EVIDENCE TO THE CONTRARY: EXTREME WEEKLY RETURNS ARE UNDERREACTIONS

A Dissertation

by

ERIC KYLE KELLEY

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2004

Major Subject: Finance

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ABSTRACT

Evidence to the Contrary: Extreme Weekly Returns Are Underreactions. (August 2004)

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The finding of reversals in weekly returns has been attributed to a combination of microstructure issues and overreaction to information. I provide new evidence eliminating overreaction as a source of reversal. I show that well-known weekly contrarian profits are followed by a long run of momentum profits. In fact, these profits are strong enough to produce a significant momentum effect over the full year following portfolio formation. Thus, the market does not appear to view extreme weekly returns as excessive, as implied by an overreaction story. To the contrary, this return continuation is consistent with *underreaction* to the news driving extreme weekly returns. This is supported by cross-sectional tests in which I find this week's news is positively related to next week's returns. The evidence presented here is consistent with growing evidence that underreaction to firm-specific information is a pervasive feature of price formation. Therefore, if any short-run contrarian profits can be realized, they are better viewed as compensation for providing liquidity than as a reward for arbitrage.

To my wife, Jenni.

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I. INTRODUCTION

Short-run individual stock returns reverse immediately. Lehmann (1990) finds that contrarian strategies which buy stocks with low weekly returns and sell stocks with high weekly returns generate positive profits over the following week. Jegadeesh (1990) shows that a one-month contrarian strategy is also profitable. This reversal pattern has spawned much discussion over the past decade. Is it due to time variation in risk premia? Is it due to market inefficiencies? Is it spurious? Lehmann highlights that return predictability over such a short horizon cannot plausibly be attributed to time variation in risk premia.[1] That leaves the debate to focus on spuriousness or market inefficiencies as the sources of short-horizon predictability.

Bid-ask bounce and nonsynchronous trading are sources of spurious reversals in returns. Kaul and Nimalendran (1990) and Conrad, Kaul, and Nimalendran (1991) show that part of return reversal is due to bid-ask bounce. Lo and MacKinlay (1990) and Boudoukh, Richardson, and Whitelaw (1994) note that nonsynchronous trading contributes to contrarian profits.[2] Lead-lag effects and market-maker inventory control are forms of market inefficiencies that can lead to return reversal, but these are not inefficiencies due to cognitive biases. Lo and MacKinlay (1990) provide evidence that that lead-lag effects explain more than half of the contrarian profits of their strategy. This could reflect delayed reactions of some stocks to a common factor. Jegadeesh and

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This dissertation follows the style of *Journal of Finance*.

[1] Conrad and Kaul (1988) identify a *positively* autocorrelated stationary process in short-run expected returns, which they interpret as a time-varying risk premium.

[2] These studies take different views on the severity of the problem. Lo and MacKinlay argue the effect of nonsychronous trading is trivial, while Boudoukh, Richardson, and Whitleaw believe it is much stronger.

Titman (1995b) observe that market-makers set prices in part to control their inventory, which also induces a return reversal.[3] Empirical researchers, however, have had great difficulty in establishing the above sources as the sole drivers of weekly reversals. Controlling for these sources of reversals in various ways, Jegadeesh and Titman (1995a), Cooper (1999), and Subrahmanyam (2003) conclude that contrarian profits are largely due to overreactions to firm-specific news.

With this short-run debate ensuing, other researchers have independently documented persistence in returns after many corporate events, such as unexpected earnings, dividend changes, stock repurchases, stock splits, and seasoned equity offerings, as well as after headline news and cash-flow news.[4] Short-run reversals and the conclusion that the market is overreacting are curious in light of the evidence of such perceived underreaction to firm-specific news. In this dissertation, I attempt to reconcile this conflict.

The duration of the return reversal found by Lehmann (1990) and Jegadeesh (1990) is less than four weeks, while the continuations following firm-specific news last up to a year. Therefore, I begin my analysis by extending the holding period of portfolios similar to those used in the short-run literature. Suppose the weekly return reversal is due solely to microstructure issues and not in any way to an intrinsic overreaction to firm-specific news. Suppose also that, as the news literature suggests,

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[3] Amihud and Mendelson (1980) and Ho and Stoll (1983) model the effects inventory has on the market-maker's quoted prices. Madhavan and Smidt (1993) and Hasbrouck and Sofianos (1993) find that changes in dealer inventory are negatively related to changes in prices.

[4] See the appendix of Daniel, Hirshleifer, and Subrahmanyam (1998) for a list of the studies that find post-event continuation in returns. Chan (2003) examines headline news and Vuolteenaho (2002) decomposes annual returns into news about cash flows and news about discount rates.

there generally is an underreaction to firm-specific news. Since the microstructure effects should dissipate in a few weeks, we should expect to see a continuation in returns once the microstructure issues fade if the market is actually underreacting to news in the formation week.

Consistent with prior studies, I find that a strategy that buys weekly extreme winners and sells weekly extreme losers generates negative profits in the first four weeks of the holding period (one can simply reverse the sign to get contrarian profits). The profits to these weekly portfolios behave quite differently, however, after four weeks. My key finding is that extreme weekly returns in fact *persist* for roughly a year once the brief return reversal dissipates. This continuation in returns is robust and steady across the subsequent weeks. Moreover, the continuation easily offsets the brief reversal that follows portfolio formation. In other words, the fifty-two-week post-formation period displays no evidence of a correction. In sum, my findings are inconsistent with an overreaction to news occurring in the formation period.

Additionally, I not only find that the subsequent continuation in returns offsets the initial reversal; I find that the continuation dominates. Across the fifty-two weeks following portfolio formation, the winners continue to outperform the losers. So I find evidence of *underreaction*. This finding is consistent with the evidence of continuation in returns following firm-specific news, mentioned above. This consistency is remarkable given that the extant literature paints a complexity of reversal and momentum patterns, with reversal in the short-run, momentum in the intermediate-run, and reversal again in the long-run.[5]

This new evidence provides some consistency across the short-run predictability and post-event drift literatures. However, it is still interesting that the event literature rarely documents any immediate reversal. In fact, there is direct evidence of no significant reversal immediately following six of the eight events Daniel, Hirshleifer, and Subrahmanyam (1998) associate with post-event drift. Appendix I provides a list of studies documenting such evidence. In light of this, I consider a subset of the main strategy with earnings announcements during the formation week. These stocks experience both an extreme return *and* a specific news announcement. After controlling for bid-ask bounce, I find (i) no immediate reversal and (ii) strong return continuation for a full year. Thus, it appears that in this subset strategy the strength of the news offsets any pressure to reverse even in week one.

Pursuing this result further and in a more general context, I find that the initial reversal in returns is not attributable to abnormal firm-specific residual returns (standardized residuals), which I interpret as firm-specific news. Instead, the reversals are strongly related to total returns, consistent with the reversals being due only to microstructure issues. Holding last week's returns constant, I find a *positive* relation between last week's news (standardized residual) and this week's return. Hence,

[5] The behavioral theories of Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) each jointly explain return momentum at three- to twelve-month horizons and return reversal at three- to five-year horizons, but fail to accommodate the short-run reversal at weekly horizons.

realizable profits to weekly contrarian strategies, if any, are better viewed as compensation for providing liquidity to the market, rather than as a reward for arbitrage.

While some researchers have challenged the overreaction interpretation of weekly reversals, they have been unable to show that microstructure effects can fully explain contrarian profits. Estimating the microstructure effects though is very difficult to do. I contribute to the literature by, in a sense, stepping back and making an observation using a longer window. This approach addresses the source of reversals without explicitly measuring various microstructure effects. The performance of the extreme-weekly return stocks over a long window refutes the overreaction hypothesis.

