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FADS, MARTINGALES, AND MARKET EFFICIENCY

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ABSTRACT

Much of the theoretical basis for current monetary and financial theory rests on the economic efficiency of financial markets. Not surprisingly, considerable effort has been expended to test the efficient markets hypothesis, usually by examination of the predictability of equity returns. Unfortunately, there are two competing explanations of the presence of such predictable variation: (1) market inefficiency and stock price 'overreaction' due to speculative 'fads' and (2) predictable changes in expected security returns associated with forecasted changes in market or individual security 'fundamentals'. These explanations can be distinguished by examining equity returns over short time intervals since there should be negligible systematic changes in the fundamental valuation of individual firms over intervals like a week in an efficient market. This study finds sharp evidence of market inefficiency in the form of systematic tendencies for current 'winners' and 'losers' in one week to experience sizeable return reversals over the subsequent week in a way that reflect apparent arbitrage profits. These measured arbitrage profits persist after corrections for the mismeasurement of security returns because of thin trading and bid-ask spreads and for plausible levels of transactions costs.

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1. Introduction

Much of the theoretical basis for current monetary and financial theory rests on the economic efficiency of financial markets. Not surprisingly, considerable effort has been expended to test the efficient markets hypothesis, usually in the form of the random walk model for stock prices. Most earlier studies supported the random walk model, typically finding that the predictable variation in equity returns was both economically and statistically small. However, much recent research has found evidence that equity returns can be predicted with some reliability.[1]

What are the implications of predictable variation in asset returns for the hypothesis of market efficiency? The answer is unclear because there are two competing explanations of this phenomenon. Financial markets may be efficient and intertemporal asset pricing theory may account for predictable changes in expected security returns. Alternatively, predictable variation in equity returns may reflect the overreaction of stock prices to speculative 'fads' or the cognitive misperceptions of investors in an inefficient market. This explanation has been emphasized in Shiller(1984), Black(1986), and Poterba and Summers(1987) and the cognitive misperceptions interpretation has been advanced by DeBondt and Thaler(1985) and Shefrin and Statman(1985).

The empirical evidence from monthly returns can plausibly be attributed to either explanation, leaving the hypothesis of market efficiency in an unsettled state. The two explanations can be distinguished to some degree by examining asset returns over short time intervals.[2] As Sims(1984) and others have emphasized, asset prices should appear to follow a martingale process over very short time intervals in an efficient capital market even if there are

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[1]See Fama(1970) for a detailed survey of the earlier research and Singleton(1986) for a corresponding survey of the recent evidence on predictable variation in asset returns.

[2]An alternative testing strategy involves examination of the behavior of security return variances for evidence of market inefficiency. The enormous variance bounds literature is in an odd state of limbo because of now well-known statistical problems and continues to be the subject of much research. French and Roll(1986) compare the variances of security returns when markets are opened and closed and conclude that there is excess volatility due to private information trading and mispricing caused by noise trading under plausible assumptions about information arrival. The tests described below address the 'fads' model and the concomitant predictability of stock price overreaction in a more direct fashion.

predictable variations in expected security returns over longer horizons. The economic intuition underlying this result is that there should be negligible systematic changes in the fundamental valuation of individual firms over intervals like a day or a week in an efficient market with unpredictable information arrival. In contradistinction, the 'fads' model predicts serial correlation in asset prices over all time intervals, although particular versions of the model presumably emphasize predictability over particular differencing intervals.[3]

There are, however, severe econometric problems associated with the construction of suitably powerful tests of this local martingale formulation of the hypothesis of market efficiency. Shiller(1981) and Summers(1986) have both emphasized that the standard tests for the presence of serial correlation in security returns typically employed in empirical work have little power to distinguish between random walk and (economically relevant) near random walk behavior. This problem is likely to be particularly severe over short differencing intervals.

Many assets are traded on organized securities markets. If the 'fads' model is true, it is reasonable to suppose that stock price overreaction infects many security returns. Hence, well-diversified portfolios composed of either 'winners' or 'losers' might be expected to experience subsequent return reversals in these circumstances. This observation suggests a simple heuristic strategy for testing the hypothesis of market efficiency: form costless (i.e., zero net investment or self-financing) portfolios which give negative weight to current 'winners' and positive weight to current 'losers'.

The local martingale and 'fads' models have differing implications for the behavior of the

[3]There is considerable evidence that there are systematic reversals in stock returns over longer differencing intervals. DeBondt and Thaler(1985), Fama and French(1986), and Poterba and Summers(1987) find evidence of such predictable variation in security returns over three to ten year intervals. Rosenberg, Reid, and Lanstein(1985) and Jegadeesh(1987) provide sharp evidence for the presence of predictable return reversals on a monthly basis. This evidence is consistent, in principle, with the hypothesis that this predictable variation represents changing expected returns and not the 'overreaction' of stock prices in an inefficient market, although the monthly evidence is more difficult to incorporate into such an explanation. In particular, Chan(1987) provides convincing empirical evidence that the results obtained by DeBondt and Thaler(1985) are attributable in part to changes in the riskiness of winners and losers.

subsequent profits of these costless portfolios over short time periods. If equity markets are efficient and a week (or other differencing interval) is sufficiently short for the model to apply, the local martingale model predicts that these costless portfolios should tend to earn zero profits since it implies that the current week's return on any security is simply noise that is not useful for predicting subsequent security returns. In contradistinction, the 'fads' model suggests that stock prices 'overreact' and, hence, that both winners and losers will experience return reversals at some point. This implies that the profits of these costless portfolios will typically be positive over some horizon. This procedure avoids the power difficulties associated with time series autocorrelation tests by extracting cross-sectional autocorrelation information.[4]

The remainder of the paper is devoted to the rigorous quantification of this intuition and to empirical examination of its implications for the hypothesis of market efficiency. The next section characterizes portfolio strategies which suggest a simple procedure for testing this hypothesis and contrasts this analysis with the more conventional approaches found in the literature. The subsequent section discusses the empirical implementation of the test and addresses empirical problems such as the presence of predictable fluctuations in measured security returns that have nothing to do with market inefficiency or the fads model. The fourth section provides empirical evidence and the final section contains concluding remarks.

