Real Estate Securities and a Filter-based, Short-term Trading Strategy

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Abstract

Anecdotal evidence provides overwhelming support to the belief that sophisticated real estate investors profit by timing long-run real estate cycles. This paper examines the investment performance benefits that sophisticated investors may derive from short-run cycles in real estate, specifically, through the publicly traded real estate markets. Using a simple strategy that filters out noise in REIT price reversals, this study shows that a contrarian strategy is many times more profitable than the associated execution costs. Furthermore, the study demonstrates that the REIT market has been sufficiently liquid to execute this trading strategy. This last point is directly related to the filter strategy since only REITs with large price movements satisfy the hypothetical investor's selection criteria.

1. Introduction

Academic research has identified a predictable pattern of overreaction behavior in REIT returns, though questions remain whether these price reversals can be economically exploited (Mei and Gao, 1995). Yet if a predictable component exists within future returns, sophisticated real estate investors should refine their trading strategies to exploit these short-term reversals. This paper examines such a refinement and employs a simple trading rule that filters out marginal price movements to more accurately reflect the trading behavior described in DeBondt and Thaler's (1985) overreaction hypothesis.

This paper highlights two essential features of DeBondt and Thaler's overreaction hypothesis. The first characteristic emphasizes the direction of price movement and proposes that *extreme* movements in REIT prices will be followed by *extreme* movements in the opposite direction (*i.e*., price reversals).[1] The second feature emphasizes the magnitude of price changes and states that the more extreme the initial movement in a REIT's price, the greater will be the subsequent price reversal. These features become the hypotheses as this study tests for economically exploitable profits from a contrarian trading strategy that takes long (short) positions in REITs that experience extreme price declines (increases) during the previous trading period. Additionally, the current concept of exploitation is potentially more robust than the prior literature's criteria for economic significance, since this study investigates whether REIT liquidity is sufficient for an investor to execute a contrarian trading strategy that filters out marginal price-movements.

A contrarian strategy may be intuitively appealing for a real estate investor since it is based upon specific characterizations of the general investment community. Substantial documentation exists that real estate markets overreact, and DeBondt (1995) presents an interesting overview of real estate cycles from the perspective of the investor psychology literature. However, transaction costs in the direct property markets generally preclude short-term flipping strategies. It is also impractical to construct a short-position in the property markets to take advantage of situations where prices deviate too far above market fundamentals. For these reasons, sophisticated real estate investors are more likely to implement a short-term trading strategy in the publicly-traded real estate markets.

To test for the economic viability of REIT market overreaction, portfolios are formed based on a ranking of the REITs' returns from the previous week. The ranking is determined by a filter-rule designed to boost the signal-to-noise ratio in the real estate security selection process. The portfolio construction process involves both features of the DeBondt and Thaler overreaction hypothesis. The hypothesis' first characteristic is addressed by taking either a long- or short-position in a security based upon the direction of its price movement. Importantly, a security is included in the portfolios only when it passes one of the filter levels that categorizes REITs by the magnitude of their previous week's return. This approach to portfolio construction taps into the non-linearity of investor overreaction since extreme returns from the previous week are more likely to identify profitable securities. In this manner, this study incorporates the second feature of the overreaction hypothesis.

This paper's findings of REIT overreaction are consistent with DeBondt and Thaler's original hypothesis. Specifically, weekly profits are found in excess of one percent over the return from a buy-and-hold strategy. Strikingly, weekly excess profits rise to two percent from portfolios produced with the filter levels that capture more extreme price movements. Over a portfolio horizon that spans a year, these profits reach as high as 50 percent demonstrating the consistency of the trading strategy compounded over multiple periods. Finally, the trading strategy is shown to be profitable on an after-transaction-cost basis and is exploitable from an execution or a trading perspective.

2. Implications of short-term price reversals for real estate investors: A brief review of the literature and methodologies

The literature on the predictability of real estate returns has evolved and focused on different attributes of return characteristics. From a returns frequency perspective, the vast majority of real estate security studies have focused on monthly returns.[2] Two exceptions to this observation are Mei and Liu (1994) which examined quarterly returns and Mei and Gao (1995) which used weekly returns. The results for real estate securities are consistent with all firms in that returns on portfolios and individual stocks appear to have a predictable component. The literature typically documents negative autocorrelation in individual security returns and positive autocorrelation in portfolio returns. However, these studies may also be categorized by their efforts to identify the source of predictability with possible explanations including market inefficiency, investor irrationality, time-varying risk premia and assorted market imperfections.

Lehmann (1990) examined predictability for all publicly traded firms in a framework that attempts to eliminate time-varying risk premia as a source of predictability. Specifically, he examined short-term (weekly) stock returns and argued that the risk premia should not change significantly in such a brief period.[3] Lehmann contended that if returns exhibit predictable reversals, then it must be due to market inefficiencies. This is the empirical approach adopted by Mei and Gao (1995) who also formed zero-cost arbitrage portfolios by selling last week's winners and buying last week's losers. By forming costless and presumably riskless arbitrage portfolios and searching for non-zero profits, Lehmann claimed to avoid the joint hypothesis problem inherent in tests of market efficiency. For Lehmann to document market inefficiency, it was sufficient to show non-zero arbitrage trading profits. He found annualized returns of 15.4 to 42.7 percent after adjusting for commission costs with the greatest overreaction profits emanating from small-capitalized stocks. In comparison, Mei and Gao, observed annualized profits of 39.1 to 46.7 percent from their sample of REIT securities.

Lehmann's work, in turn, motivated several studies addressing short-term overreaction. Lo and MacKinlay (1990) decomposed the overreaction profits into the negative autocorrelation of individual securities and the positive covariances of individual securities with the market. They showed that up to 50 percent of overreaction profit was due to lagged forecastability across large and small securities. Similar to Lehmann, Lo and MacKinlay found the greatest magnitude of profit on small-capitalized stocks. Conrad, Gultekin and Kaul (1997) examined short-run contrarian strategies similar to Lehmann and Mei and Gao and assessed the importance of bid-ask bias and risk. They observed that profits are eliminated when the analysis includes risk and transaction costs.

Overall, these studies contend that short-term overreaction is not an economically significant phenomenon. This conclusion is consistent across the broader financial economics literature as well as for real estate securities. The findings on small stocks, which partially characterizes Mei and Gao's sample, are clouded by microstructure issues, and the results on larger capitalized stocks disappear after incorporating plausible transaction costs. The central difference between these earlier studies and this paper is that the current study constructs portfolios using a filter strategy based on the previous week's gains or losses to determine whether a REIT is included in a short or long portfolio.