This dissertation also contributes to a growing body of research suggesting return persistence is a pervasive feature of the price formation process. In concert with the momentum and post event drift literatures, Vuolteenaho (2002) and Chan (2003) provide general evidence of a delayed response to news identified over a monthly horizon. Gutierrez and Pirinsky (2004) show large news shocks measured over periods as short as a month and as long as three years is associated with drift that never reverses. My findings round out this picture of return persistence. Patterns of return predictability across time horizons and events are consistent with each other and perhaps much simpler than originally perceived. The only effect of firm-specific news on future returns is that of continuation.

The remainder of this dissertation is organized as follows. Section II contains a detailed literature review, primarily focusing on return-based predictability. Section III describes the data and portfolio construction. Section IV presents empirical results and robustness tests. Section V concludes.

II. LITERATURE REVIEW

A. Short-Run Reversals

Individual stock returns are predictable at weekly and monthly horizons. The predictability manifests in positive profits to trading strategies that buy short-term (i.e., weekly or monthly) losers and sell short-term winners. There is no current consensus on the source of the predictability or its implications for market efficiency. Some argue these patterns are driven by numerous market microstructure issues such as bid-ask bounce, non-synchronous trading, and market maker inventory concerns. After controlling for these issues in various ways, other researchers still find evidence of reversals and attribute the patterns to market overreaction. This implies extreme weekly returns are excessive, and subsequent reversals represent corrections. In this section, I describe the empirical facts regarding short-term predictability and summarize explanations provided by the literature.

A.1. Initial Findings

Lehmann (1990) and Jegadeesh (1990) document short-run predictability in individual stock returns that is both statistically and economically significant. Lehmann (1990) considers a contrarian strategy that exploits profitability at the weekly horizon. His strategy invests in all securities, where weights are determined by the previous week's returns, and holds these positions for one week. The weighting scheme gives positive weights to the prior week's losers and negative weights to the prior week's winners. In addition, securities with more extreme returns are given greater weight.

Lehmann's strategy generates average 1-week profits of 1.79% over the 1962-1986 time period that do not dissipate over time. The average positive profits persist even after transactions costs up to .30%. Strategy profits are positive in over 90% of the individual weeks, 99% of non-overlapping 4-week investment periods, and 100% of all 13-, 26-, and 52-week non-overlapping investment periods. Lehmann views this as evidence of a measured arbitrage opportunity since an investor appears to have been able to *consistently* earn positive trading profits. Finally, the profits to the trading strategy are short-lived. When current weights are based on returns two weeks ago, profits disappear with moderate transactions costs.

Jegadeesh (1990) uses cross-sectional regressions and finds that monthly returns are strongly negatively related to lagged monthly returns and positively related to monthly returns at longer lags. To gauge the economic significance of this predictability, he considers trading strategies based his cross-sectional models. Each month, he ranks firms into deciles by their out-of-sample return forecasts. He then forms a strategy that buys an equal-weighted portfolio consisting of the top decile firms and sells an equal-weighted portfolio of the bottom decile firms. Finally, he holds the positions for one month and is left with a time series of monthly strategy profits.

When only the first lag of monthly returns is used in the forecasting model, the strategy's monthly raw (risk-adjusted) return is 2% (1.53%). When returns from months -1 to -12, -24, and -36, are all used, the monthly raw (risk-adjusted) return increases to

2.5% (1.77%). Clearly the majority of the strategy's profits are attributable to information in the first lagged monthly return. Since returns are negatively related to lag 1 returns in the cross-sectional models, these strategies are buying securities that were losers over the previous month and selling securities that were winners over the previous month. Thus, they are contrarian strategies.

A.2. Market Microstructure

The well-known bid-ask bounce leads to spurious reversals. Roll (1984) illustrates this with a simple model in which a bid-ask spread exists and the "true" stock price does not change over time. In this situation, all return variation is caused by movements between the bid price and the ask price. If the "true" price of the stock is the midpoint between the bid and ask prices and trades are equally likely to occur at the bid and the ask, spurious negative serial correlation will exist in observed returns. This is especially problematic for an econometrician calculating profits for a trading strategy based on past returns. The intuition is simple. An econometrician who selects stocks with high returns is likely to select a disproportionately high number of stocks with final trades at the ask price, since the ask price is the high end of the spread. Conversely, stocks with very low returns are more likely to have final trades at the bid price.[6] Thus, the presence of the bid-ask bounce will induce reversals in observed (transaction) returns of past winner and loser portfolios. Since these reversals are simply driven by

[6] Ball, Kothari, and Wasley (1995) verify this notion using data from a sample of NASDAQ stocks from 1983-1990.

movements between the bid and ask prices, they are not exploitable by a trader seeking arbitrage opportunities.

A number of researchers highlight the role of bid-ask bounce by computing returns with bid prices or bid-ask midpoints. Bid-to-bid or midpoint returns arguably better reflect true price changes. Researchers contrast patterns found in these returns with those documented using transaction returns from CRSP. The chief limitation to this approach is data availability. When the literature developed, bid prices were only available for certain NASDAQ stocks. Furthermore, this data series begins in 1983. Since these papers were published in the early 1990s, they use the already limited data set over a short sample period. These points not withstanding, the evidence suggests bid-ask bounce may be largely driving the reversals.

Kaul and Nimalendran (1990) compare transactions returns with returns based on bid prices for NASDAQ stocks from 1983-1987. If stock prices follow a random walk, return variance should increase linearly with the return measurement interval. In other words, the variance of 2-day returns should be twice the variance of 1-day returns. More generally, they write the variance ratio as:

$$\mathrm{VR}(k) = \frac{1}{k}\frac{\mathrm{var}\left(R_t^k\right)}{\mathrm{var}\left(R_t\right)},$$

where

R_t = return for day t,

R_t^k = return for a k-period interval at day t.

The random walk hypothesis predicts variance ratios to be 1 for all return horizons. Negative (positive) serial correlation will result in variance ratios less than (greater than)

1. Kaul and Nimalendran calculate average variance ratios for each return series over 1- to 12-week horizons. Consistent with the findings of Jegadeesh (1990) and Lehmann (1990), variance ratios are less than 1 for the transactions returns through the 4-week return interval. However, variance ratios are close to 1 even at the 1-week horizon for the bid-to-bid returns. Furthermore, they increase with the return interval. This suggests there may actually be return continuation.

Conrad, Kaul, and Nimalendran (1991) also use NASDAQ returns from 1983-1987. They consider both time-variation in expected returns and bid-ask errors as drivers of time series variation in individual security returns. As a proxy for expected return, they use an AR(1) out-of-sample forecast for the appropriate size-based portfolio. The bid-ask error is defined as the difference between the actual return and a return calculated with bid-ask midpoints. Individual firm regressions of returns on expected returns and bid-ask errors reveal two key findings. First, time-variation in expected returns and bid-ask errors can explain up to 24% of the variance of security returns. Second, there is little evidence of serial covariance in the regression error terms. This suggests time-varying expected returns and bid-ask errors can explain most of the serial covariance in the security returns of the given sample.

Two other recent papers attempt to alleviate concern with results based solely on NASDAQ data. Ball, Kothari, and Wasley (1995) note that bid-ask bounce predicts a positive relation between returns in weeks -1 and +1 relative to portfolio formation (Portfolios are defined using week 0 returns.), while overreaction predicts no relation. This relation is indeed significantly positive for NASDAQ transaction returns from

1983-1990, but it is insignificant for bid-to-bid returns. This same relation is also significantly positive for NYSE and Amex returns from 1962-1988. This indirect evidence suggests that the conclusions drawn from the short NASDAQ sample could possibly be generalized to all stocks. Conrad, Gultekin, and Kaul (1997) use NASDAQ returns from 1985-1989 and NYSE and Amex returns from 1990-1991. The Lehmann (1990) decomposition for bid-to-bid returns reveals no profits due to own serial covariance in the NASDAQ stocks and only small profits in the NYSE and Amex stocks. Further, transactions costs greater than .1% typically make the latter profits disappear. It is also interesting to note that there is small, positive serial covariance in the bid-to-bid returns of the NASDAQ sample. This is consistent with continuation – not reversals.