2. The Profits on Return Reversal Portfolio Strategies in an Efficient Market

As noted above, portfolios that involve short positions in securities that have experienced recent price increases and long positions in those that have suffered price declines might be expected to earn abnormal profits if asset prices in part reflect overreaction to speculative fads. The key to employing this intuition to test the hypothesis of market efficiency is the development of measures of abnormal profits. This section is devoted to a discussion of the comparative merits of several such strategies.

[4]This intuition has been exploited by Jegadeesh(1987) to develop powerful cross-sectional tests of linear asset pricing relations.

Consider the following simple portfolio strategies involving a given set of N securities over T time periods. At the beginning of each period t+k, buy w_{it} dollars of each security i. This involves going long security i when w_{it} is positive and short selling it when this quantity is negative. Each position is closed out at the end of each time interval (i.e., at the end of period t+k). Choose the weights w_{it} 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}) less the arithmetic average of the returns on all securities in that period ($\bar{R}_t$) (i.e., the return of an equally weighted portfolio of these N assets). Ignoring the factor of proportionality, the weights are given by:

$$(1) \qquad w_{it} = -[R_{it} - \bar{R}_t]$$

where:

$$(2) \qquad \bar{R}_t = \frac{1}{N}\sum_{i=1}^{N} R_{it}$$

The goal is the measurement of abnormal profits on this class of portfolio strategies. Simple accounting profits in period t+k ($\pi_{t,k}$) are given by:[5]

$$(3) \qquad \pi_{t,k} = \sum_{i=1}^{N} w_{it}R_{it+k} = -\sum_{i=1}^{N} [R_{it} - \bar{R}_t][R_{it+k} - \bar{R}_{t+k}]$$

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

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

Algebraic manipulation of this expression reveals:

$$(5) \qquad \bar{\pi}_k = \frac{N}{T}\sum_{t=1}^{T} [\bar{R}_t - \bar{\bar{R}}][\bar{R}_{t+k} - \bar{\bar{R}}] - \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N} [R_{it} - \bar{R}_i][R_{it+k} - \bar{R}_i] - \sum_{i=1}^{N} [\bar{R}_i - \bar{\bar{R}}]^2$$

where:

[5]These are profits (and not returns) because this is a costless (i.e., zero net investment) portfolio strategy and, hence, returns are not defined.

(6) $$\bar{\bar{R}} = \frac{1}{T}\sum_{t=1}^{T} \bar{R}_t$$

is the average return across both securities and time (i.e., the average return of an equally weighted portfolio over the T periods) and:

(7) $$\bar{R}_i = \frac{1}{T}\sum_{t=1}^{T} R_{it}$$

is the average return of security i over the T periods.

In short, average return reversal 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 have any implications for the behavior of either $\bar{\pi}_k$ or $\pi_{t,k}$?

The traditional answer to this question reflects Fama's (1970) 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" (pp. 413-414). For example, it is common to assume that security returns are independently distributed (and often identically distributed as well) with constant expected returns in the filter rule literature and the monthly studies of return reversals.

It is easy to see the implications of the ancillary hypothesis that security returns are independently distributed over time for return reversal portfolio profits. The population autocovariances of both individual securities and the equally weighted portfolio are zero when security returns are independently distributed. Hence, expected average profits on the return reversal portfolio strategies are:

(8) $$E\left\{\bar{\pi}_k\right\} = -E\left\{\sum_{i=1}^{N} [\bar{R}_i - \bar{\bar{R}}]^2\right\}$$

because the strategies typically involve going long securities with below average returns and short those with above average returns. The testable implication of this observation is that the expected average profits of these portfolio strategies should be identical for each value of k.[6]

As with most market efficiency tests (which involve joint hypotheses), rejection of the hypothesis that average portfolio profits are identical for each value of k might simply indicate that returns are not independently distributed. This interpretation is consistent with the hypothesis that predictable variation in equity returns is attributable to 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.

Now consider an alternative model of market equilibrium, one based on continuous trading possibilities, bounded price uncertainty, and the absence of arbitrage opportunities. Divide the T period observation interval into J equally spaced disjoint intervals of length h(J) (i.e., T=Jh(J)). Suppose that it is possible to trade securities at any point in the interval {0,T}. Finally, assume that returns can be decomposed into predictable and unpredictable components at each time j:

(9) $R_{ij} = E_{ij} + \varepsilon_{ij}$

where E_{ij} is the population conditional expected return of asset i given the conditioning information set $I_{i(j-1)}$ which includes past price changes and other information available at time j-1. Note that the population conditional expected return E_{ij} is a purely mathematical construct that has nothing to do with the hypothesis of market efficiency.

The analysis requires one weak assumption about the stochastic properties of security price changes. Loosely speaking, the requirement is that price changes exhibit bounded uncertainty over arbitrarily small time intervals (i.e., over h(J) as $J \rightarrow \infty$). In particular, the requirement is:

(10) $\lim_{J \rightarrow \infty} E\left\{ \varepsilon_{ij}^2 \right\} < \infty$ a.s. $\forall\, i = 1,\ldots, N;\ j=1,\ldots, J$

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

where a.s. denotes almost sure convergence.[7] It is also sufficient that price changes have finite variance per unit time (i.e., of order h(J)) over arbitrarily small time intervals. This assumption is made in models that presume security price changes follow mixed jump/diffusion processes with discontinuous sample paths.

This setting has implications for the behavior of security returns in the absence of arbitrage opportunities which follow from the analysis of a simple portfolio strategy. At the beginning of each time interval j, buy E_{ij} dollars of security i (which is a short sale when this quantity is negative) and close out the position at the end of each time interval j. The profit on this strategy is:

$$(11) \quad \pi = \sum_{j=1}^{J} \left\{ E_{ij}^2 + E_{ij}\varepsilon_{ij} \right\}$$

The quantities $E_{ij}\varepsilon_{ij}$ constitute a sequence of martingale differences with bounded variance under these assumptions. Hence, the unexpected portion of profits on this strategy must converge to a finite random variable by the martingale convergence theorem (cf., Hall and Heyde(1980)) as J grows without bound. The profits on this portfolio strategy will have bounded risk and must be bounded in well-functioning capital markets so that:[8]

$$(12) \quad \lim_{J\to\infty} \sum_{j=1}^{J} E_{ij}^2 < \infty \text{ a.s. } \forall\, i = 1,\ldots, N$$

and, hence:

$$(13) \quad \lim_{J\to\infty} J^{-1} \sum_{j=1}^{J} E_{ij}^2 = 0 \text{ a.s. } \forall\, i = 1,\ldots, N$$

In other words, the serial correlations of individual security returns must be negligible for virtually all trading periods because it is easy to construct portfolio strategies which diversify away the risk

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[7]The variance restriction can be replaced by boundedness of the conditional first absolute moment if restrictions on the behavior of ε_{ij} are added to insure that the first absolute moment of their sum is bounded. Note that the variance restriction may place implicit restrictions on the information set $I_{i(j-1)}$.

