1
Three	0.0005	0.0053	3.27	0.0458	−0.0289	23.00	0.16	284.2
Four	0.0006	0.0049	4.15	0.0407	−0.0259	26.23	0.10	394.2
Five	0.0006	0.0045	4.81	0.0365	−0.0230	52.14	0.03	497.3

TABLE IV

WEEKLY RETURNS AND CHARACTERISTICS OF SELECTED DOLLAR PORTFOLIOS OF LOSERS BY QUINTILE, 1962–1986

						Average portfolio characteristics		
Portfolio quintile	Mean	Standard deviation	t statistic	Maximum	Minimum	Portfolio turnover (cents)	Investment per firm (cents)	Market value in millions of dollars
Panel A: Portfolio weights based on previous week's return								
One	0.0065	0.0084	27.71	0.0918	−0.0274	24.34	0.29	110.9
Two	0.0027	0.0066	14.47	0.0747	−0.0260	23.60	0.17	198.6
Three	0.0016	0.0059	9.70	0.0668	−0.0282	24.14	0.12	294.7
Four	0.0010	0.0053	6.51	0.0537	−0.0295	26.54	0.08	385.9
Five	0.0007	0.0049	4.92	0.0451	−0.0271	52.37	0.03	480.9
Panel B: Portfolio weights based on first four days of previous week's return								
One	0.0036	0.0080	16.14	0.0854	−0.0307	22.50	0.30	113.4
Two	0.0019	0.0065	10.61	0.0726	−0.0286	22.79	0.17	198.9
Three	0.0013	0.0059	8.01	0.0638	−0.0277	23.72	0.12	297.0
Four	0.0010	0.0054	6.43	0.0566	−0.0281	26.72	0.08	397.6
Five	0.0008	0.0048	5.82	0.0457	−0.0256	53.49	0.03	489.8
Panel C: Portfolio weights based on one-week return two weeks ago								
One	0.0014	0.0076	6.44	0.0766	−0.0304	21.99	0.29	111.6
Two	0.0011	0.0063	6.36	0.0516	−0.0292	21.85	0.17	199.9
Three	0.0011	0.0057	6.77	0.0508	−0.0252	23.56	0.12	295.8
Four	0.0009	0.0052	6.39	0.0501	−0.0274	26.90	0.08	387.0
Five	0.0008	0.0047	6.12	0.0412	−0.0226	53.90	0.03	481.6
Panel D: Portfolio weights based on one-week return three weeks ago								
One	0.0009	0.0075	4.39	0.0607	−0.0312	21.70	0.29	111.5
Two	0.0009	0.0063	5.00	0.0656	−0.0273	21.53	0.17	199.9
Three	0.0008	0.0056	4.95	0.0438	−0.0269	23.17	0.12	295.0
Four	0.0008	0.0051	5.27	0.0419	−0.0242	26.57	0.08	386.2
Five	0.0007	0.0046	5.59	0.0323	−0.0244	54.01	0.03	480.1

TABLE V

PROFITS ON SELECTED TWENTY-SIX WEEK COSTLESS RETURN REVERSAL PORTFOLIO STRATEGIES BY ONE-WAY TRANSACTIONS COST, 1962–1986