3. Determining returns with a filter-based strategy

This paper modifies the overreaction portfolio formation methodologies used in past papers in order to address the economic viability of trading rules based upon "predictable" REIT price movements. This methodology boosts the "signal-to-noise" ratio of the security selection process that forms contrarian portfolios by using filters that screen on the magnitude of past price movements.[4] Unlike earlier studies, this paper's methodology does not invest in all securities, but only those securities whose price last period moves up or down by at least a certain level. The filter level places restrictions on the minimum unadjusted return required for a security to be included in a long-position or short-position portfolio. Securities are defined as losers (winners) if the past period's returns decrease (increase) by the amount of the filter level. Next, equally weighted long (short) portfolios are formed of losers (winners). Statistically significant positive returns to both the long and short portfolios are taken as evidence of predictable reversals.

Previous overreaction studies typically employ a portfolio formation method that did not screen on the magnitude of lagged-returns. For example, DeBondt and Thaler (1985) included the top (bottom) 30 securities in winner (loser) portfolios in every portfolio formation period regardless of the return magnitude. Similarly, studies in the short-term reversal literature form portfolios by investing in all securities in their sample, giving greater weight to securities with relatively-larger, cross-sectional returns for the prior period (Lehmann, 1990; Lo and MacKinlay, 1990; Conrad, Gultekin, and Kaul, 1997; Mei and Gao, 1995). Yet these studies may be obscuring the impact of investor overreaction by not screening the securities before they are grouped into long and short portfolios.[5] In contrast, the use of filters in the security selection process results in a REIT being included in a long (short) portfolio of past losers (winners) only if its previous week's return moved down (up) by a specified level.

3.1. A simple filter-rule methodology

This paper uses a filter rule where the previous week's returns are used to predict future returns by forming contrarian portfolios of REITs. Specifically, if a REIT return is negative (a loser) the hypothetical investor takes a long position in the security in anticipation of a subsequent price reversal. Likewise, a short position is taken when a REIT's return is positive (a winner) in the past week.

Past week's returns are classified as winners or losers using the following criteria:

$$\textbf{Return states} = \begin{cases} \text{For } k = 0,1,\ldots,4: & \begin{cases} \text{loser}_{k*A} \text{ if } -k*A > R_{i,t-1} \geq -(k+1)*A \\ \text{winner}_{k*A} \text{ if } k*A \leq R_{i,t-1} < (k+1)*A \end{cases} \\ \text{For } k = 5: & \begin{cases} \text{loser}_{k*A} \text{ if } R_{i,t-1} < -k*A \\ \text{winner}_{k*A} \text{ if } R_{i,t-1} \geq k*A \end{cases} \end{cases} \tag{1}$$

where:

$R_{i,t}$ is the return (unadjusted) for security i in week t

k is the filter counter that ranges from 0, 1, …5.
A is a parameter equal to two percent.

The filter breakpoints span the distribution of past returns in equally sized ranges to generate maximum dispersion in the return distributions. Specifically, the return filters start at zero percent and increment in steps of two percent, to a maximum (minimum) of positive (negative) ten percent for short (long) filters. The securities whose previous week's returns meet the filter constraints are formed into equally-weighted portfolios during week t.[6] All portfolios are held for a period of one week and then liquidated. The resulting portfolios' mean returns are calculated for weeks in which non-zero positions are held. If mean returns of the portfolios are significantly different from zero, this is taken as evidence in favor of return predictability. Thus, the null hypothesis of no predictability is that the mean return of a portfolio equals zero.[7]

An important statistical innovation in this paper involves the use of moment conditions for hypothesis testing. The study estimates moment conditions with a generalized method of moments estimator (Hansen, 1982). This approach makes use of Newey and West (1987) weights on the variance-covariance matrix to compute the mean and standard errors of the time series of trades for each portfolio and to perform comparisons between the means of different strategies. Comparing the mean returns in a GMM framework has the advantage of controlling for contemporaneous and time series correlations in the portfolio returns.

Using return filters to form portfolios results in two main differences with the portfolio selection techniques of earlier overreaction papers. First, the use of the filter rules results in certain weeks in which no portfolios may be formed. The flexibility of not being invested in certain weeks may be an important source of profits. Second, by varying the filter level, this paper examines how the degree of return reversals changes as the filter levels vary in magnitude. Previous short-term overreaction papers do not allow for this type of analysis since their portfolio formation rules require investing in all securities in their sample at all times.[8] The flexibility in this study's analysis is important because it permits the empiricist to examine the degree of return reversals conditioned on larger lagged-returns. The results show that the sample of real estate firms experiences greater reversals for both long- and short-position portfolios at filter levels of greater magnitude. This finding is evident only because the methodology can screen securities for larger past price movements that may be more prone to greater overreaction and to eliminate securities that experienced smaller lagged-returns and would more likely be noise to a contrarian strategy. This approach is particularly appealing since the use of filters reflects what a contrarian investor would do when forming portfolios based upon the magnitude of price changes.

4. Potential returns and the art of execution

4.1 The data

The data set is constructed from all publicly-traded REITs, as identified by the National Association of Real Estate Investment Trust. From this universe, 301 REITs exist on the CRSP files for the period 1973 through 1995, although, there is considerable variation in the length of the return series across securities. REITs are included in the sample for week *t* if they trade in each of the previous ten trading days. Consistent with previous studies, the weekly returns are constructed from Wednesday to Wednesday closing prices.

Exhibit 1 provides descriptive statistics for the REIT sample. The average market value of equity over the entire sample period is 119 million dollars while the mean share price is approximately 15.4 dollars. This paper excludes from its sample all REITs with a share price less than 5 dollars as a precaution against bid-ask bounce effects. The cross-sectional average of weekly autocorrelation coefficients for individual securities is –7.07 percent at the first lag and –2.77 percent at the second lag. Though the negative autocorrelation is consistent with overreaction behavior for individual stocks, it may also indicate the effects of a bid-ask spread.

To ensure that the data and test results are not overly affected by spurious reversals emanating from a bid-ask bounce (Roll (1984)), this paper also employs four-day "skip-day" returns in the portfolio formation week. Since this study employs CRSP data which only contain closing prices and not closing bid-ask spreads, it is possible that the last transaction for a loser (winner) stock may be reported at the bid (ask) price. If, on the average, fifty percent of the securities in the loser (winner) portfolio move to the ask (bid) price at the end of the next week, then this will result in the appearance of greater profits to the reversal strategies than actually exist. A common remedy for this problem involves constructing “skip-day” returns in the portfolio formation period. The skip-day returns are formed from four-day Wednesday-close to Tuesday-close returns. Thus, spurious reversals due to the bid-ask bounce are removed when the last day’s return prior to the trade week is dropped from the portfolio formation period. The weekly autocorrelation of -3.24 percent for the four-day (skip-day) return is presented in Exhibit 1. The magnitude of this statistic strongly suggests that negative autocorrelation induced by the bid-ask spread is not primarily responsible for the negative autocorrelations exhibited in the full weekly returns.