[8]This is related to the local martingale property of asset prices in an efficient market studied by Sims(1984). The essential difference is that Sims' analysis also provides conditions under which each of the E_{ij} are asymptotically negligible (i.e., of order h(J).

associated with price changes over time and this, in turn, places implicit bounds on the magnitude of expected price changes.[9] None of this is surprising—it is commonplace to assume that the conditional means and variances of continuous time stochastic processes are both of order h(J) as h(J) becomes infinitesimal.

To facilitate the analysis of return reversal portfolio profits, consider the population linear projection (which is again a purely mathematical construct) of the return on asset i in period j on returns k periods ago:

$$(14)\qquad R_{ij} = \beta_{i(j-k)}[R_{i(j-k)} - \bar{R}_{j-k}] + v_{ij}$$

where the random variables v_{ij} are uncorrelated with $[R_{i(j-k)} - \bar{R}_{j-k}]$ by construction. These random variables include both unexpected portion of returns ε_{ij} and the part of expected returns that is not explained by returns k intervals ago.

Recall that average return reversal portfolio profits are given by:

$$(15)\qquad \bar{\pi}_k = \frac{1}{J}\sum_{j=1}^{J}\sum_{i=1}^{N}[R_{i(j-k)} - \bar{R}_{j-k}][R_{ij} - \bar{R}_j]$$

$$= \frac{1}{J}\left\{\sum_{j=1}^{J}\sum_{i=1}^{N}\beta_{i(j-k)}[R_{i(j-k)} - \bar{R}_{j-k}]^2 + \sum_{j=1}^{J}\sum_{i=1}^{N}[R_{i(j-k)} - \bar{R}_{j-k}]\varepsilon_{ij}\right\}$$

By the analysis leading up to (13), average profits converge to:

$$(16)\qquad \lim_{J\to\infty} \bar{\pi}_k = \frac{1}{J}\sum_{j=1}^{J}\sum_{i=1}^{N}\beta_{it+(j-k)h(J)}[R_{it+(j-k)h(J)} - \bar{R}_{it+(j-k)h(J)}]^2$$

since $\bar{\pi}_k$ is the profit on a costless, intertemporally well-diversifed portfolio (i.e., with weights of order J^{-1}) and, hence, the uncertain portion of portfolio profits (from the perspective of time j-k) is

[9]The following numerical example illustrates the simple intertemporal diversification argument. Suppose that the typical annualized standard deviation of daily returns is 20% per year. If the covariance between daily expected returns and security volatility makes a negligible contribution to portfolio profit variance, the expected annual profit on this daily strategy is on the order of 1.7 million times its variance. All but the most risk averse investors would treat such a strategy as virtually riskless and this implies that the daily expected return and the variance of daily expected returns (on which expected profits and their variance both depend) must be very small if there are no 'near' arbitrage opportunities.

eliminated through intertemporal diversification. Since costless and riskless portfolio strategies cannot earn nonzero profits in the absence of riskless arbitrage opportunities, it follows that average profits must be zero in these circumstances.

These continuous trading strategies will earn riskless profits when security prices 'overreact' sufficiently to information in the marketplace and experience subsequent nontrivial predictable price reversals. The overreaction or fads model implies that $\beta_{i(j-k)}$ is typically negative and these strategies will earn riskless profits if 'most' of these coefficients are negative by investing in current expected winners and selling short securities which are current expected losers. In principle, these observations permit a simple direct test of the hypothesis of market efficiency—a test for the presence of particular arbitrage opportunities.[10]

Of course, it is not a trivial matter to translate this observation into an operational test since it is not possible to examine return reversal portfolio profits over an infinite number (i.e., as $J \rightarrow \infty$) of infinitesimal time periods (i.e., as $h(J) \rightarrow 0$). Suppose that we proceed under the ancillary hypothesis that a finite differencing interval such as a day or a week is a reasonable approximation to an infinitesimal time period and that a finite number of such time intervals such as six months or a year is a reasonable approximation to the infinite number of intervals required by the analysis.

The constructive nature of the argument leading up to (16) suggests a simple test based on this approximation. Consider the J period profits:

$$\text{(17)} \quad \pi^J_{t,k} = \sum_{j=t+1}^{t+J} \pi_{j,k}$$

The return reversal portfolio 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. Such a finding constitutes evidence against the hypothesis of market efficiency. Failure to find a measured arbitrage opportunity involves failure to reject the joint hypothesis that the market is efficient and

[10]As is well-known, the absence of unexploited arbitrage opportunities is necessary, but not sufficient, for prices to 'fully reflect available information' in the absence of asymmetrically informed investors.

that a finite number of non-infinitesimal time periods approximates continuous time.

There is a major difference between the impact of this ancillary hypothesis on the test based on measured arbitrage opportunities and that predicated on a model of market equilibrium. The adoption of the hypothesis that J discrete periods approximate continuous time can result in a failure to reject the hypothesis of market efficiency when it is false (i.e., a Type II error). The probability of committing a Type I error (i.e., rejection of the null hypothesis when it is true) is the presumably negligible probability of picking a costless portfolio strategy at random which had profits of the same sign for T/J consecutive periods.[11] This stands in sharp contrast to the conventional approach where the probability of false rejection of the null hypothesis includes both the usual sampling problems and the probability that the underlying model of market equilibrium (such as constant expected returns) is false.