Non-synchronous trading is a second microstructure issue that can induce contrarian profits. Simply put, non-synchronous trading means all securities do not trade in a given interval. The model of Lo and MacKinlay (1990a) illustrates how the returns of portfolios with higher non-trading probabilities lag those with lower non-trading probabilities. Furthermore, Lo and MacKinlay (1990c) empirically decompose the profits of a strategy similar to Lehmann (1990) and find that over half of the profits are attributable to lead-lag effects. This finding suggests non-synchronous trading warrants further examination as a driver of observed contrarian profits.

Using the Lo and MacKinlay (1990a) model of non-trading, Lo and MacKinlay (1990c) show that the implied probabilities of non-trading are too high to fully explain contrarian profits driven by lead-lag relations. Boudoukh, Richardson, and Whitelaw (1994), on the other hand, argue that Lo and MacKinlay (1990c) understate the impact of non-synchronous trading. Under more general conditions, such as heterogeneity in non-trading probabilities and betas within a portfolio, non-synchronous trading can have a much greater affect on cross serial correlations than previously believed.

A third microstructure issue involves the role of the market maker. Lehmann (1990) conjectures that reversals reflect inefficiencies in the short-term market for liquidity. Perhaps market makers act as intermediaries between patient and impatient traders by providing liquidity over very short time horizons. The market maker induces reversals as compensation for providing this service. This scenario represents a type of market inefficiency; however, it is not related to the market's processing of information or cognitive biases of investors.

Campbell, Grossman, and Wang (1993) provide a formal model of risk-averse agents acting as market makers for liquidity traders. When liquidity traders sell, the market makers require compensation for offsetting their orders. This compensation comes in the form of higher expected returns, thus leading to reversals. Liquidity trading is characterized by elevated trading volume, thus reversals should be stronger for securities with abnormally high volume. Conrad, Hameed, and Niden (1994) provide supporting evidence. They form a weekly contrarian strategy using NASDAQ midpoint returns from 1983 to 1990. Securities with increases in trading volume over the formation week exhibit reversals. Interestingly, securities with decreases in trading volume actually display return continuation.

Jegadeesh and Titman (1995b) discuss the market maker's inventory concerns and implications for return reversals. As in the model of Ho and Stoll (1981), the market maker adjusts quoted prices when inventories deviate from their desired levels. For example, when inventory is too high – presumably from filling an imbalance of sell orders – the market maker drops quoted prices to induce buy orders. Quotes will remain depressed until the inventory concerns are alleviated. When the quotes return to "normal" levels, a reversal is observed. Madhavan and Smidt (1993) and Hasbrouck and Sofianos (1993) provide evidence that specialists engage in this type of price setting behavior.

A.3. Overreaction

The microstructure issues and related evidence discussed above have raised the bar for researchers that attribute contrarian profits to overreaction. In addition, Lo and MacKinlay (1990c) show that less than half of the profits of their contrarian strategy are driven by serial covariances of individual stock returns (see their Appendix I for the decomposition). They use this portion as an upper bound for the contribution of an overreaction component.[7] However, numerous researchers have acknowledged these issues in various ways and still find contrarian profits. Their main interpretation is that the market overreacts in the short run. This research is discussed below.

Since its inception, the short-run reversals literature has acknowledged biases associated with bid-ask bounce. According to Roll's simple model, the bid-ask bounce only induces spurious negative serial correlation in *adjacent* returns. This suggests that

[7] Lo and MacKinlay's (1990) empirical methodology limits the sample to stocks with no missing weekly returns over from 1962-1987. To alleviate some sample selection concerns, they repeat the analysis for securities with no missing observations over each half of the sample period and find similar results.

skipping a certain time period between the formation period and the holding period provides a control for bid-ask effects.[8] Early work by Jegadeesh (1990) and Lehmann (1990) does this precisely. Jegadeesh measures past monthly returns, excluding the final trading day of the month. Lehmann does the same thing with weekly returns. In both cases, trading strategy profits are diminished, but not eliminated. Both authors argue that even after controlling for microstructure concerns about the bid-ask bounce, short-run contrarian profits are statistically significant and economically meaningful. Jegadeesh's monthly abnormal return falls from 1.53% to 1.08%, while Lehmann's weekly raw return falls from 1.79% to 1.21%. Jegadeesh clearly leaves the door open to an overreaction story. As stated earlier, Lehmann conjectures the profits are due to inefficiencies in the market for liquidity around large price changes.

Jegadeesh and Titman (1995a) take a much stronger stance in favor of overreaction. They show the decomposition from Lo and MacKinlay (1990c) is misleading with respect to overreaction because delayed reactions to common factors affect both own and cross serial covariances. Thus, the average cross serial covariance does not accurately estimate the portion of contrarian profits due to lead-lag effects. As an alternative, Jegadeesh and Titman use a factor model based decomposition. Their decomposition separately measures contrarian profits due to over- or underreaction to common factors and firm-specific information. In short, they find that prices react with a delay to common factors (resulting in a lead-lag effect), but overreact to firm-specific information. The majority of contrarian profits are due to the latter. Furthermore, they

[8] Jegadeesh and Titman (1995b) note that skipping a day does not fully control for bid-ask bounce if the spread contains a component related to the market maker's inventory concerns.

control for the bid-ask bounce by repeating the experiment with bid returns and find similar results.

Cooper (1999) considers strategies involving the 300 largest NYSE and Amex stocks between 1962 and 1993 and present evidence consistent with overreaction. These stocks should be less susceptible to microstructure concerns such as liquidity problems and non-trading. In addition, they are likely to have lower transactions costs, smaller spreads, and smaller price pressure effects. Rather than investing in all securities as in Lehmann (1990), Cooper uses filter rules to determine which securities to trade.[9] This avoids the noise associated with including securities with very small price movements. When filters are based on lagged weekly returns, the contrarian strategies are profitable over a one week holding period. Profits are greater with more extreme return filters.

He also incorporates change in trading volume into the filter rules. Contrarian profits are much stronger in decreasing volume stocks. There is even evidence of slight continuation in increasing volume stocks. These results are consistent with the model of Wang (1994), in which informed investors trade on private information, which predicts continuation following extreme returns accompanied by high trading volume. The result is inconsistent, however, with the theoretical work of Campbell, Grossman, and Wang (1993) and empirical findings of Conrad, Hameed, and Niden (1994), which are discussed above.

A recent advance in the theoretical literature is Subrahmanyam (2003), who develops a model that includes both microstructure and behavioral effects. Specifically,

[9] Cooper (1999) also considers the Lehmann (1990) strategy with the large cap sample and finds positive contrarian profits. However, these profits are smaller in magnitude than those from the filter rules.

this is a framework in which risk averse agents absorb order flow from other investors. These market makers have inventory concerns and will require expected return premia as compensation to fill liquidity orders. According to the model, an inventory-based explanation for short-run reversals implies a negative relation between returns and lagged order imbalance.[10] On the other hand, overreaction and corrections suggest a negative relation between returns and lagged returns. Subrahmanyam tests these predictions using monthly returns from 1988-1998. Returns are calculated using the bid-ask midpoints to circumvent problems associated with bid-ask bounce.

Monthly cross-sectional regressions reveal that returns are negatively related to lagged returns. Furthermore, a contrarian strategy based on monthly returns earns significantly positive profits. These observations serve as out-of-sample evidence consistent with Jegadeesh (1990). More importantly, lagged order imbalance is unrelated to returns when it is the only independent variable the cross-sectional regressions. When lagged order imbalance is included in the cross-sectional regressions along with lagged return, the magnitude and significance of the coefficient on lagged return is unchanged. Subrahmanyam concludes that there exist reversals in individual short-horizon returns after controlling for bid-ask bounce, and this predictability is driven by belief reversion (i.e., overreaction). However, he also argues (p. 25) that "the magnitude of the coefficient is not overwhelmingly high, so that it does not suggest a gross violation of market efficiency."