In addition, since the weights placed on individual securities used to form portfolios are based on unadjusted or not-market-adjusted returns, the profits to the filter-based strategies should not emanate from index autocorrelation.[9] In other words, since the current method employs weights conditioning on raw returns, the profits from this filter strategy are based upon individual security autocovariances and individual security unconditional mean weekly returns. The mean return or average weekly unconditional return of the REIT sample is 0.267 percent which is analogous to the return generated from a buy-and-hold strategy for the analysis period. This unconditional return is relatively small compared to the magnitude of the profits from many of this paper’s filter strategies, suggesting that the primary source of predictability is indeed individual security autocovariances.

4.2 Returns to a contrarian strategy

Exhibit 2 reports the average weekly returns to the contrarian, filter strategies for the prior week’s losers and winners. Panel A (B) presents the strategy of buying last week’s losers (winners) based on full 5-day *t*-

1 weekly returns, and the strategy of buying last week's losers (winners) based on the skip-day (4-day) *t-1* returns. The profit figures reported throughout the paper are for positive investments. Hence, reversals in the short portfolios appear as negative returns and reversals in the long portfolios appear as positive returns.

A striking feature of Exhibit 2 is the magnitude of the portfolios' weekly returns, especially at the higher filter levels. Greater magnitudes of reversal emerge as the filter levels increase across both the long and short portfolio strategies. The long strategies' average weekly returns begin at 0.202 percent (t-statistic = 2.7) for the strategy using the 0 to -2% previous week's return filter and increase steadily to a 2.20 percent weekly return (t-statistic = 6.3) at the less than -10%" filter.

The short-position strategies also exhibit greater reversals as the filter levels are raised. For example, the average weekly returns for the short-position strategy start out at 0.19 percent (t-statistic = 3.6) for the "0 and 2%" filter and decrease to -0.38 percent (t-statistic = -1.7) for the "greater than 10%" filter. The t-statistics of the short-position strategies are smaller than the long-position strategies and generally do not indicate significant reversals. The clear asymmetry between the magnitude and statistical significance of reversals for past losers and winners is consistent with findings in other short-term predictability papers. The findings in this study are also consistent with much of the filter literature that observes that short positions for various holding periods are usually not as profitable as long positions (Brown and Harlow, 1988; Sweeney, 1988; Bremer and Sweeney,1991; Cox and Peterson, 1994). These results are also consistent Downs, Hartzell and Torres (1997) finding that REIT price adjustments respond more quickly to positive announcements than to negative information. Their study supports the claim that real estate investors face short-selling constraints in the public and private markets. Hence, downward transaction prices change more slowly than they do in up-markets.

While the results thus far suggest profitable trading opportunities through a combination of contrarian and filter techniques, some concern remains about the impact of the bid-ask bounce and other microstructure problems on the results. For example, at extreme filter levels, *unusual* securities may be selected, such as those with large bid-ask spreads. As discussed previously, large conditional bid-ask spreads may result in extra profits to the filter strategies that emanate from a bid-ask bounce (Roll, 1984). Thus, Exhibit 2 also presents results for portfolios formed from conditioning on skip-day returns in the formation period.

The results for the skip-day returns are presented with the five-day returns in Exhibit 2 for ease of comparison. The skip-day long- and short-position strategies yield lower profits than the strategies that employ a full 5-day conditioning period. Interestingly, the pattern of predictability among the short-position skip-day portfolios appears to be more suggestive of a continuation in prices.

While the skip day results are not as strong as the five day results, there is evidence that an investor may be able to open positions in the skip-day strategies facing a smaller effective spread than for the non skip-day strategies. Lee, Mucklow, and Ready (1993) show that on the first day following large information events, the effective spread does indeed increase. However, they find that on the second day after the event the effective spreads drop (page 367, table 5).

Additionally, the filter strategy is distinct from previous short-horizon contrarian papers in that securities are included in a portfolio only when they satisfy the filter. To provide the potential investor a sense of trading activity, the number of weeks that a portfolio trades out of a possible 1294 weeks is reported in Table 2. At a filter of 0% to –2%, the strategy traded 1279 weeks with an average of 19 securities per portfolio (the number of securities per portfolio is not reported in Table 2). However for the largest magnitude loser portfolio (< 10% previous week's return), the strategy traded only 477 weeks with an average of 2.94 securities per week. Another consideration for traders implementing this strategy is the growth in the number of REIT securities across the sample period. For instance, the –2% to –4% portfolio was comprised of an average of 4, 9 and 15 securities per week during the decades of the 1970s, 80s and 90s, respectively. This trend in the number of securities in a moderate long portfolio is consistent with other filter levels.[10]

4.3 Consistency of returns over longer horizons.

In addition to examining the magnitude of reversals at the weekly horizon, this paper aggregates weekly returns over a long time horizon to examine the consistency of the filter rule results. Lehmann (1990) and Mei and Gao (1995) examine longer horizon *J* period returns, where *J* ranges from four to fifty-two weeks. Exhibit 3 presents the results of one, four, thirteen, and fifty-two week non-overlapping horizon returns for the long- and short-position strategies. The average *J*-week horizon return to portfolio *p* is calculated as $R_p^J = \left[\prod_{t=1}^{J}(1+R_{p,t})\right] - 1$. The *J* week return is calculated for periods in which there is at least one weekly return. A zero-return value is assigned to any missing return weeks within the *J* week period. Thus, the *J*-week aggregate return is simply the return an investor would realize over *J* weeks by using this paper's strategy of buying or selling securities based on their previous week's returns, holding the portfolio for one week, closing the position at the end of one week and then repeating the process.

The results show that trading strategies using filters of greater magnitude and for longer horizons produce returns that are more consistently profitable than investments using filters of lower magnitude at shorter periods. For example, at a one-week horizon, returns are positive to the long-position strategy at the "0 and –2%" filter for approximately 57 percent of the weeks. This percentage of positive returns increases to 66 percent for the filter of the most extreme losers. At the fifty-two week horizon, the degree of consistent profitability for the more extreme loser filters attains levels of 80 to 90 percent with annual returns of between 50 to 60 percent. This performance can be compared to the annualized portfolio return of a buy-and-hold strategy composed of the component assets (the individual REIT securities); those securities experienced positive returns in 75 percent of the years and had an average annual return of 13.1 percent. The strategy using a short-position produces consistent results, though not as strong. Overall, the results reflect a filter-based strategy that experiences annual returns of approximately 35 to 45 percent in excess of the unconditional REIT sample annual returns, a proxy for a buy-and-hold strategy.