Another way to see this distinction is to examine the analogous Fama(1970) strategy for this model of market equilibrium. As noted above, average return reversal portfolio profits $\bar{\pi}_k$ converge to zero in the limit of continuous trading. A test of the null hypothesis that $\bar{\pi}_k$ is zero encounters the same conceptual difficulty as that based on independence of security returns. The probability of rejecting this null hypothesis when it is true depends on the sampling error in the estimate of $\bar{\pi}_k$ as well as the probability that discrete trading over a finite number of non-infinitesimal time periods well approximates continuous trading.

Of course, this test of the hypothesis of market efficiency 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 which might make it difficult to reject the market efficiency hypothesis when it is false. 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 asset pricing models in which prices deviate from fundamental values because of speculative fads or noise trading and yet no

[11]This ignores potential measurement error in portfolio profits and any retrospective bias.

riskless arbitrage opportunities arise.[12] Alternatively, speculative fads may be marketwide phenomena that give 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 their presence will not be unambiguously reflected in measured arbitrage profits on these portfolio strategies.

3. Empirical Methods, Potential Problems, and Safeguards

While the discussion of the previous section pointed to a general strategy for testing some of the implications of market efficiency, it left considerable leeway for its actual empirical implementation. In particular, the analysis left several choices open: (1) the appropriate asset menu (i.e., the N securities); (2) the appropriate lag length k; (3) the horizon over which to measure portfolio profits (i.e., J); and (4) the length of time interval that is sufficiently short for the local martingale model to apply under the hypothesis of market efficiency (i.e., h(J)). Moreover, the discussion presumed that market conditions were ideal (i.e., no taxes, transactions costs, or impediments to trade), that prices could be measured without error, and that the examination of a finite sample of portfolio profits can determine the presence or absence of arbitrage opportunities.

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 for testing the hypothesis of market efficiency suggested by the analysis involves the search for evidence of unexploited arbitrage opportunities in market prices. It is obviously trivial to generate portfolio strategies which were profitable *ex post* but which need not have been profitable *ex ante*. This observation suggests that these issues should be resolved prior to empirical investigation to avoid false rejection of the null hypothesis (i.e., Type I errors). Of course, it is imperative that these choices be reasonable ones in order to avoid failure to reject false null hypotheses (i.e., Type II errors).[13]

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[12]See Campbell and Kyle(1987) for an explicit model of this form. Note that there is a fundamental identification problem inherent in such models. Such models require explicit structural relations for the fundamental value of a security from which measured asset prices deviate due to fads or noise trading. In these circumstances, there will presumably always be a candidate observational equivalent structural relation in which price equals fundamental value.

[13]There is one kind of retrospective bias that cannot be easily mitigated: the fact that I read papers in the monthly and longer horizon return reversal literature prior to embarking on this study

The empirical work that follows reflects one plausible set of *a priori* choices. 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. This permits the measurement of the returns on several thousand assets over reasonably short time periods such as days and weeks. Since the fads model predicts return reversals over some horizon, it made sense to base the portfolio weights underlying the investment strategies on previous period returns. Hence, portfolio weights were taken to be proportional to the difference between the current return on security i and the average return on all securities in the portfolio (i.e., the return on an equally weighted portfolio) and lagged values of these differences were used to form portfolios as well. Finally, a week was taken to be a sufficiently short period for the local martingale model to apply while the horizon of the portfolio strategy was set to twenty-six weeks.[14] Shorter intervals such as days were deemed inappropriate differencing intervals for reasons discussed below and other strategy horizons are reported below.

In short, the empirical work below reports summary statistics for the following explicit portfolio strategy. Consider a strategy based on the relationship between returns this week and k weeks from now. A week was taken to begin on Wednesday and end on Tuesday to minimize the number of days that exchanges were closed. Every week, all securities that were listed on the New York and American Stock Exchanges in that week and k weeks from then were selected for inclusion in the portfolio strategy.[15] The number of dollars invested in each security was set to be proportional to the current week's return less the arithmetic average of the current week's returns

(particularly Jegadeesh(1987)). It is worth noting that there is one *ex ante* forecast implicit here: the results for 1986 were obtained after the first draft of this paper was circulated.

[14]The choice of twenty-six weeks was predicated on the loose notion that this constitutes a reasonably large sample when innovations in returns are independently and identically distributed.

[15]There is some room for selection or survivorship bias here 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 proper accounting for this bias would probably have a negligible impact on the results. In addition, delisting alone overstates any upward bias in portfolio profits since firms typically cease to exist on the CRSP tapes for many reasons besides bankruptcy including name changes and takeovers.

on all securities meeting the criterion for inclusion.[16] The factor of proportionality chosen was the inverse of the sum of the positive deviations of individual security returns from this grand mean so that the portfolios are scaled to be long and short one dollar of equity securities. In this case, these costless portfolios have profits that are the difference in the returns on two dollar portfolios and, hence, are measured in units of percent per unit time.[17]

Hence, the number of dollars invested in security i in week t was:

$$(18) \quad w_{it} = \frac{-[R_{it}-\bar{R}_t]}{\sum_{\{R_{it}-\bar{R}_t>0\}} R_{it}-\bar{R}_t}$$

These quantities were then multiplied by the return on the corresponding security k weeks hence and these returns were summed to arrive at portfolio profits for that week:

$$(19) \quad \pi_{t,k} = \sum_{i=1}^{N} w_{it}R_{it+k}$$

This process was then repeated for J weeks to generate the total profits on the strategy for the portfolio horizon J:

$$(20) \quad \pi^{J}_{t,k} = \sum_{j=t+1}^{t+J} \pi_{j,k}$$

Evidence against the hypothesis of market efficiency arises if these profits are consistently of one

[16]This involves buying securities with negative returns relative to the market average in this week and financing the purchase by selling short securities which had returns in excess of the market average this week. Unfortunately, the implicit assumption that investors have full use of the proceeds of short sales is not valid in the marketplace. There are two reasons why this observation is probably not cause for too much concern. The first reason is that 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. Secondly, existing margin requirements require putting up margin for half of the market value of the long position. This is a modest cost and proper accounting of borrowing costs does not much affect computed portfolio profits since interest expense is typically less than 0.2% per week.