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[10] A positive (negative) order imbalance occurs when there is a disproportionate number of buy (sell) orders.

B. Momentum

Individual stock returns are also predictable over 3- to 12-month horizons. While weekly and monthly returns display reversals, returns at these intermediate horizons exhibit continuations. This is referred to as "momentum." Researchers have spent much of the last decade attempting to explain this phenomenon and have reached no clear agreement. In this section, I will describe the existing evidence related to momentum as well as numerous potential explanations.

B.1. The Existence of Momentum

Jegadeesh and Titman (1993) are the first to document the momentum phenonemon that has received substantial attention over the past decade. Trading strategies that take long positions in stocks characterized as winners over the past three to twelve months and short positions in similarly characterized losers earn positive profits over the following three to twelve months. For example, a strategy with a six month formation period and a six month holding period (6-6 strategy) generates profits around 1% per month.[11] These profits are statistically significant and economically meaningful.

Jegadeesh and Titman evaluate the momentum strategy in the following manner. Consider the 6-6 strategy, for example. Each month, they rank securities in the cross-section by their prior six-month returns and form equally-weighted decile portfolios. Next, they form a zero-investment portfolio that is long the top decile (extreme winners)

[11] Subsequent momentum studies find profits of similar magnitudes. Profits are also shown to be larger for small stocks.

and short the bottom decile (extreme losers) and hold these positions for the following six months. The portfolios are rebalanced each month. Since strategies are formed every month, there are six open strategies at any point in time (i.e., the portfolios formed in months t-1, t-2,…, t-6). These strategies are referred to as overlapping portfolios. The overall momentum portfolio return in month t is the average of the returns to each open strategy. The use of overlapping portfolios increases the power of the test statistics used to make inferences.

It is possible that the momentum result is either spurious or a result of data mining. For example, Lo and MacKinlay (1990b) argue that, even under market efficiency, some anomalous results will surface as countless researchers continuously search through the same data set. Cooper, Gutierrez, and Marcum (2004) cast doubt as to whether a real-time investor could recognize the profitability of the momentum strategy ex ante. Even investors that have followed momentum strategies may not realize abnormal profits. Carhart (1997) finds no evidence of abnormal performance for mutual funds that employ momentum strategies. Recent research has also considered the profitability of momentum strategies after transactions costs. The estimates of Lesmond, Schill, and Zhou (2004) suggest transactions costs fully offset momentum profits. On the other hand, Korajczyk and Sadka (2003) argue transactions costs reduce, but do not eliminate momentum profits, especially in strategies that use value-weighted portfolios.

In the midst of these criticisms, there exists a substantial body of evidence indicating that momentum is a robust phenomenon. Three out-of-sample tests show that momentum is not specific to the Jegadeesh and Titman (1993) sample. Momentum exists in international markets. Rouwenhorst (1998) finds evidence of momentum in a sample of twelve European countries. Griffin, Ji, and Martin (2003) show that momentum profits exist in much wider cross-section of countries. There is also momentum in the U.S. market through the 1990s [see Jegadeesh and Titman (2001)]. Thus, momentum is neither time period nor country specific.

B.2. Momentum and Market Efficiency

Several authors have attempted to reconcile momentum with market efficiency. In an efficient market, riskier securities are priced with higher expected returns. If winners have, on average, higher expected returns than losers, momentum profits *should* exist. Jegadeesh and Titman (1993) consider this reasoning but find the winner portfolios have smaller betas and larger market caps than the loser portfolios. Thus, two measures of risk – beta and size – suggest the losers are actually riskier than the winners. Ultimately, they conclude that momentum is a result of underreaction to firm-specific information. Fama and French (1996) also fail to explain momentum profits using the 3-factor model from Fama and French (1993). Rather than concluding markets are inefficient, these authors attribute momentum to a failure of the model.

Instead of using decile portfolios, Conrad and Kaul (1998) form a momentum strategy using weights of the same magnitude, but opposite in sign, of those in Lehmann (1990).[12] They use Lehmann's decomposition and attribute momentum profits to cross-sectional dispersion in expected returns. Many researchers do not view this finding as

[12] Conrad and Kaul (1998) base their weights on 6-month returns, while Lehmann (1990) uses 1-week returns.

sufficient for reconciling momentum with market efficiency. First, the empirical methodology assumes individual stock returns are stationary over their entire histories. Second, if past winners truly have higher expected returns than past losers, momentum strategies should be profitable over longer holding period horizons. Both Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) provide direct evidence that this is not the case. They show that momentum profits begin to reverse after about twelve months.

Chordia and Shivakumar (2002) link momentum profits to lagged macroeconomic variables. They estimate expected return using the one-period ahead forecast based on lagged values of the dividend yield, the term premium, the default premium, and the t-bill yield. Momentum profits vanish after controlling for expected returns, and the authors conclude that momentum is consistent with rational asset pricing and time-varying risk. This conclusion is not undisputed either. Cooper, Gutierrez, and Hameed (2004) show that momentum profits do not disappear for a strategy that skips a month between the formation and holding periods. It is also possible that the macroeconomic variables capture some type of systematic irrationality.

Grundy and Martin (2001) also consider time-varying risk as an explanation for momentum in efficient markets. They estimate individual stocks' expected returns using both a 2- and 3-factor model. These estimates change with every formation period. Momentum profits actually increase after controlling for expected returns. However, Grundy and Martin do find that the momentum strategy lost money in over 25% of the months of their sample period. This suggests that momentum may not be an arbitrage opportunity and could still be reflective of a priced factor.

The general failure of asset pricing models to explain momentum could indicate market inefficiencies. On the other hand, it could indicate these models are simply the "wrong" models. This is the joint hypothesis problem associated with tests of market efficiency. Ahn, Conrad, and Dittmar (2002) attempt to avoid this problem with a stochastic discount factor approach. This is useful because the tests do not rely on a particular asset pricing model. They show that half of the profits to the Jegadeesh and Titman (1993) strategy can be achieved with a combination of their basis assets, which consist of 20 industry portfolios. Further, when expectations are allowed to vary over time, the momentum profits largely disappear.[13] This result is consistent with rational asset pricing. One limitation of the analysis, as the authors recognize, is that it assumes the set of basis assets are correctly priced.

Recent theoretical work also provides hope that momentum can exist in conjunction with rational asset pricing. Brav and Heaton (2002) review this literature. They explicitly point out differences between the traditional "efficient markets, rational expectations" framework, in which investors are both rational *and* have access to unbiased estimators of the true economic model's coefficients, and the less restrictive "rational structural uncertainty" framework, in which investors are still fully rational, but they lack knowledge of the true model's parameters. In the latter framework, markets are efficient, in that they process current information in a rational manner. However, the

[13] Time-variation in expected returns is based on variation in the S&P 500 dividend yield, the T-bill yield, and the Treasury yield spread.

market's learning process will result in predictability from the vantage point of the econometrician.[14] More importantly, Brav and Heaton provide simulation evidence that shows rational learning is empirically indistinguishable from patterns predicted by underreaction and overreaction theories.

B.3. Underreaction, Overreaction, and Behavioral Finance

Jegadeesh and Titman (1993) take the position that momentum profits reflect underreaction to firm-specific information. The market responds to new information, but the magnitude of the response is insufficiently small. Chan, Jegadeesh, and Lakonishok (1996) take a similar stance. They evaluate return patterns following a specific informational event, namely earnings surprises. Earnings surprises are measured by standardized unexpected earnings, stock returns around earnings announcements, and revisions in analysts' earnings estimates over a 6-month period. Using each measure, they form a strategy that buys stocks with high earnings surprises and sells stocks with low earnings surprises. These strategies generate positive profits over a 6- to 12-month holding period. Chan, Jegadeesh, and Lakonishok present evidence that this "earnings momentum" is empirically distinct from stock price momentum and conclude that both reflect underreaction to firm-specific information.