For the longer horizon returns, reported in Exhibit 3, a similar decrease in consistency occurs between the full 5-day *t-1* return strategies and the skip-day strategies as seen at the weekly horizon. However, the relatively lower 52-week returns of the more extreme loser filters may be caused by the methodology. Specifically, a zero-return is designated for periods when the trading strategy does not form portfolios. Yet the overall pattern of predictability among the skip-day portfolios yields large returns with a high degree of consistency at the longer horizons even after controlling for negative autocorrelation arising from the bid-ask bounce.

4.4 Alternative weighting methodologies

To provide additional information about the size and patterns of returns produced by the filter-rule methodology, this section contrasts the attributes of this portfolio formation technique to the techniques used in earlier studies. The approaches used to form portfolios in previous papers are based upon relative cross-sectional rankings of lagged-returns. One possible disadvantage of these weighting techniques is that they include all securities in their portfolios. The presence of such a large number of securities may imply that many securities will contribute primarily to increasing transaction costs instead of adding to profit levels.

To compare these results directly with other methodologies, portfolios are formed using the current data sample and the contrarian portfolio weights similar to Mei and Gao (1995), Conrad, Hameed, and Niden (1994), Lo and MacKinlay (1990) and Lehmann (1990). Two weighting schemes are tested. The first comparison incorporates market-adjusted returns to construct portfolio weights. In this case, the weight given to security *i* during week *t* for a portfolio of past losers or winners is:

$$w_{p,i,t} = \frac{-\left[R_{i,t-1} - \overline{R}_{t-1}\right]}{\sum_{i=1}^{N_p}\left[R_{i,t-1} - \overline{R}_{t-1}\right]} \tag{2}$$

where *p* indicates a long or short portfolio and $\overline{R}_{t-1}$ is the average weekly cross-sectional return at time *t-1* for all REITs in the sample. The second weighting scheme employs unadjusted or not-market-adjusted returns to construct the weights:

$$w_{p,i,t} = \frac{-R_{i,t-1}}{\sum_{i=1}^{N_p} R_{i,t-1}} \tag{3}$$

where *p* is a long or short portfolio and $R_{i,t-1}$ is the security *i* weekly return for time *t-1*. Portfolios are formed so that the weights of both the long and short portfolios sum to one.

The average weekly return for the first weighting method is 1.12 percent for the long-position and -0.47 percent for the short-position. The results for the second weighting scheme, which does not employ market-adjusted returns, is 0.94 percent per week for long portfolio and -0.70 percent per week for the short portfolio. Using skip-day returns, the first weighting method has returns of 0.32 (-0.19) percent for the long (short) portfolio while the second weighting method produces returns of 0.58 (0.07) percent for the long (short) position. In general, the portfolios based on the filter rule's more extreme price movements are statistically greater than the returns generated by the alternative weighting schemes. For example, a test in differences of means between the "less than –10%" filter portfolio, and the loser portfolio of the first weighting method using 5 days in week *t-1* is significant (χ^2= 8.8, p < .01).[11] Thus, one interpretation of the differences in returns between the filter portfolios and the relative cross-sectional weighting portfolios is a confirmation of DeBondt and Thaler's second hypothesis; the more extreme the initial movement in a REIT's price, the greater will be the subsequent price reversal.

This direct comparison suggests that even though alternative methodologies give somewhat greater weight to larger overreactions, the variation in weights is not sufficient to offset the inclusion of all securities in the portfolios. Essentially, the previous studies' weighting schemes may obscure the search for profitability by not specifically searching for securities that overreact. In contrast, by investing in securities that meet filter constraints on the level of last week's price movement and then forming equally-weighted portfolios, the filter method identifies the securities that overreact and eliminates those securities whose minimal price movements may be noise.

A potential advantage of the methodologies used in earlier papers is that they invest every week, thus they may have greater longer-horizon returns even though, in most cases, they have lower weekly average profits. For example, the most profitable 52-week return horizon from the previous overreaction weighting methods is from the 5-day Lehmann weighting method portfolio, which has an average 52-week return of 93.4 percent and experiences positive returns in 23 of 25 years (not reported in the exhibits). The returns of this long-position portfolio outperform the 58 percent return on the largest magnitude filter over a 52-week horizon. Thus, the Lehmann portfolio, with a lower average weekly return, outperforms the filter portfolio at the 52-week horizon for strategies based only on 5-day week *t-1* returns.

However, the returns decline when the skip-day approach is applied to the Lehmann strategy, producing an average 52-week return of 16.9 percent and experiencing positive returns in 19 out of 25 years. As such, many of the portfolios in Exhibit 3 using middle to extreme value filters experience as great or greater 52-week returns than that of the skip-day Lehmann portfolios. Thus, even though the cross-sectional weighting method is invested every week, it does not appear to outperform many of the more moderate to extreme filter strategies at longer return horizons for the skip-day portfolios.

A possible explanation for the strong results favoring a filter-based method of trading in real estate securities is related to the underlying asset. Studies such as Mengdon and Hartzell (1986) and Liu and Mei (1994) have documented differences in the return generating process for real estate securities relative to other common stocks, specifically small capitalization issues. The general consensus is that cash flow variability is more significant in explaining real estate security returns than discount process changes. Thus, short-term overreaction may be greater in real estate securities because changes in cash flows are more idiosyncratic than discount changes. Likewise, industry leaders such as Roulac (1988) argue that real estate markets are perceived by analysts to be complex since the valuation of real estate securities is often considered to be difficult and costly.

4.5 The art of execution, transaction costs and liquidity

Transaction costs may seriously affect the profitability of both the previous papers' weighting schemes and the filter portfolios. Portfolios formed from either type of weighting strategy undergo considerable rebalancing, thus transaction costs are of paramount importance. For example, many of the intermediate to more extreme filters earn weekly profits of between 1 to 2 percent per week invested. If one assumes that the portfolios completely turn over every week, then the implied transaction costs to equate the filter returns to the sample's unconditional mean weekly return of 0.267 percent is between approximately 0.7 to 1.7 percent per round-trip. In contrast, the implied transaction costs to equate the returns from portfolios formed on this paper's sample using previous papers' portfolio weights to the unconditional mean weekly return range from 0.05 to 0.85 percent per round-trip.