[17]This is not necessarily innocuous since the scaling factor changes from week to week. All of the analysis was performed with and without this scaling factor and none of the conclusions reported below were altered appreciably. The scaling factor can be thought of as a measure of the cross-sectional variation in returns in a given week.

sign over the forty-nine six month periods covered by the CRSP daily returns files.[18]

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 or the fads model. There are two well-known sources of such movements: bid-ask spreads and thin trading. 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). Similarly, measured security returns reflect the price of a security on the last trade of the day without indicating when that trade occurred. This, too, can give the appearance of negative serial correlation: firms with very high (low) measured current returns will probably experience subsequent measured return reversals since the current high (low) measured return on average overstates (understates) the true return.

This problem is largely mitigated by the employment of a few simple precautions. First, note that 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 greatly reduces the severity of the bid-ask spread and thin trading problems. 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 in this modified portfolio strategy virtually eliminates bid-ask spread bias and substantially reduces the thin trading bias as well.[19] Note that this is a conservative procedure—it eliminates the informative Tuesday returns (i.e., for securities which traded) as well as the uninformative ones (i.e., for securities which did not trade) and, hence, is likely to overstate the contribution of bid-

[18] 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.

[19] In other words, this modification virtually eliminates the correlation between the portfolio weights and the measurement error in subsequent returns. In particular, the probability of a security listed on either exchange not trading on both Monday and Tuesday is quite small and the fact that a security traded at the bid or the ask price on Monday is likely to be unrelated to which of these states occurred at the close of trade on Tuesday.

ask spread and thin trading bias to portfolio profits.

Another important issue associated with the measurement of portfolio profits involves transactions costs. These portfolio strategies involve extreme portfolio turnover since more than two thousand stocks are typically bought and sold each week. Of course, anyone seriously considering implementing such a strategy would modify it to reduce the frequency of trading. Similarly, it is not clear what transactions costs are relevant because the relevant transactions costs would be smaller for an investor treating this portfolio strategy as a marginal change in an existing active trading strategy. Rather than engage in experimentation to determine superior low transactions costs versions of these strategies and risk the potentially serious retrospective bias that could then arise, portfolio profits were computed under various assumptions about transactions costs. Transactions cost per security per week were 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.[20]

There are several minor empirical problems which are not accounted for here but which probably do not much affect inferences about portfolio profits. The empirical results presume 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.[21] In addition,

[20] Sweeney(1986) reports that a reasonable range includes 1/20 of one per cent for floor traders (i.e., transactions taxes and clearing house fees), 1/10 to 1/5 of one per cent for money managers, and 4/10 of one per cent for private investors using a discount broker. The latter number is somewhat suspect since discount brokers are a relatively recent innovation. Note that any price pressure generated by this trading strategy is ignored in the computation of transactions costs.

[21] The issue is that the closing price on the CRSP tapes is either a bid or ask price so that half the time the profit calculation assumes that one is buying (short selling) at too low (high) a price since one buys (sells) at the asked (bid) price. Of course, this same observation 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 the Blume and Stambaugh(1983) analysis, this bias in profits (given true returns) is approximately:

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

SEC regulations require that short sales take place only on upticks. This probably has a small impact on the results especially since most of the measured profits comes 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.

Finally, it is worth emphasizing the limitations of this method of analysis. As is commonplace in empirical work, the null hypothesis of market efficiency is given special status and the tests are constructed to avoid false rejection of this null hypothesis. This is especially true in this context since rejection of the hypothesis of market efficiency is only strictly appropriate if the portfolio strategies yield measured arbitrage profits—nonzero profits of the same sign for each of the forty-nine six month periods covered by the data. The evidence could easily fail to meet this stringent criterion even when the market was inefficient. For example, one week may not closely approximate an infinitesimal differencing interval and individual security returns might be too noisy to be used as reliable indicators of expected returns. Similarly, all securities listed on the NYSE and the AMEX are included in the analysis even though a reasonable *ex ante* expectation is that the small winners and losers contribute primarily to transactions costs and not to portfolio profitability. While these potential power problems could presumably be alleviated by experimentation with alternative differencing intervals, expected return predictors, and selection criteria, this practice would increase the possibility of generating portfolio strategies which were profitable *ex post* but which need not have been profitable *ex ante*. As it stands, most reasonable alterations of the analysis would probably increase measured portfolio profits.

4. Empirical Results

This section provides the promised empirical evaluation of the profitability of the costless portfolio strategy described in the previous section. This strategy was applied to virtually all

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where δ_i is the percentage bid-ask spread. The bias is obviously trivial even if the bid-ask spread is two or three percent (since the squared percentage bid-ask spread is negligible) and is rendered even smaller by the observation that the portfolio weights sum to zero.

securities listed on the New York and American Stock Exchanges between July 1962 and December 1986, the data contained on the CRSP daily returns file. The results shed considerable light on the hypothesis of market efficiency.

Table 1 describes the main results of the paper. The portfolio strategies all involve buying securities with negative returns relative to the market average over some interval and selling them at the end of the next week and financing the purchase by selling short securities which had returns in excess of the market average over the same interval and covering the short position at the end of the next week. The portfolio weights were based on: the previous full week's returns, four day returns to mitigate thin trading and bid-ask spread bias, and on the returns two, three, four, thirteen, twenty-six, and fifty-two weeks ago. The last six lags (i.e., values of k) were chosen to shed light on any persistence of return reversal effects.

The table reports the profits for five portfolio strategy horizons (i.e., values of J): one week, four weeks (i.e., monthly), thirteen weeks (i.e., quarterly), twenty-six weeks (i.e., semiannually), and fifty-two weeks (i.e., annually). Six summary statistics are provided to characterize the profits earned over these five horizons: the mean profit, its standard deviation, and the t statistic of the mean profit as well as the maximum and minimum profit and fraction of periods for which profits were positive. The number of observations on each portfolio horizon is also reported. All of these computations ignore transactions costs which will be dealt with below.

The results in Table 1 sharply reject the hypothesis that equity prices reflect the absence of arbitrage opportunities in frictionless markets. The two one-week portfolio strategies earned strictly positive profits for each of the forty-nine observations of the *a priori* portfolio horizon of twenty-six weeks as well as for each of the ninety-eight quarterly observations and twenty-four annual observations. It is hard to imagine a more overwhelming rejection of the hypothesis of market efficiency in frictionless markets.[22]

[22]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

Table 1 also reveals that there is little measured persistence in the return reversal effect. The portfolio strategy based on returns two weeks ago did earn strictly positive profits in each of the forty-nine six month periods but, as is readily apparent, this observation does not survive the inclusion of transactions costs (which is reported in Table 5 below). None of the other strategies even came close to earning strictly positive profits across the sample for any portfolio horizon.