Transactions cost (percent)	Mean	Standard deviation	t statistic	Maximum	Minimum	Fraction positive	Number of observations
Panel A: Portfolio weights based on previous week's return							
0.05	0.4267	0.1445	20.67	0.9099	0.2171	1.000	49
0.10	0.3877	0.1442	18.82	0.8702	0.1786	1.000	49
0.20	0.3097	0.1436	15.10	0.7909	0.1018	1.000	49
0.30	0.2317	0.1429	11.35	0.7114	0.0249	1.000	49
0.40	0.1537	0.1423	7.56	0.6321	−0.0520	0.898	49
1.00	−0.3143	0.1374	−16.01	0.1561	−0.5133	0.041	49
Panel B: Portfolio weights based on first four days of previous week's return							
0.05	0.2760	0.0921	20.98	0.5558	0.1131	1.000	49
0.10	0.2374	0.0920	18.07	0.5168	0.0747	1.000	49
0.20	0.1602	0.0917	12.24	0.4389	−0.0021	0.979	49
0.30	0.0830	0.0914	6.36	0.3610	−0.0789	0.898	49
0.40	0.0059	0.0911	0.45	0.2830	−0.1558	0.449	49
1.00	−0.4573	0.0893	−35.85	−0.1846	−0.6168	0.000	49
Panel C: Portfolio weights based on one-week return two weeks ago							
0.05	0.0922	0.0656	9.84	0.3551	−0.0136	0.939	49
0.10	0.0541	0.0654	5.79	0.3165	−0.0513	0.837	49
0.20	−0.0220	0.0651	−2.36	0.2394	−0.1269	0.306	49
0.30	−0.0981	0.0647	−10.61	0.1622	−0.2024	0.041	49
0.40	−0.1742	0.0644	−18.94	0.0851	−0.2780	0.020	49
1.00	−0.6308	0.0613	−72.03	−0.4377	−0.7314	0.000	49
Panel D: Portfolio weights based on one-week return three weeks ago							
0.05	0.0095	0.0700	0.95	0.2431	−0.1550	0.551	49
0.10	−0.0282	0.0698	−2.83	0.2050	−0.1913	0.306	49
0.20	−0.1036	0.0693	−10.46	0.1288	−0.2639	0.041	49
0.30	−0.1790	0.0689	−18.18	0.0525	−0.3365	0.020	49
0.40	−0.2544	0.0685	−26.00	−0.0237	−0.4092	0.000	49
1.00	−0.7068	0.0660	−74.96	−0.4811	−0.8451	0.000	49

opportunity. Note that the plausibility of my transactions cost assumptions is crucial here: neither one-week strategy yields a measured arbitrage opportunity if one-way transactions costs exceed 0.20 percent; and mean profits are zero if they are 0.40 percent.

Figure I provides two additional summary measures of the behavior of the two one-week portfolio strategies: time series plots and histograms of their weekly profits gross of transactions costs.[24] The series are dominated by white noise with positive mean. There is no noticeable pattern in the portfolio profits processes and, in particular, no tendency for profits or their mean to decline over time. Large (i.e., 1 to 4 percent per week) profits are the rule rather than the exception, and the profitability of these strategies is pervasive throughout the sample period.[25]

It is interesting to summarize these results by considering the profits for strategies that are long $100 million of losers and short $100 million of winners. The average semiannual profits net of the 0.10 percent one-way transactions costs that might be relevant for floor traders and large broker-dealers were $38.77 million for the conventional one-week strategy and $23.74 million for that based on four-day returns. The minimum semiannual profits were $17.86 million and $7.47 million, respectively, while the largest semiannual profits were $87.02 million and $51.68 million, respectively. Moreover, market liquidity is typically sufficient to accommodate transactions of this scale—typically $300,000 in the extreme losers and $500,000 in the extreme winners. These costless portfolio strategies earned measured arbitrage profits despite generating $300 million of transactions a week (the theoretical maximum is $400 million), more than one third of which was generated by the unprofitable transactions in the fifth quintile of smallest winners and losers. It is hard to believe that these numbers are either trivial or were

24. The cells of the histograms are ± 0.5 percent of the integer displayed (i.e., 1 percent denotes the cell with observations ranging from 0.5 to 1.5 percent). The histograms exclude cells with fewer than 12 (out of 1,276) observations. There are 9 negative observations and 38 positive observations not reflected in the histograms.

25. Fama and French [1987], Chan [1988], and Jegadeesh [1987] provide evidence that the return reversal effects measured at longer differencing intervals are, in part, attributable to the now well-known turn-of-the-year effect—the pronounced tendency for the returns on stocks with small market capitalizations to exceed those of stocks with large market capitalizations in the month of January. Results not reported here suggest that return reversal strategies are, if anything, more profitable outside of the month of January. This is primarily a consequence of the returns on the winners portfolio outside of the month of January. The average return on each version of the winners portfolio was more negative, and negative returns occurred in a slightly larger fraction of twenty-six-week periods than the corresponding observations including January returns.