The results of Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) present a challenge to a pure underreaction story. Underreaction predicts cumulative momentum profits to flatten once information is fully incorporated into the stock price.

[14] See Lewellen and Shanken (2002) for a rational learning model that that illustrates the wedge between return distributions *perceived* by investors and those estimated in empirical tests.

Empirically, cumulative profits begin to reverse after about twelve months. This pattern of reversals complements the evidence of DeBondt and Thaler (1985), who report positive profits for a contrarian strategy the buys 3-year losers and sells 3-year winners. DeBondt and Thaler argue that the stock market overreacts in the long-run and their strategy's profits reflect the subsequent corrections. The coexistence of intermediate-term continuation and longer-term reversals poses a challenge to researchers. One outcome is the emergence of the behavioral finance literature. These papers rely on certain cognitive biases (i.e., investor irrationality) to explain documented return patterns.

Barberis, Shleifer, and Vishny (1998) present a behavioral model in which investors suffer from two biases. *Conservatism* means they do not fully price high-weight events. These events, by their very nature, carry substantial valuation information. Quarterly earnings announcements are considered high-weight because of their informational content regarding the current status of a firm. Conservatism results in underreaction. Investors also suffer from the *representativeness heuristic*. This is marked by the tendency to focus too strongly on high-strength events. High-strength events are events marked by size or extremity. An example of a high-strength event is a long string of positive earnings changes. Under the representativeness heuristic, investors assume such a string is representative of the underlying data generating process without considering the likelihood of the pattern persisting into the future. This bias results in overreaction. Thus, the model presented here predicts underreaction in the short-run (momentum) and overreaction in the long run (reversals).

Daniel, Hirshleifer, and Subrahmanyam (1998) provide a model in which investors suffer from two other cognitive biases – *overconfidence* and *biased self-attribution*. Investors are overconfident about their abilities to process private information, resulting in overreaction. Biased self-attribution refers to how investors respond to future signals regarding their private information. If the private information is subsequently confirmed by a public signal, the biased investors become even more overconfident. On the other hand, if there is a disconfirming signal, investors attribute the new information to chance and insufficiently revises confidence downward. Return continuation occurs on average. Eventually, when all information is revealed, misvaluations are corrected, resulting in reversals. Thus, momentum profits are a result of continued overreaction, not underreaction as suggested in prior empirical work and the model of Barberis, Shleifer, and Vishny (1998).

A third model is provided by Hong and Stein (1999). Rather than describing investors with cognitive biases, Hong and Stein consider two types of investors, newswatchers and momentum traders, each of which is rational with respect to available information. According to the model, private information regarding fundamentals diffuses slowly to the newswatchers. This gradual information diffusion leads to underreaction and, hence, momentum in stock returns. Momentum traders cannot process fundamental information; they are only able to observe the behavior of the newswatchers. They follow the newswatchers' trades, arbitraging away any leftover underreaction. Herding by momentum traders eventually leads to overreaction. Reversals occur when prices return to their fundamental values. This model predicts stronger momentum in stocks for which information diffuses slowly. Hong, Lim, and Stein (2000) provide consistent evidence by showing momentum is most profitable in the smallest stocks and those with the lowest analyst coverage after controlling for firm size.

B.4. Recent Developments

Chan (2003) compares momentum profits for firms with and without headline news during a 1-month formation period. The returns of firms with headline news show momentum, while the returns of firms without headline news reverse. He argues that the results are consistent with certain ideas from the behavioral finance literature. The momentum could be underreaction to public information since these stocks have news announcements, and the reversals could be overreaction to private information, since these stocks have extreme returns without news announcements. Both of these predictions are made by Daniel, Hirshleifer, and Subrahmanyam (1998). The results are also consistent with the slow reaction to information and feedback trading as in Hong and Stein (1999). However, the evidence shows no link between continuation and reversals, as predicted by each theory.

The market's pricing of firm-specific news is at the center of much debate in the momentum literature. The empirical papers described above form momentum portfolios based on total returns, which are composed of an expected return and an unexpected residual. Since the residual is often viewed as firm-specific news, Gutierrez and Pirinsky (2004) examine returns following large residuals to add clarity to the debate. A momentum strategy that is long stocks with residuals greater than one standard deviation and short stocks with residuals less than the negative of one standard deviation generates positive profits over the following six months.[15] More remarkably, the profits to the residual momentum strategy *do not* reverse over the following five years. This is in stark contrast to the total return momentum strategy of Jegadeesh and Titman (1993).

A news interpretation of the residual momentum in Gutierrez and Pirinsky (2004) is consistent with the findings of Chan (2003). It is also consistent with Vuolteenaho (2002), who uses a vector autoregression to show evidence of continuation following cash-flow news. However, Gutierrez and Pirinsky question the empirical validity of the overreaction theories of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999) as they find no evidence of reversals. Residual momentum is consistent with underreaction to firm-specific information, but, as Gutierrez and Pirinsky are careful to note, underreaction is virtually impossible to distinguish from rational learning [Brav and Heaton (2002)]. These recent results clearly pose new challenges to the behavioral finance literature.

C. Short-Run Reversals and Momentum

Researchers have devoted little attention to the coexistence of short-run reversals and momentum. The apparent view from the short-run reversals and momentum literatures is that the two phenomena are unrelated. For example, Jegadeesh and Titman

[15] Standard deviations are based on each stock's own distribution. The results hold for five different models used to estimate residuals. These strategies are profitable when formed using 1-, 6-, or 36-month residuals.

(1993) simply acknowledge short-run reversals and skip one week between the formation and holding periods to study momentum in isolation. Other momentum studies follow suit by skipping either a week or a month. Authors justify this practice because microstructure issues, such as the bid-ask bounce, that contribute to positive short-run contrarian profits will negatively bias the profits of a momentum strategy.

Attributing short-run reversals to microstructure issues greatly simplifies behavioral explanations of momentum. Existing behavioral theories explain the coexistence of intermediate momentum and longer-run reversals. Adding a short-run reversal to momentum and long-run reversal would lead to a much more convoluted theory. Given some of the early evidence on reversals [e.g., Kaul and Nimelendran (1990); Conrad, Kaul, and Nimelendran (1991)], this approach is reasonable. However, the more recent evidence in Cooper (1999) and Subrahmanyam (2003) makes the argument much less compelling. In fact, just as Gutierrez and Pirinsky (2004) are suggestive that behavioral literature need not link momentum to long-run reversals, the overreaction arguments of these recent empirical papers imply that same behavioral literature should, in fact, consider short-run reversals.

III. DATA AND PRELIMINARY SETUP

A. Data

The main sample includes all primary shares traded on the NYSE, AMEX, and NASDAQ between 1963 and 2001, as listed on the CRSP daily return file.[16] Weekly returns are computed from Wednesday's close to the following Wednesday's close. I only consider stocks whose prices exceed five dollars at the end of portfolio formation periods. This removes some initial microstructure concerns associated with thinly traded stocks. Market capitalization and trading volume data are also obtained from CRSP. Earnings announcement data are from the quarterly Compustat file.

B. Portfolios

I use lagged weekly returns to form portfolios similar to those studied in the momentum literature. Trading strategies are estimated with zero-cost portfolios that are long past winners and short past losers. In all cases examined, positive trading strategy profits reflect return continuation, while negative profits represent return reversals. To view my results from the perspective of the short-run contrarian literature, one can simply reverse the sign. This will reflect contrarian, as opposed to momentum, profits.