Table 2 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 1 with one exception. The number of observations is replaced by the sample correlation between the winner and loser portfolio returns for each of the portfolio horizons. Note that these are portfolio returns per dollar invested and, hence, the statistics for the winners portfolio are the opposite of those implicit in the profits on the costless portfolios reported in Table 1 (i.e., the winners portfolio is sold short in the costless portfolios).

These statistics account for the sources of the measured arbitrage profits reported in Table 1. The weekly mean returns of the two one-week portfolio strategies were of opposite sign and the mean return of the winners portfolio was on the order of one-half the magnitude of that of the losers portfolio in absolute absolute value. 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 strategy based on the previous week's return and 0.873 for the strategy based on the first four days of the previous week's return. As a consequence, a short position in the winners portfolio has a large negative correlation with a long position in the losers portfolio, greatly reducing the variance of the resulting costless portfolio (by approximately 60% of the standard deviation of the losers portfolio) and increasing its average profit (by approximately 40% over the mean of the losers portfolio).

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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. The principal alteration in this analysis is the employment of available information on many securities (i.e., winners and losers) as opposed to the 'weak form' tests based on only lagged individual security prices.

Put differently, the winners and losers portfolios have weekly mean returns within an order of magnitude of their standard deviations. This implies that the weekly mean returns are 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. 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 (i.e., the local martingale hypothesis). The resulting costless portfolios have mean profits approximately equal to their standard deviations 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.

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, being positive in 65% to 70% of the weeks. Similarly, the short position in the winners portfolio typically had positive returns in more than half of the weeks. Rather the short position in the winners portfolio had a large negative correlation with the winners portfolio, rendering the costless portfolio profits positive in between 85% and 94% 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 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 dismisses the suggestion that these measured arbitrage profits are evidence of market inefficiency. For example, suppose that market prices were determined by the consumption-based capital asset pricing model with time-varying consumption betas and risk premia. If firms that had consumption betas above the market average this week typically had consumption betas above the market average next week as well, then the consumption risk premium would have to be highly negatively serially correlated from week to week. It is certainly difficult to think of a story that could rationalize such a short run relation.[23]

Table 2 also accounts for the failure to find pronounced persistence in the return reversal effect. The winners portfolio only has negative mean returns in the subsequent week and has positive and increasing mean returns over time. Similarly, the losers portfolio has large positive mean returns in the subsequent week which diminish as time passes. This is a reflection of measured mean reversion in stock returns which is the subject of some of my ongoing research.[24]

Tables 3 and 4 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 profit, its standard deviation, and the t statistic of the mean return as well as the maximum and minimum profit for each quintile (i.e., for each twenty cents of the dollar invested in the winners or losers portfolio). In addition, the tables provide three summary measures of portfolio characteristics by quintile: average portfolio 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 twenty cents divided by the number of firms in each quintile in each week.

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

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

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 (or any zero consumption beta) asset, and ε_{ict} is the portion of the return on security i conditionally uncorrelated with aggregate consumption which has zero mean. If the unconditional covariances $\text{cov}\{\beta_{ict}\beta_{ict+1},[R_{ct}-R_{ft}][R_{ct+1}-R_{ft+1}]\}$ and $\text{cov}\{\varepsilon_{ict},\beta_{ict+1}[R_{ct+1}-R_{ft+1}]\}$ are both zero (which ignores, for example, the probably small impact of weekly leverage changes on consumption betas), then $E\{[R_{ct}-R_{ft}][R_{ct+1}-R_{ft+1}]\}<0$ if $\text{cov}\{\beta_{ict},\beta_{ict+1}\}>0$ (or vice versa) 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.

[24]This measured mean reversion reflects market inefficiency if a week as a short enough time period for the local martingale model to apply. It may represent time-varying expected returns if weekly trading does not well approximate continuous trading.

The market value calculation is the average across weeks in the sample of the weighted (by portfolio weight) average 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%), 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 nontrivial 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, could have been easily implemented since they 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 1. In particular, the costless portfolio strategies typically generate more than two thousand round trip transactions per week and, hence, the resulting transactions costs might be expected to wipe out the profits reported in Table 1. Table 5 reports the profits over six month periods for the two one-week strategies and those based on one-week returns two and three weeks ago under different assumptions about one-way transactions costs—the 0.05% to 0.1% that would confront floor traders, the 0.1% to 0.2% costs relevant for large money managers, and the higher values of 0.3% and 0.4%, with the latter value being approximately that charged to individual investors by discount brokers. Note that the transactions costs generated by each portfolio strategy implicit in Table 5 probably overstate those that would actually be incurred since 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.

Table 5 changes some of the details of the interpretation of the results in Table 1 without altering the main conclusions. The two one-week portfolio strategies still yielded measured arbitrage profits at the levels of transactions costs that would be incurred by floor traders and large money managers. In contradistinction, the strategy based on returns two weeks ago did not yield strictly positive profits in each of the forty-nine six month periods covered by the CRSP data for any level of transactions costs and, hence, its profits do not constitute a measured arbitrage opportunity inclusive of transactions costs. Since these transactions costs computations probably overstate the actual transactions costs, it seems reasonable to conclude that both one-week strategies reflect measured arbitrage opportunities while the persistence of return reversals is not sufficient to yield arbitrage profits with the other strategies.

Finally, Figure 1 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.[25] As is readily apparent, the series appear 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. The histograms suggest that large (i.e., one to four percent per week) weekly profits are the rule rather than the exception. In other words, the profitability of these portfolio strategies is pervasive througout the sample period.[26]

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% one-way transactions costs that are probably relevant for floor traders and investment

[25] The cells of the histograms are ±0.5% of the integer displayed (i.e., 1% denotes the cell with observations ranging from 0.5% to 1.5%). The histograms exclude cells with fewer than twelve (out of 1276) observations. Hence, there are nine negative observations and thirty-eight positive observations not reflected in the histograms.