An important issue is whether these projected costs are large relative to trading costs faced by investors. While commission costs may be relatively low, the more important components of transaction costs likely relate to implicit trading costs such as effective bid-ask spreads and price pressure effects. Keim and Madhavan (1997) report round-trip total execution costs of 0.96 percent (price impact, bid-ask spreads, and commission costs) calculated from actual trades placed by 21 institutional investors on the next-to-smallest quintile of NYSE securities, which are close in average size to this REIT sample, over the 1991 to 1993 period for medium sized trades ($24,000 average trade size). Thus, it is likely that a trader facing the above transaction costs could successfully implement the filter strategies for these medium sized trades, but the prior papers' profits would most likely not be profitable net of transaction costs. This finding that the previous papers' portfolio weighting methodologies do not result in profitable trading net of realistic transaction costs is consistent with Mei and Gao (1995). Mei and Gao find that for one-way trading costs of over 0.5 percent, the contrarian strategies examined in their paper would most likely not be profitable.

To the extent that an investor places relatively small orders so that price pressure effects are minimized and to the extent that an investor is skillful in the use of limit orders to minimize bid/ask spreads, then the trading costs may well be limited to commission costs.[12] In these cases, the trader may be able to profitably trade both the filter strategies and prior papers' strategies. Recent quotes from Internet trading sites (e.g., www.etrade.com) list one-way commission costs for *limit* orders at approximately $19.99 for 5000 shares or $0.008 per share/round-trip. Based on the average REIT price in the sample of $15.43 round-trip commission costs would equate to 0.052%, suggesting that both the filter strategies and relative cross-sectional weighting strategies of the prior papers would be profitable. However, if an investor attempts to place orders for larger size trades, then the evidence above indicates that much of the profit-ability from the cross-sectional weighting method and the less extreme filter strategies will probably not survive the likely trading costs. Overall, both the filter and cross-sectional strategies are likely to be affected by transaction costs. The magnitude of this effect will depend on the trader's skills in obtaining favorable spreads and lessening the price impact of the trades.

An additional consideration for executing the filter strategy involves the depth or, more generally, the liquidity of the securities being traded. This study examines trade-week liquidity based on volume to provide additional analysis in determining whether the securities selected at various filters experience unusual conditions that may affect the profitability of the portfolios. Thus, this paper uses three measures of trading volume to proxy for liquidity. The volume in week *t-1*, week *t*, and opening trade-day volume (the first day of week *t*) are divided by the previous 40 weeks' average to give three relative volume measures. The premise is that extremely large or small relative volume in the trade week may result in greater microstructure problems and hence lower profitability or greater impediments to implementing the filter portfolios. The specific results for the long- and short-position strategies are not reported here, however, the general interpretation is as follows.[13]

The pattern that emerges is one of increasing opening day, week *t-1*, and week *t* volume as the filters are raised for both long- and short-portfolios. For example, long portfolios formed at the lowest filter level, "between 0 and -2%", experience weekly volume for all three measures close to their trailing 40 week means (1.09, 1.02, and 1.05 for open day, week *t-1* and week *t*, respectively). For the intermediate level filters, there is a steady increase in trade-week volume, but many of the volume averages remain relatively low in a 1.1 to 1.5 range. In contrast, the portfolio formed from the extreme long-position filter, "less than -10%", experiences increases in volume of approximately twice the normal weekly volume (2.57, 2.50, and 1.70 for open day, week *t-1* and week *t*, respectively). In addition, the skip-day strategies reflect similar patterns of increased relative volume as compared to the five-day strategies.

It may be difficult to determine whether the higher volume at the more extreme filters will significantly impede the execution of the filter strategies. For example, the long-position strategy with the highest trade week opening day relative volume is the "less than -10%" skip-day filter. Although its opening day volume is 2.64 times normal volume, it is still well within one standard deviation of the unconditional opening day relative volume.[14] Overall, the analysis of trade-week volume measures shows that many of the intermediate filter strategies and even some of the more extreme filter strategies do not experience trade-week volume much greater than one standard deviation away from their unconditional means. These results imply a liquid REIT market in which a trader could execute a majority of the filter strategy trades at relatively favorable bid-ask and price pressure conditions, especially since the trader would most likely be helping to supply liquidity on the opposite side of the majority of orders.

4.6 Additional evidence based on recent trends in the REIT market

An interesting empirical question is whether these results are robust given the recent trends in the REIT market toward larger, growth-oriented REITs. To address this concern additional evidence is provided on the profitability of filter strategies by focusing on characteristics of REIT size as measured by market equity and on REITs that have traded exclusively in the 1990s.

Exhibit 4 reports the results for the filter strategy applied to REITs with a market capitalization in excess of $100 million. For comparison, Exhibit 4 repeats the returns for the full sample of REITs. Generally, there is not a significant difference between the trading profits associated with larger REITs and the full sample, with the exception of portfolios formed from the most extreme loser filter. In contrast, the returns from the 1990s suggest that a filter-based, contrarian strategy is potentially more profitable than during earlier periods. This result is consistent with Ling and Ryngaert's (1997) argument that the valuation uncertainty associated with REITs persists in the 1990s.

5. Conclusion

This paper examines a short-term trading strategy based on a filter methodology that exploits the behavior of real estate returns. Striking evidence of large contrarian portfolio returns emerge when securities are grouped according to the magnitude of previous returns. In a comparison with earlier methodologies (Mei and Gao, 1995), this strategy yields generally larger trading profits, even when controlling for microstructure issues such as the bid-ask bounce. The pattern of relatively large magnitude filter-based contrarian profits exists over different time horizons, from weekly to 52-week periods. Additionally, the profits from the filter strategies appear to survive the inclusion of transaction costs, with the 1990s being an especially profitable period.

The authors offer the idiosyncratic nature of real estate cash flows (Mengdon and Hartzell, 1986, and Liu and Mei, 1992), as a possible explanation for the economic success of the filter-based, short-term trading strategy.[15]

References

Bharati, R. and M. Gupta, Asset Allocation and Predictability of Real Estate Returns, *Journal of Real Estate Research*, 1992, 7, 469-84.

Bremer, M. and R. Sweeney, The Reversal of Large Stock-Price Decreases, *Journal of Finance*, 1991, 46, 747-54.

Brown, K. and W. Harlow, Market Overreaction: Magnitude and Intensity, *The Journal of Portfolio Management*, 1988, 14, 6-13.

Conrad, J., M.N. Gultekin, and G. Kaul, Profitability of Short-Term Contrarian Strategies: Implications for Market Efficiency, *Journal of Business and Economic Statistics*, 1997, 15, 379-86.

Conrad, J., A. Hameed, C.M. Niden, Volume and Autocovariances in Short-Horizon Individual Security Returns, *Journal of Finance*, 1994, 49, 1305-29.