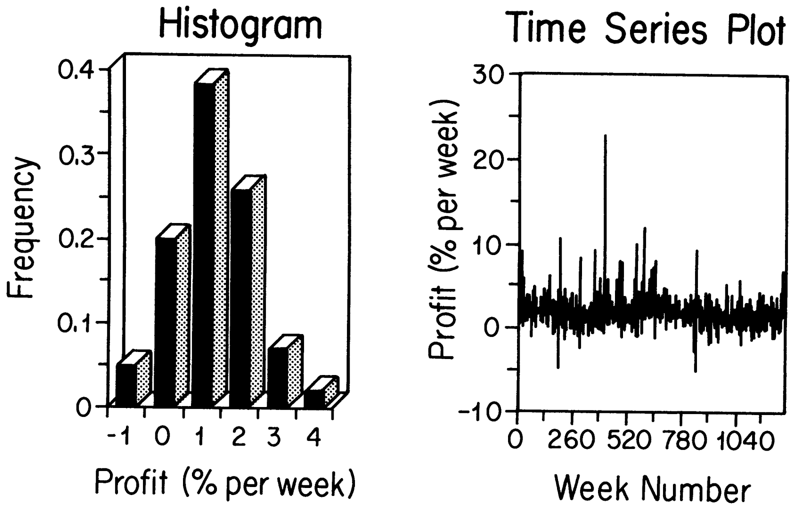

FIGURE Ia
Weekly Portfolio Profits—Full Week Strategy

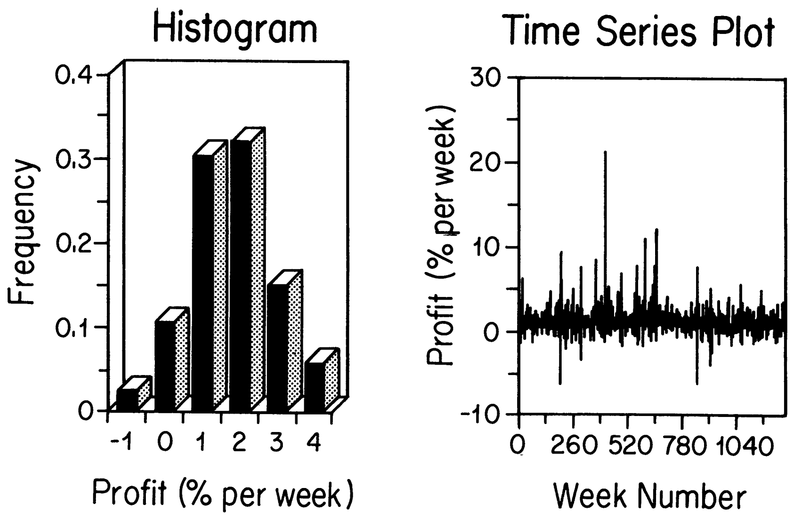

FIGURE Ib
Weekly Portfolio Profits—Four Day Strategy

unattainable for investors unless stocks are typically illiquid following large price movements.[26]

V. Conclusion

Financial economics has enjoyed considerable success in interpreting stock price movements as reflections of the arrival of new information in an efficient capital market. Early empirical studies found little evidence against the hypothesis that equity prices were set in an efficient market with constant expected returns. Theoretical developments since then have suggested that expected returns typically vary in our equilibrium asset pricing models, and not surprisingly, recent empirical research has found evidence of predictable variation in security returns. While it is conventional practice to refer to this evidence as a reflection of time-varying expected returns, the suggestion that predictable variation in security returns arises instead from security price overreaction to speculative fads or the cognitive misperceptions of investors in an inefficient market is currently enjoying a resurgence not seen in two decades.