At each point in time, I sort stocks into deciles by their past 1-week return. The 1-week total return strategy takes a long position in the top return decile and a short position in the bottom return decile. The winner and loser portfolios are equally

[16] Table A-I provides a quick reference for forming the sample as well as defining and evaluating the strategies.

weighted across stocks. I examine the profits to the weekly portfolios over various holding period windows using a calendar-time method with overlapping portfolios as in Jegadeesh and Titman (1993). For example, consider the performance of the portfolios in weeks t+1 to t+4 (week t represents the formation week). In a given calendar week τ, there are four open strategies – one formed in week τ-1, one formed in week τ-2, and so on. The profit in calendar week τ is the mean profit across the four cohort portfolios. This procedure generates a single weekly time series of profits representing the t+1 through t+4 window.

The raw strategy profit (mean return) for a particular holding period window is simply the mean of the time series of profits. I also calculate weekly CAPM and Fama-French alphas by regressing the time series of strategy profits on the appropriate factors. I calculate weekly factor returns by compounding daily factor returns.[17] In these regressions, I use a risk free rate derived from the 1-month T-bill return. Unreported tests reveal positive autocorrelation in the various holding period return series.[18] Therefore, I calculate all test statistics using the consistent estimator of Gallant (1987) with four lags.[19]

[17] I thank Kenneth French for providing daily Fama-French factor data via his website.
[18] For example, the winner and loser portfolio for week t+1 each exhibit positive autocorrelation for the first four lags.
[19] I repeated all analysis using eight lags and found similar results.

IV. ANALYSIS AND RESULTS

A. Performance of Extreme Return Portfolios

Table I reports the profitability of the total return strategy. There are significant reversals of -133 basis points in the first week following portfolio formation. This finding is consistent with prior literature. Also consistent with prior literature, the reversal is relatively short-lived. Average profit is -47 basis points in weeks one through four.[20] Table II shows that reversals exist for both past winners and losers. All of the patterns also hold after CAPM and Fama-French adjustments.

The main contributions of this study are the performance of the weekly portfolio beyond the first four weeks and implications for interpreting immediate reversals. Table I shows the portfolio generates positive profits of about 7 basis points per week in weeks five through fifty-two. These profits are robust to CAPM and Fama-French adjustments. So the formation-week returns in fact persist for a year once the brief reversal in returns ends. Moreover, the persistence is spread evenly throughout the year.[21] Figure 1 plots the cumulative raw profits to the weekly portfolios across the fifty-two weeks, estimating the profits in each week separately.[22] The figure shows a dramatic run-up in the cumulative profits after week four. The run-up is strong enough in fact to overcome the short-run reversal. The profits in weeks one to fifty-two are significantly positive in

[20] In unreported tests, I find reversals decline in magnitude between weeks 1 and 4, with week 4 average profit being indistinguishable from 0.

[21] Average profit is 7.36 and 6.68 basis points per week in weeks 5 through 26 and 27 through 52, respectively.

[22] Using the calendar time method, I calculate average profits separately for weeks *t*+1, *t*+2, and so on. I then report average profits cumulated in event time.

Table I
1-Week Total Return Strategy

Each week, I rank firms in the cross section by their returns over the prior week and form equal-weighted portfolios for each return decile. I evaluated a strategy that takes a long position in the top decile ("Winners") and a short position in the bottom decile ("Losers"). Overlapping calendar-time portfolios with weekly rebalancing are considered over various horizons. Numbers in the table represent the performance of these portfolios, in basis points, over the specified holding period week(s). The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-132.90	-46.72	7.02	2.55
	(-30.90)	(-18.94)	(7.08)	(2.49)
CAPM Alpha	-130.76	-45.07	7.22	2.87
	(-31.06)	(-19.71)	(7.46)	(2.92)
FF Alpha	-131.14	-45.61	7.50	3.34
	(-31.08)	(-18.53)	(7.39)	(3.24)
Average n	355			

Table I across the three performance metrics. Hence, there is no reversal; there is actually a continuation.

This finding is a complete turnaround for the literature on the short-run predictability of individual stock returns. Reversal has been the stylistic fact of weekly returns. Consequently the underlying sources of reversals have been extensively examined. Controlling for bid-ask bounce, nonsynchronous trading, and dealer inventory effects, Jegadeesh and Titman (1995a), Cooper (1999), and Subrahmanyam (2003) point toward overreaction as a driver of the reversal. The findings in Table I contradict this notion. There is no evidence of a correctional reversal. The extreme price changes that occur during the formation week *t* are not excessive. To the contrary, the abnormal profits are positive in the year following extreme weekly returns.

It is important to note that, in contrast to the authors cited above, I have made no attempt to control for bid-ask bounce. Thus, portfolio performance is biased *toward* immediate reversal and negative performance over year one. This makes the main result even more striking – the drift in Table I is strong enough to overshadow an immediate reversal that is known to be at least partially spurious. To eliminate spurious autocorrelation induced by bid-ask bounce, I repeat the analysis using returns computed from daily closing bid-ask midpoints for NASDAQ stocks from 1983 through 2001.[23] Midpoint returns represent a more precise measure of actual price changes than do transaction returns reported by CRSP. This provides a more accurate depiction of the size of the drift relative to the size of the immediate reversal.

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[23] Bid-to-bid returns produce similar results.

Table II
1-Week Total Return Strategy: Winners and Losers

I report Winners and Losers separately for the strategy defined in Table I. Overlapping calendar-time portfolios with weekly rebalancing are considered over various horizons. Numbers in the table represent the performance of these portfolios, in basis points, over the specified holding period week(s). Panel A presents mean returns. Panel B presents CAPM alphas. Panel C presents Fama-French alphas. The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

Panel A: Mean Returns

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Winners	-28.38	4.13	27.29	25.59
	(-4.28)	(0.61)	(3.80)	(3.59)
Losers	104.52	50.85	20.28	23.05
	(13.76)	(6.60)	(2.68)	(3.05)

Panel B: CAPM Alphas

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Winners	-51.30	-19.05	4.05	2.14
	(-13.91)	(-5.52)	(1.13)	(0.60)
Losers	79.45	26.03	-3.17	-0.76
	(19.25)	(1.25)	(-0.81)	(-0.19)

Panel C: Fama-French Alphas

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Winners	-51.48	-20.44	2.19	0.42
	(-19.96)	(-13.41)	(1.56)	(0.31)
Losers	79.67	25.17	-5.31	-2.92
	(27.40)	(11.50)	(-2.53)	(-1.41)
Average n	355			