[26] Fama and French(1986), Chan(1987), and Jegadeesh(1987) provide evidence that the return reversal effects measured at longer differencing intervals are, in part, attributable to the now well-known size effect—the pronounced tendency for the returns on stocks with small market capitalizations to exceed those of stocks with large market capitalizations, especially 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.

banks 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 the size required by these strategies on this scale—typically three hundred thousand dollars in the extreme losers and half of a million dollars 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 sustain the notion that these numbers are either trivial or were unattainable for investors.[27]

5. 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

[27]It is difficult to provide a quantitative measure of the degree of inefficiency 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% one-way transactions costs. This suggests a typical pricing error estimate of 0.80% if it is reasonable to assume that this measured inefficiency represents unmeasured transactions costs (i.e., the value of time). Under these assumptions, this calculation probably understates true 'total' (i.e., unmeasured plus out-of-pocket) transactions costs because the two one-week strategies are probably much less profitable than optimal return reversal strategies.

inefficient market is currently enjoying a resurgence not seen in two decades.

These observations raise an old question: are equity markets efficient? It is especially difficult to address this question with the conventional strategy of specifying a particular model for expected returns and conditioning tests of market efficiency on this choice. Unfortunately, empirically successful economic models of expected return variation are perhaps a few years off and, hence, any rejection of market efficiency that might follow from such a test would probably (and properly) be laid at the doorstep of the chosen model of market equilibrium.

This paper has followed an alternative approach in testing the hypothesis of market efficiency by examining security prices for evidence of unexploited arbitrage opportunities. It does 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.

Despite the stringency of the test, the results suggest overwhelming rejection of the hypothesis that equity prices are set in an efficient capital market. Portfolios of securities that had positive returns in one week typically had negative returns in the next week (on average, -0.35 to -0.55 per cent per week) while those with negative returns in one week typically had positive returns in the next week (on average, 0.86 to 1.24 per cent per week). The costless portfolio that is the difference between the winners and losers portfolios had positive profits in roughly 90% of the weeks and, if the strategy is viewed as having a horizon of twenty-six weeks, the profits were positive in each of the forty-nine six month periods covered by the data. These measured arbitrage profits persist after corrections for the mismeasurement of security returns because of thin trading and bid-ask spreads and for plausible levels of transactions costs. In addition, the portfolio strategies involved only modest positions in liquid securities, suggesting that they could have been implemented without generating substantial price pressure. 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.

Of course, these results may not stand up under closer scrutiny because of some source of bias or measurement error that was not considered in the analysis. This seems unlikely since most reasonable modifications of the analysis (such as eliminating transactions in the small winners and losers) would increase portfolio profits. On the hypothesis that the main conclusions survive further examination, it is interesting to consider its implications for future research.[28]

Since there is little persistence in these measured return reversal effects, there will probably be two typical responses by investigators who take the results seriously. One group will emphasize the short-run nature of the measured effects and will presume that security prices can be treated as though they were set (on average) in an efficient market over longer horizons such as a month. On this view, these results provide an interesting puzzle for students of security market microstructure which may be interpreted as suggesting that total transactions costs greatly exceed the out-of-pocket costs considered in Table 5.[29] The other group will correctly suggest that these tests have little power to detect longer term market inefficiencies and will continue to seek additional evidence (and reinterpret existing evidence) of capital market inefficiency. These investigators will probably construct models of fair market value in inefficient markets and attempt to measure deviations from market efficiency. Both efforts will presumably increase our understanding of the determination of security prices.

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[28] I offer some anecdotal evidence on behalf of this interpretation that I encountered after completing this research. Rosenberg Institutional Equity Management successfully markets a version of the portfolio strategy described in Rosenberg, Reid, and Lanstein(1985). In addition, this firm sells a program trading product that goes long a version of the losers portfolio and short S&P 500 futures contracts. We academicians apparently benefit from return reversal strategies—the College Retirement Equity Fund has successfully pursued such a strategy (not the Rosenberg version) as part of its actively managed portfolio. My understanding is that this investment practice has become increasingly widespread. Presumably their activities, especially the computer-generated program trading 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!

[29] 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. See also footnote 27.

Table 1

Profits on Costless Return Reversal Portfolio Strategies By Portfolio Horizon—1962-1986

Panel A: Portfolio Weights Based on Previous Week's Return

Portfolio Horizon (Weeks)	Mean	Standard Deviation	t Statistic	Maximum	Minimum	Fraction Positive	Number of Observations
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

Table 1—Continued

Profits on Costless Return Reversal Portfolio Strategies By Portfolio Horizon—1962-1986

Panel E: Portfolio Weights Based on One Week Return Four Weeks Ago

Portfolio Horizon (Weeks)	Mean	Standard Deviation	t Statistic	Maximum	Minimum	Fraction Positive	Number of Observations
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 2

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

Table 3

Weekly Returns and Characteristics of Selected Dollar Portfolios of Winners By Quintile—1962-1986

Portfolio Quintile	Mean	Standard Deviation	t Statistic	Maximum	Minimum	Average Portfolio Characteristics: 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 4

Weekly Returns and Characteristics of Selected Dollar Portfolios of Losers By Quintile—1962-1986

Panel A: Portfolio Weights Based on Previous Week's Return

Portfolio Quintile	Mean	Standard Deviation	t Statistic	Maximum	Minimum	Average Portfolio Characteristics: Portfolio Turnover (Cents)	Investment per Firm (Cents)	Market Value in Millions of Dollars
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 5

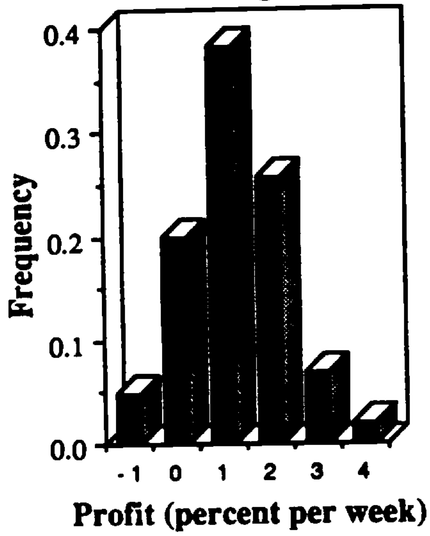
Profits on Selected Twenty-six Week Costless Return Reversal Portfolio Strategies By One-way Transactions Cost—1962-1986