Cooper, M., D.H. Downs, and G.A. Patterson, Asymmetric Information and the Predictability of Real Estate Returns, *Journal of Real Estate Finance and Economics*, 1998, forthcoming.

Corrado, C. and S. Lee, Filter Rule Tests of the Economic Significance of Serial Dependencies in Daily Stock Returns, *Journal of Financial Research*, 1992, 15, 369-87.

Cox, D. and D. Peterson, Stock Returns following Large One-Day Declines: Evidence on Short-Term Reversals and Longer-Term Performance, *Journal of Finance*, 1994, 49, 255-67.

Darrat, A. and J. Glascock, On the Real Estate Market Efficiency, *Journal of Real Estate Finance and Economics*, 1993, 7, 55-72.

DeBondt, W., Real Estate Cycles and Animal Spirits in J. Pagliari, editor, *The Handbook of Real Estate Portfolio Management*, Chicago: Irwin Professional Publishing, 1995, 1153-83.

DeBondt, W. and R. Thaler, Does the Stock Market Overreact?, *Journal of Finance*, 1985, 40, 793-805.

Downs, D.H., D. Hartzell and M. Torres, Why Do REIT Prices Change? The Effect of Announcements on Market Activity, *University of Georgia*, 1997, working paper.

Fabozzi F., C. Ma, W. Chittenden, and R. Pace, Predicting Intraday Price Reversals, *The Journal of Portfolio Management*, 1995, 21, 42-53.

Fama, E.F., and M.E. Blume, Filter Rules and Stock-Market Trading, *Journal of Business*, 1966, 39, 226-41.

Hansen, L.P., Large Sample Properties of Generalized Method Of Moments Estimators, *Econometrica*, 1982, 50, 1029-54.

Keim, D.B., and A. Madhavan, Transaction Costs and Investment Style: An Inter-exchange Analysis of Institutional Equity Trades, *Journal of Financial Economics*, 1997, 46, 265-92.

Lakonishok, J. and T. Vermaelen, Anomalous Price Behavior around Repurchase Tender Offers, *Journal of Finance*, 1990, 45, 455-77.

Lee C., B. Mucklow, and M. Ready, Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis, *Review of Financial Studies*, 1993, 6, 345-74.

Lehmann, B., Fads, Martingales, and Market Efficiency, *Quarterly Journal of Economics*, 1990, 105, 1-28.

Ling, D.C. and M. Ryngaert, Valuation Uncertainty, Institutional Involvement, and The Underpricing of IPOs: The Case of REITs, *Journal of Financial Economics*, 1997, 43, 433-56.

Li, Y. and K. Wang, The Predictability of REIT Returns and Market Segmentation, *Journal of Real Estate Research*, 1995, 10, 471-82.

Liu, C., and J. Mei, Predictability of Returns on Equity REITs and Their Comovement with Other Assets, *Journal of Real Estate Finance and Economics*, 1992, 5, 401-18.

Lo, A.W., and A.C. MacKinlay, When are Contrarian Profits Due to Stock Market Overreaction?, *Review of Financial Studies*, 1990, 3, 175-205.

Mei, J., and C. Liu, The Predictability of Real Estate and Market Timing, *Journal of Real Estate Finance and Economics*, 1994, 8, 115-35.

Mei, J., and B. Gao, Price Reversal, Transaction Costs, and Arbitrage Profits in the Real Estate Securities Market, *Journal of Real Estate Finance and Economics*, 1995, 11, 153-65.

Mengdon, A. and D. Hartzell, Real Estate Investment Trusts - Are They Stocks or Real Estate?, New York: Salomon Brothers, 1986.

Nelling, E. and J. Gyourko, The Predictability of Equity REIT Returns, *Journal of Real Estate Research*, 1998, 16, 251-68.

Newey, W.K., and K.D. West, A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 1987, 55, 703-7.

Roll, R., A Simple Implicit Measure of the Bid-Ask Spread in an Efficient Market, *Journal of Finance*, 1984, 39, 1127-39.

Roulac, S., How to Value Real Estate Securities, *Journal of Portfolio Management*, 1988, 14, 35-9.

Sims, C.A., Martingale-Like Behavior of Prices and Interest Rates, *University of Minnesota*, 1984, working paper.

Sweeney, R.J., Beating the Foreign Exchange Market, *Journal of Finance*, 1986, 41, 163-82.

Sweeney, R.J., Some New Filter Rule Tests: Methods and Results, *Journal of Financial and Quantitative Analysis*, 1988, 23, 285-300.

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Exhibit 1
Summary Statistics

	Mean	Median	Std. Dev.	Min.	Max.	$\overline{r_1}$ (s.d.)
5 day return (%)	0.27	0.0	3.91	-46.08	112.00	-7.07 (13.65)
4 day return (%)	0.20	0.0	3.53	-40.30	96.30	-3.24 (11.40)
$VR_{i,t}$ (%)	67.36	-2.15	643.52	-100.00	1049.00	-17.81 (12.23)
Capitalization ($, millions)	119.0	57.2	168.0	0.02	1760.0	
Price ($ per share)	15.43	13.75	8.95	5.00	132.00	

This exhibit provides summary statistics for the sample of REITs (N=310) from 1973 through 1995. Five day return is a Wednesday-to-Wednesday close weekly holding period return. Four day return is a skip-day Wednesday-to-Tuesday close four day holding period return. Stocks with prices less than $5 per share are excluded from the sample. The mean, median, and standard deviation of capitalization and price are calculated across time and across securities. The statistic ρ_1 is the average first-order autocorrelation coefficient of weekly returns of individual stocks. The population standard deviation (s.d.) is given in parentheses. Since the autocorrelation coefficients are not cross-sectionally independent, the reported standard deviations cannot be used to draw the usual inferences; they are presented as a measure of cross-sectional variation in the autocorrelation coefficients.