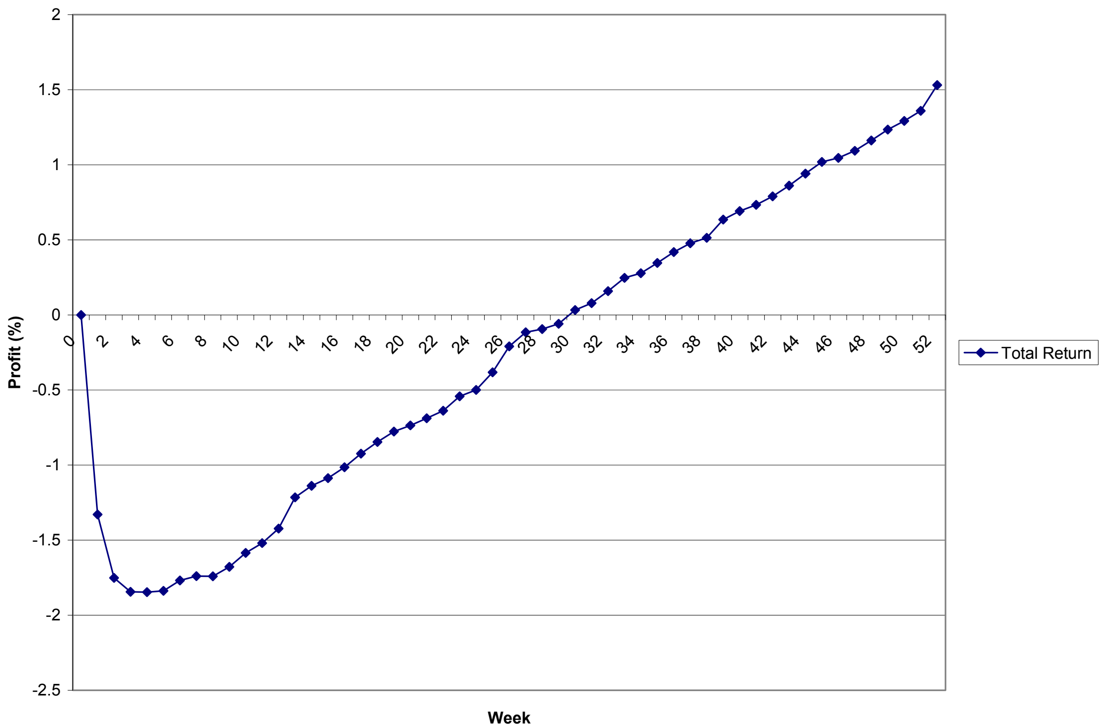

Figure 1: Cumulative returns for 1-week total return strategy. Each week, stocks are ranked into equally-weighted deciles based on their returns over the past week. The total return strategy is long the top decile and short the bottom decile. Cumulative returns for the zero-cost portfolio are plotted in event time for the 52 weeks following portfolio formation.

Table III reports average profits of the weekly portfolios using midpoint returns. Reversals are dampened, but not eliminated. Average week one profit is -62 basis points as opposed to the -133 basis points reported in Table I.[24] The drift is stronger at 12 basis points per week over weeks five through fifty-two. The full first year profit is 9 basis points. Again, all results hold after CAPM and Fama-French adjustments. Figure 2 illustrates how the drift dwarfs the immediate reversal. For an alternative control for bid-ask bounce, I skip a day between the formation and holding periods. Untabulated results reveal the week one reversal collapses from -133 basis points to -80 basis points. This finding is shown in Figure 2 as well.

It is of course questionable that any of these profits can be realized in practice given trading costs. This does not imply that the finding of return continuation should be ignored though. Any difficulty in effectively arbitraging this pattern speaks only to why the pattern persists, not to why it exists in the first place. Second, return momentum is also detected at longer six- to twelve-month horizons where the effect is more likely to generate profits after costs [Jegadeesh and Titman (1993)].[25] More importantly, the consistency of the pattern across formation horizons indicates that insights into the price-formation process and why momentum exists can potentially be gained with weekly returns. Lastly, for traders who are committed to buying stocks, trading costs become much less of a concern. That is, if trading costs are to be incurred anyway, this pattern

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[24] Conrad, Hameed, and Niden (1994) find no profits to their weekly contrarian strategy using midpoint returns. I calculated the profits of my strategy during their time period and also found no significant week 1 reversals.

[25] The profitability of momentum strategies after transactions costs has sparked recent debate as well. Korajczyk and Sadka (2003) argue some profitability survives transactions costs. Lesmond, Schill, and Zhou (2004) provide evidence that transactions costs eliminate momentum profits.

Table III
Midpoint Returns

I calculate Wednesday to Wednesday returns for NASDAQ stocks from 1983 through 2001 based on closing bid-ask midpoints. Each week, I rank firms in the cross section by their returns over the prior week and form equal-weighted portfolios for each return decile. I evaluate a strategy that takes a long position in the top decile ("Winners") and a short position in the bottom decile ("Losers"). Overlapping calendar-time portfolios with weekly rebalancing are considered over various horizons. Numbers in the table represent the performance of these portfolios, in basis points, over the specified holding period week(s). The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-62.33	-28.43	12.47	8.64
	(-7.93)	(-6.30)	(6.23)	(4.43)
CAPM Alpha	-58.32	-25.56	12.56	8.98
	(-7.58)	(-6.23)	(6.36)	(4.73)
FF Alpha	-60.91	-29.07	12.05	8.28
	(-7.86)	(-6.27)	(5.63)	(3.94)
Average n	226			

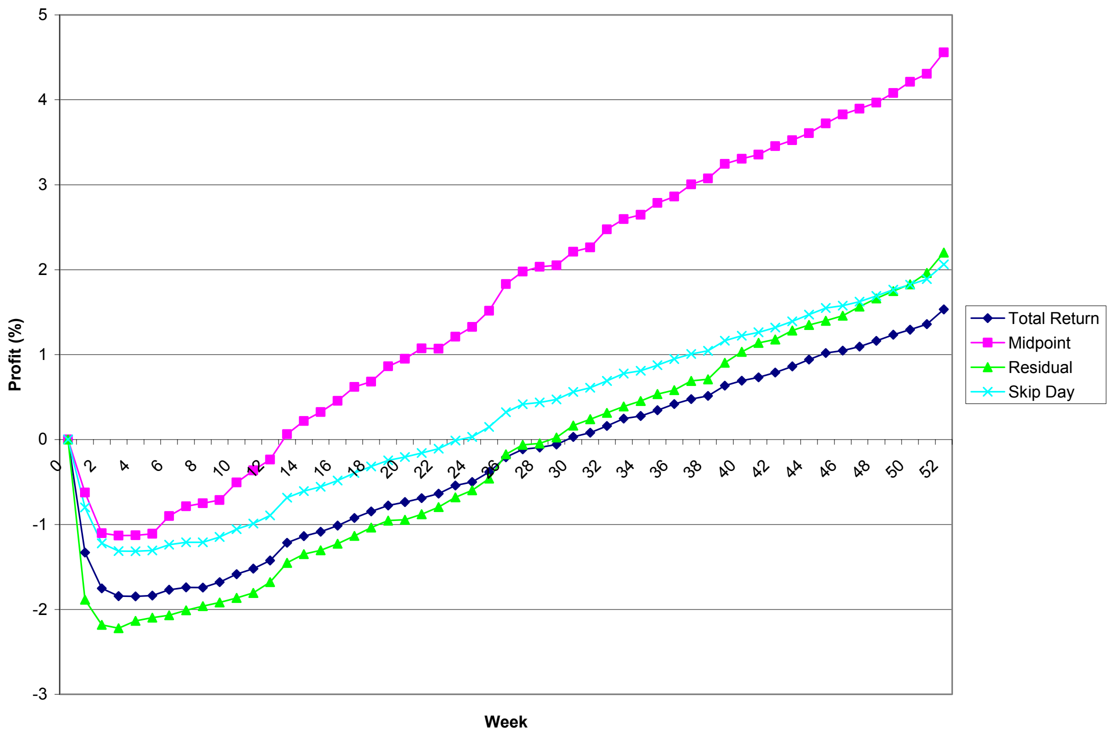

Figure 2: Cumulative returns for various strategies. Cumulative returns of four variant strategies are plotted in event time for the 52 weeks following portfolio formation. The total return strategy from Figure 1 is shown for reference purposes. Under the midpoint strategy, returns are calculate according to closing bid-ask midpoints (using NASDAQ data from November 1983 through December 2001. The residual strategy forms portfolios based on market model forecast errors scaled by respective residual standard deviations. The strategy is long stocks with forecast errors greater than two standard deviations and short stocks with forecast errors less than negative two standard deviations. The skip day strategy selects the same stocks as the total return strategy, but skips one day between the formation and holding periods.

of return continuation can still be valuable to traders deciding which stocks on the margin to invest in. [26]

B. Short-Run Reversals and Post Earnings Announcement Drift

A large literature finds return persistence for several months following certain corporate news events. The most well-known of these events is an earnings surprise [see, for example, Bernard and Thomas (1989)]. Other events associated with persistence include stock splits, dividend initiations and omissions, and seasoned equity offerings [see Daniel, Hirshleifer, and Subrahmanyam (1998) and Fama (1998) for reviews]. The salient feature is that announcement returns and subsequent drift have the same sign. This literature markedly differs from the weekly return predictability literature, which strictly associates extreme returns with reversals. [27] In this section, I explore these differences, focusing on return predictability following earnings announcements. This analysis provides further insight into the sources of reversals and continuation.