This paper has tested the market efficiency hypothesis by examining security prices for evidence of unexploited arbitrage opportunities. It did so by examining the profits on feasible ex ante costless portfolios that should not earn riskless profits in an efficient market but could earn such profits if stock price overreaction affects many equity returns. This practice avoids the problems associated with specifying a model for variation in expected returns at the cost of requiring the presence of measured arbitrage opportunities to reject the hypothesis of market efficiency—a very stringent test.

The results strongly suggest rejection of the efficient markets hypothesis. Portfolios of securities that had positive returns in one week typically had negative returns in the next week (-0.35 to -0.55 percent per week on average), while those with negative

26. It is difficult to provide a quantitative measure of the inefficiency in the market for liquidity represented by these results. The following calculation may provide an order of magnitude estimate of the typical pricing error. If a week is sufficiently short for the local martingale model to apply, the costless return reversal portfolios should have mean zero profits net of transactions costs. The mean profits of the two one-week strategies are approximately zero at 0.40 percent one-way transactions costs. This suggests a typical pricing error estimate of 0.80 percent if it is reasonable to label this measured inefficiency as unmeasured transactions costs. This calculation probably understates true "total" transactions costs because the two one-week strategies are probably much less profitable than optimal return reversal strategies.

returns in one week typically had positive returns in the next week (0.86 to 1.24 percent per week on average). The costless portfolio that is the difference between the winners and losers portfolios had positive profits in roughly 90 percent of the weeks and, if the strategy is viewed as having a twenty-six-week horizon, the profits were positive in each of the 49 six-month periods covered by the data.

It is difficult to account for these results within the efficient markets framework. These measured arbitrage profits persist after corrections for the mismeasurement of security returns due to bid-ask spreads and for plausible levels of transactions costs. In addition, the strategies involved only modest positions in liquid securities, suggesting that they could have been implemented without generating substantial price pressure unless markets are illiquid following large price changes. Finally, it is hard to rationalize short-run return reversals of this magnitude within an intertemporal asset pricing framework even ignoring the evidence of market inefficiency suggested by the measured arbitrage opportunities.[27]

In fact, the return reversals associated with winners and losers probably reflect imbalances in the market for short-run liquidity. This is consistent with the notion that market makers are only intermediaries between patient and impatient traders and, hence, supply only very short-term (i.e., intraday) liquidity as in Treynor [1981]. By contrast, market-wide proprietary trading by large broker-dealers (who are patient traders) is probably the natural source of supply of liquidity over intervals like days or weeks in response to transitory changes in the demand for liquidity by impatient traders. Such trading is only a recent phenomenon, however, and so the results probably reflect an inefficiency in the market for short-term liquidity.

Since there is little persistence in the return reversal effects, there are two potential responses to these results. First, one could emphasize the short-run nature of the arbitrage opportunity and presume that equity markets are (on average) efficient over longer

27. After completing this research, I learned that Rosenberg Institutional Equity Management successfully markets a version of the portfolio strategy described in Rosenberg, Reid, and Lanstein [1985]. In addition, this firm does index arbitrage with a long position in a version of the losers portfolio and a short position in S&P 500 futures contracts. We academicians apparently benefit from similar strategies—the College Retirement Equity Fund has successfully pursued such a return reversal strategy as part of its actively managed portfolio. Similarly, computerized proprietary trading operations seeking to exploit reversals are now commonplace. Presumably their activities, especially the systematic computer-generated versions, will eliminate any such arbitrage opportunities in the future, yielding the opportunity to write a paper entitled "Return Reversals Revisited" at a future date!

horizons, such as a month. On this view, these results provide an interesting puzzle for students of security market microstructure and of the market for short-run liquidity.[28] Alternatively, one could emphasize the low power of these tests for detecting longer term market inefficiencies and continue to seek additional evidence (and reinterpret existing evidence) of market inefficiency. Both responses will presumably increase our understanding of the determination of security prices.

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28. Equity desks and research groups have traditionally been organized by industry with comparatively little internecine contact concerning individual securities. Since winners and losers freely cross industry bounds, this institutional observation suggests a possible reason why this apparent inefficiency has been overlooked and why it may have been costly to exploit.

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