Exhibit 2
Weekly portfolio returns to filter-based, short-term trading strategies

Panel A: Long-position strategies

Strategy:		**Previous week's return filter (%)**					
		<0 and ≥-2	<-2 and ≥-4	<-4 and ≥-6	<-6 and ≥-8	<-8 and ≥-10	<-10
Long-position	Mean (%)	0.202	0.561	0.835	1.212	1.354	2.200
Returns	Stand. dev.	1.944	2.519	3.342	4.236	5.499	7.008
	N	1279	1260	1097	786	496	477
	T-stat.	2.677	6.624	7.843	7.579	5.271	6.338
Skip-day,	Mean (%)	0.197	0.346	0.501	0.708	0.690	1.218
Long-position	Stand. dev.	2.016	2.560	3.569	4.489	5.686	6.995
Returns	N	1278	1263	1079	737	420	385
	T-stat.	2.783	4.265	4.253	4.117	2.330	3.233

Panel B: Short-position strategies

Strategy:		**Previous week's return filter (%)**					
		≥0 and <2	≥2 and <4	≥4 and <6	≥6 and <8	≥8 and <10	≥ 10
Short-position	Mean (%)	0.192	0.121	0.063	-0.086	-0.021	-0.376
Returns	Stand. dev.	1.499	2.165	3.177	4.003	4.612	5.687
	N	1278	1256	1151	925	662	748
	T-stat.	3.597	1.665	0.643	-0.643	-0.064	-1.676
Skip day,	Mean (%)	0.235	0.325	0.386	0.170	0.316	0.306
Short-position	Stand. dev.	1.494	2.194	3.183	4.029	5.562	6.037
Returns	N	1281	1258	1139	848	583	630
	T-stat.	4.247	4.320	3.994	1.255	1.371	1.173

Panel A reports the average weekly portfolio returns to these strategies: (1) long-position, a strategy of buying last weeks losers based on full 5 day *t-1* weekly returns, and (2) skip-day long-position, a strategy of buying last weeks losers based on a 4 day *t-1* return. Panel B in Exhibit 2 documents the same strategies for winner stocks. For a security to be included in a long- or short-portfolio, its previous week's return must be within the given filter ranges (See equation 1 in the text). The sample of REITs cover the period from January 1973 to December 31, 1995. Included are the corresponding portfolios means, standard deviations, and t-statistics for a mean equal to zero null hypothesis for weeks in which equity positions are held. In Panels A and B, N is the number of portfolio weeks the strategy traded at the respective price filter level out of a possible 1294 weeks.

Exhibit 3
Weekly portfolio returns for longer horizons.

Panel A: Mean Return and Percent of Positive Returns for One, Four, Thirteen and Fifty-two Week Horizons for Loser Portfolios

Previous week's return filter (%)

Strategy:	Portfolio Horizon (weeks)		**<0 and ≥-2**	**<-2 and ≥-4**	**<-4 and ≥-6**	**<-6 and ≥-8**	**<-8 and ≥-10**	**<-10**
Long-position	One	Mean (%)	0.202	0.561	0.835	1.212	1.354	2.200
		Positive (%)	57.23	62.30	63.71	64.63	58.46	65.82
		N(1)	1279	1260	1097	786	496	477
	Four	Mean (%)	0.845	2.261	2.292	3.340	2.826	4.527
		Positive (%)	62.50	70.00	68.14	69.66	61.86	67.80
		N(4)	320	320	317	290	236	236
	Thirteen	Mean (%)	2.829	7.582	9.740	10.342	7.154	12.664
		Positive (%)	66.33	78.57	81.63	75.51	67.02	69.23
		N(13)	98	98	98	98	94	91
	Fifty-two	Mean (%)	11.330	34.703	45.240	50.306	30.019	58.116
		Positive (%)	75.00	83.33	91.67	87.50	75.0	87.50
		N(52)	24	24	24	24	24	24
Skip-day, Long-position	One	Mean (%)	0.197	0.346	0.501	0.708	0.690	1.218
		Positive (%)	54.77	56.77	58.01	57.12	54.76	57.66
		N(1)	1278	1263	1079	737	420	385
	Four	Mean (%)	0.815	1.381	1.699	1.871	1.283	2.253
		Positive (%)	60.63	63.13	58.49	58.80	53.52	59.62
		N(4)	320	320	318	284	213	213
	Thirteen	Mean (%)	2.749	4.625	5.701	5.462	3.345	5.460
		Positive (%)	65.31	70.41	67.35	60.20	59.98	69.66
		N(13)	98	98	98	98	86	89
	Fifty-two	Mean (%)	11.440	20.347	24.366	22.680	10.667	23.233
		Positive (%)	70.83	83.33	66.67	70.83	58.33	75.00
		N(52)	24	24	24	24	24	24

Exhibit 3 *(continued)*

Panel B: Mean Return and Percent of Positive Returns for One, Four, Thirteen and Fifty-two Week Horizons for Winner Portfolios

Previous week's return filter (%)

Strategy:	Portfolio Horizon (weeks)		**≥0 and <2**	**≥2 and <4**	**≥4 and <6**	**≥6 and <8**	**≥8 and <10**	**≥ 10**
Short-position	One	Mean (%)	0.192	0.121	0.063	-0.086	-0.021	-0.376
		Positive (%)	56.88	52.22	47.08	46.27	49.39	43.04
		N(1)	1278	1256	1151	925	662	748
	Four	Mean (%)	0.781	0.507	0.244	-0.258	-0.037	-0.950
		Positive (%)	61.56	50.63	47.02	45.63	47.67	41.18
		N(4)	320	320	319	309	279	289
	Thirteen	Mean (%)	2.601	1.799	0.917	-0.57	0.068	-2.322
		Positive (%)	68.37	54.08	51.02	43.88	49.48	43.30
		N(13)	98	98	98	98	97	97
	Fifty-two	Mean (%)	11.156	7.898	5.226	-1.086	0.912	-9.380
		Positive (%)	70.86	54.17	54.17	41.67	50.00	37.80
		N(52)	24	24	24	24	24	24
Skip-day, Short-position	One	Mean (%)	0.197	0.235	0.325	0.386	0.170	0.316
		Positive (%)	59.01	58.18	54.69	50.94	47.85	49.20
		N(1)	1278	1281	1258	1139	848	583
	Four	Mean (%)	0.961	1.310	1.390	0.458	0.695	0.681
		Positive (%)	65.00	60.31	55.00	49.02	45.86	48.33
		N(4)	320	320	320	306	266	269
	Thirteen	Mean (%)	3.275	4.382	4.571	1.581	1.976	2.241
		Positive (%)	75.51	66.33	67.35	45.92	49.47	45.74
		N(13)	98	98	98	98	95	94
	Fifty-two	Mean (%)	13.750	19.275	19.225	5.199	10.150	7.605
		Positive (%)	75.00	70.83	70.83	50.00	50.00	66.67
		N(52)	24	24	24	24	24	24

Panels A and B report the mean return and percentage of positive return weeks for one, four, thirteen and fifty-two week horizons for long- and short-position portfolios, respectively. N(1), N(4), N(13), and N(52) are the number of periods that portfolios were formed for the one, four, thirteen and fifty-two week horizon returns out of a maximum of 1294, 323, 99, and 24 periods, respectively. The longer horizon portfolios are only formed in periods in which there is at least one weekly return to form the longer period return.