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
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
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
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

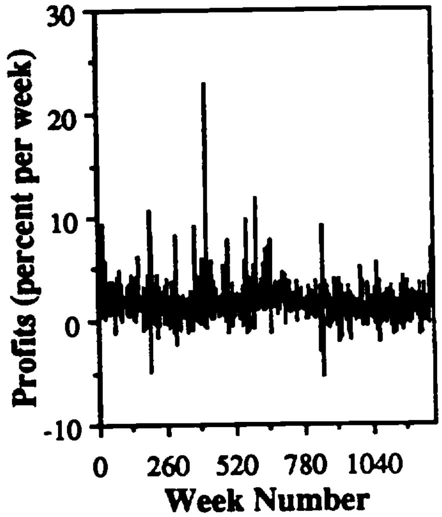
Figure 1

Weekly Portfolio Profits—Full Week Strategy

Histogram

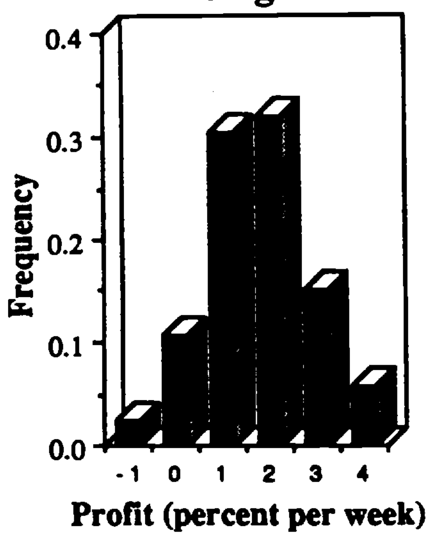


Time Series Plot



Weekly Portfolio Profits—Four Day Strategy

Histogram



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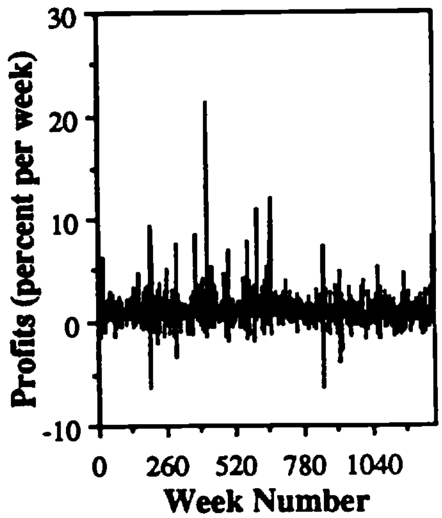

Bibliography

Black, Fischer, 1986, "Noise," Journal of Finance 41, pp. 529-543.

Blume, Marshall E. and Robert F. Stambaugh, 1983, "Biases in Computed Returns: An Application to the Size Effect," Journal of Financial Economics 12, pp. 387-404.

Chan, K. C., 1987, "On the Return of the Contrarian Investment Strategy," unpublished manuscript, School of Business, Ohio State University.

De Bondt, Werner F. M. and Richard Thaler, 1985, "Does the Stock Market Overreact?" Journal of Finance 40, pp. 793-805.

Fama, Eugene F., 1970, "Efficient Capital Markets: A Review of Theory and Empirical Work," Journal of Finance 25, pp. 383-417.

—— and Marshal E. Blume, 1966, "Filter Rules and Stock Market Trading," Journal of Business 39, pp. 226-241.

—— and Kenneth R. French, 1986, "Permanent and Temporary Components of Stock Prices," CRSP Working Paper No. 178, University of Chicago.

French, Kenneth R. and Richard W. Roll, 1986, "Stock Return Variances: The Arrival of Information and the Reaction of Traders," Journal of Financial Economics 17, pp. 5-26.

Hall, Peter E. and C. C. Heyde, 1980, Martingale Limit Theory and Its Applications (New York: Academic Press).

Jegadeesh, Narasimhan, 1986, "Evidence of the Predictability of Equity Returns," unpublished manuscript, Graduate School of Business, Columbia University.

Lo, Andrew W. and A. Craig MacKinlay, 1987, "Stock Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test," NBER Working Paper No. 2168.

Merton, Robert C., 1982, "On the Mathematics and Economic Assumptions of Continuous Time Models" in William F. Sharpe and C. M. Cootner (eds.), Financial Economics: Essays in Honor of Paul Cootner (Englewood Cliffs, New Jersey: Prentice-Hall)

Poterba, James M. and Lawrence H. Summers, 1987, "Mean Reversion in Stock Prices: Evidence and Implications," NBER Working Paper No. 2373.

Roll, Richard W., 1983, "On Computing Mean Returns and the Small Firm Premium," Journal of Financial Economics 12, pp. 371-86.

Rosenberg, Barr; Kenneth Reid; and Ronald Lanstein, 1985, "Persuasive Evidence of Market Inefficiency," Journal of Portfolio Management 12, pp. 9-16.

Shefrin, Hersh M. and Meir Statman, 1985, "The Disposition to Ride Winners Too Long and Sell Losers Too Soon: Theory and Evidence," Journal of Finance 41, pp. 774-790.

Shiller, Robert J., 1981, "The Use of Volatility Measures in Assessing Market Efficiency," Journal of Finance 36, pp.291-304.

——, 1984, "Stock Prices and Social Dynamics," Brookings Papers on Economic Activity 12, pp. 457-498.

Sims, Christopher A., 1984, "Martingale-like Behavior of Prices and Interest Rates," Discussion Paper No. 205, Center for Economic Research, University of Minnesota.

Singleton, Kenneth J., 1987, "Specification and Estimation of Intertemporal Asset Pricing Models" in Benjamin Friedman and Frank Hahn, eds., Handbook of Monetary Economics (New York: North-Holland).

Summers, Lawrence H., 1986, "Does the Stock Market Rationally Reflect Fundamental Values?" Journal of Finance 41, pp. 591-600.

Sweeney, Richard J., 1986, "Some New Filter Rule Tests: Methodology and Results," unpublished manuscript, Claremont McKenna College and Claremont Graduate School.

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