Exhibit 4
Recent trends analysis: Robustness

			Previous week's return filter (%)					
Strategy:	**Period**		**<0 and ≥-2**	**<-2 and ≥-4**	**<-4 and ≥-6**	**<-6 and ≥-8**	**<-8 and ≥-10**	**<-10**
Long-position	Full-Sample	Mean (%)	0.202	0.561	0.835	1.212	1.354	2.200
		t-stat	2.677	6.624	7.843	7.579	5.271	6.338
	> $100m	Mean (%)	0.313	0.524	0.740	1.233	1.470	0.680
		t-stat	3.317	4.383	4.429	5.208	3.026	1.014
	1990s	Mean (%)	0.332	0.650	1.101	2.077	1.810	2.694
		t-stat	3.705	5.469	5.543	8.884	3.697	3.867
Short-position	Full-Sample	Mean (%)	0.192	0.121	0.063	-0.086	-0.021	-0.376
		t-stat	3.597	1.665	0.643	-0.643	-0.064	-1.676
	> $100m	Mean (%)	0.291	0.344	0.162	0.043	0.186	-0.159
		t-stat	3.923	3.640	1.254	0.017	0.539	-0.569
	1990s	Mean (%)	0.244	0.043	-0.140	-0.372	-0.342	-1.167
		t-stat	2.601	0.370	-0.800	-1.667	-0.754	-2.501

This exhibit presents two distinct subsets of the data set for comparison with recent trends in the emerging REIT markets. The full-sample returns are included for comparison purposes. The first subset is based on market capitalization. This subset reflects the recent trend toward larger REITs. The second subset of the full sample is based on the recent time period examined by Ling and Ryngaert (1997). The t-statistics are robust to heteroskedasticity and autocorrelation.

Notes

[1] The emphasis is added by the authors.

[2] Bharati and Gupta (1992), Liu and Mei (1992), Darrat and Glascock (1993), Mei and Liu (1994), Li and Wang (1995), and Nelling and Gyourko (1997).

[3] Specifically, Lehmann cites work by Sims (1984). Sims hypothesizes that as time intervals shorten, prices should follow a random walk because there should be few systematic changes in valuation over daily and weekly periods if information arrival is unpredictable.

[4] Other papers that used variations of the filter-rule method include Fama and Blume (1966), Sweeney (1988), Sweeney (1986), Lakonishok and Vermaelen (1990), Bremer and Sweeney (1991), Cox and Peterson (1994), and Corrado and Lee (1992), Fabozzi, Ma, Chittenden, and Pace (1995), and Brown and Harlow (1988). Specifically, Fama and Blume (1966) examined filter rules on the Dow Jones 30 stocks and concluded that while some of the filter rules they examined produced returns superior to a buy and hold strategy, the inclusion of transaction costs eliminated the profits. Sweeney (1988) reexamined the Fama and Blume work and claimed to find profitable trading rules by optimizing the security selection process. Sweeney (1986) examined filter-based trading strategies on the foreign exchange markets and Lakonishok and Vermaelen (1990) employed filter rules to predict returns to repurchase tender offers. Contrarian filter rule papers include Bremer and Sweeney (1991), Cox and Peterson (1994), and Corrado and Lee (1992), who all examined daily return filter strategies. Fabozzi, Ma, Chittenden, and Pace (1995) used filters to examine intraday reversals while Brown and Harlow (1988) examined longer horizon return behavior via filters.

[5] Past short-horizon contrarian papers’ inclusion of all securities in their sample was likely an intentional device designed to examine evidence of market-wide security behavior while minimizing the portfolio weights placed on large-magnitude, prior-period winners and losers. The pros and cons of previous papers'

weighting methods are contrasted in a later section with this paper's filter weights.

[6] For each combination of filter values, the securities whose weekly returns meet those levels are formed into equally-weighted portfolios during week *t*. Thus the weight for security *i* in week *t* is:

$$w_{i,t} = \frac{1}{N_{k,t-1}}$$

where $N_{k,t\text{-}1}$ is the number of securities that meet a specific filter level, k, during the previous week's trading as defined in equation 1.

[7] This study follows the practice of other short-horizon contrarian papers and reports mean equal to zero t-statistics. t-statistics (not reported in the paper) are also calculated by subtracting the unconditional weekly mean return of the sample from the return of each filter portfolio and find that this measure of excess returns produces little variation in the reported t-statistics. As a further test of the null hypothesis and similar to Lehmann's (1990) methodology, this study examines how consistently profitable the filter portfolios are over longer horizon *J*-period returns, where *J* ranges from four to fifty-two weeks.

[8] See Lehmann (1990), Lo and MacKinlay (1990), Conrad, Hameed, and Niden (1994), Mei and Gao (1995) and Conrad, Gultekin and Kaul (1997).

[9] Conrad, Gultekin and Kaul (1997) and Lo and MacKinlay (1990) found that the profit decomposition originally derived in Lehmann (1990) indicated that contrarian strategies that base their weights on a security's deviation from an equally-weighted index of those securities result in a large percentage of profits attributable to positive autocovariances of the returns of the component assets.

[10] Additional analysis was performed on the trading activity of an individual security, Bershire Realty. This security was selected because its market equity ($243 million as of the end of the sample period) and return characteristics seemed typical for the sample during this period. The analysis shows that a trader following this paper's strategy would include Bershire Realty in their moderate (-4% to –6%), long portfolio 14 times during the 1990s and an additional 14 times in their moderate (4% to 6%), short

portfolio. The average weekly returns for this security alone were 1.96% for the long portfolio and –1.17% for the short position. Although this security lost money in only 5 out of 28 weeks of trading, it is important to emphasize the notion that this strategy is intended for portfolios, not individual securities.

[11] The results of further comparisons are available from the authors.

[12] The extreme filter portfolios may experience relatively smaller transaction costs than the more moderate filter portfolios. Lehmann, 1990, hypothesizes that a security that is a big winner (loser) may have a majority of buy (sell) orders being executed at the ask (bid). Thus, a contrarian trader who wants to sell short (go long) the winners (losers) might actually be able to open a position closer to the ask (bid) than would normally be possible. This effect could be stronger for bigger winners and losers, resulting in smaller than normal effective bid-ask spreads at more extreme filter levels.

[13] In order to conserve space, this exhibit is not shown. A copy may be obtained from the authors.

[14] The unconditional first day of the week relative volume has a mean of 1.19 and a standard deviation of 4.50.

[15] This paper is an extended version of the first half of an earlier working paper (Cooper, Downs and Patterson, 1998). The second half of the earlier working paper has been revised to focus on the price dynamics associated with trading strategies examined in this study.