To begin, note that while the aforementioned event study literature associates certain events with average abnormal announcement returns, these returns are *not* necessarily in the total return extremes. For example, Chan, Jegadeesh, and Lakonishok (1996) report abnormal returns on the four days around earnings surprises. Average abnormal returns are 2.2% and -2.3% around positive and negative surprises, respectively. In my total return strategy, average return for the winners and losers are

[26] This discussion assumes that the trends in returns are mispricings that should be arbitraged if possible. They may not be mispricings. Brav and Heaton (2002) and others show how patterns in returns can be consistent with rational learning.
[27] Note also that even event studies that do not find post event drift rarely report evidence of immediate reversals.

12.0% and -8.7%. In light of this, I facilitate a more direct comparison between the short-run reversal and post-event drift literatures by considering stocks with both earnings announcements *and* extreme stock returns.

I obtain earnings announcement dates from the quarterly Compustat file. I restrict the universe to include, for a given firm, weekly returns beginning three months prior to its first available quarterly earnings announcement date and ending the date of its final earnings announcement.[28] This allows me to accurately determine whether or not an earnings announcement has occurred for every firm-week in the sample. Weekly winners and losers are defined as before using this restricted universe, which spans the time period from 1971 through 2001. I divide the winner and loser portfolios each into two groups based on whether an earnings announcement occurred during the formation week. This portfolio formation makes the magnitudes of formation week returns roughly comparable across earnings announcement groups. A given strategy cohort only trades following formation periods when there are at least ten stocks selected in each of the winner and loser portfolios. Requiring a minimum number of stocks reduces heteroskedasticity in the calendar time portfolios returns and increases the precision in the estimation of factor loadings.

Table IV reports the profits of the two earnings announcement groups separately.[29] There are clear differences across groups. The results in Panel A are based

[28] For firms whose final earnings announcement is within three months of the end of the CRSP returns file, I include returns through the last date available.
[29] Because I report differences across groups, average profits for the no announcement group are calculated only using the observations when both groups trade. The strategies trade following 78% of all possible formation weeks. Results for the no announcement group using all possible observations are qualitatively similar to those reported in Table IV.

Table IV
Earnings Announcement Groups

I restrict the universe to only include firms with available earnings announcement data. Using this restricted universe, I define Winners and Losers as in Table I. I then separate the resulting portfolios into those experiencing an earnings announcement (ANN) during the formation week and those that did not (NO ANN). I report results for each earnings announcement group separately as well as the difference between the groups. The average number of firms in each side of the strategy is also provided. Panel A presents results based on transactions returns as reported in the CRSP returns file. Panel B presents results based on NASDAQ returns from 1983 to 2001 calculated using closing bid-ask midpoints. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

Panel A: Transactions Returns (Winners – Losers)

	Week 1			Weeks 5-26		
	ANN	NO ANN	Difference	ANN	NO ANN	Difference
Mean Return	-61.98	-145.57	83.59	20.75	5.41	15.35
	(-8.40)	(-24.05)	(11.89)	(10.74)	(3.30)	(9.79)
CAPM Alpha	-61.25	-143.73	82.48	20.89	5.79	15.11
	(-8.37)	(-23.88)	(11.90)	(10.81)	(3.62)	(9.66)
FF Alpha	-61.88	-145.82	83.95	20.27	5.64	14.64
	(-8.30)	(-24.57)	(12.16)	(10.53)	(3.41)	(9.57)
Average n	39	275				

	Weeks 5-52			Weeks 1-52		
	ANN	NO ANN	Difference	ANN	NO ANN	Difference
Mean Return	14.68	5.99	8.69	12.37	1.25	11.12
	(9.59)	(5.05)	(7.31)	(8.14)	(1.03)	(9.59)
CAPM Alpha	14.69	6.16	8.53	12.45	1.53	10.91
	(9.57)	(5.29)	(7.14)	(8.21)	(1.31)	(9.39)
FF Alpha	14.17	6.35	7.81	11.82	1.63	10.19
	(9.09)	(5.20)	(6.89)	(7.49)	(1.31)	(9.03)

Table IV: continued

Panel B: Midpoint Returns (Winners – Losers)

	Week 1			Weeks 5-26		
	ANN	NO ANN	Difference	ANN	NO ANN	Difference
Mean Return	-14.18	-101.21	87.03	26.27	11.09	15.18
	(-1.15)	(-8.12)	(7.22)	(7.11)	(4.25)	(4.88)
CAPM Alpha	-9.77	-94.96	85.20	26.73	11.76	14.98
	(-0.79)	(-7.69)	(7.08)	(7.29)	(4.66)	(4.78)
FF Alpha	-13.06	-98.67	85.60	25.34	11.00	14.34
	(-1.04)	(-8.13)	(7.17)	(6.81)	(4.08)	(4.69)
Average n	32	177				

	Weeks 5-52			Weeks 1-52		
	ANN	NO ANN	Difference	ANN	NO ANN	Difference
Mean Return	17.34	10.14	7.20	17.10	6.16	10.94
	(5.76)	(5.13)	(2.79)	(5.69)	(3.08)	(4.54)
CAPM Alpha	17.52	10.33	7.18	17.49	6.56	10.92
	(5.87)	(5.30)	(2.79)	(5.93)	(3.38)	(4.58)
FF Alpha	16.07	10.01	6.06	15.69	5.99	9.69
	(5.14)	(4.74)	(2.33)	(5.00)	(2.81)	(3.96)

on transaction returns. The earnings announcement group displays a weaker immediate reversal at -62 basis points as opposed to -146 basis points for the no announcement group. This difference is highly statistically significant (t=11.89). Moreover, extreme weekly returns that are accompanied by earnings announcements display stronger drift than those unaccompanied by earnings announcements. For example, the mean weekly return in weeks 5 through 26 is about 20 basis points for the announcement group and about 5 basis points for the no announcement group. The difference is highly significant. This suggests the persistence of weekly returns in the unconditional strategy may be related to post earnings announcement drift.

Panel B repeats the analysis using midpoint returns for NASDAQ stocks from 1983 through 2001 to control for bid-ask bounce. In this case, week one profit is indistinguishable from zero for the announcement group, while it remains significantly negative at -101 basis points for the no announcement group. As with the transaction returns, the drift is reliably greater for the announcement group. But even for the no announcement group, average profit over the full year is positive and statistically significant. The implication is that the market's (seemingly insufficient) response to earnings announcements does not fully explain the persistence of weekly returns in general. In other words, weekly returns still persist, even if they are not accompanied by earnings announcements.

These findings speak to the nature of return predictability following weekly extreme returns. The evidence appears consistent with a market that responds to news with a delay. Moreover, in the case of earnings announcements, the news effect is so strong that, after controlling for bid-ask bounce, it offsets any tendency to reverse even in the first week. This is also consistent with the fact that event studies, in which stocks are *explicitly identified* by information releases, often document post event drift, but rarely identify immediate reversals.

The evidence thus far points to two components in extreme returns that are related to diametrically opposite patterns in future returns. I conjecture there is a news component that drifts for about a year and a second, non-news component that briefly reverses. Reversals are unlikely due to time-varying expected returns as expected returns are close to zero over a one week period. However, microstructure issues such as temporary price pressure or price setting by specialists with inventory concerns both should ultimately be reversed and are a likely culprit for the non-news component.

If these competing effects exist, the strength of drift and reversal in a portfolio is a function of the relative news and non-news components in the returns of its member stocks. All else equal, larger news underlying extreme returns should result in weaker reversal and stronger drift. Alternatively, the reversal effect should dominate, especially in the short run, when news is not present. Since every stock selected in the announcement group has, by definition, experienced news, its stronger drift is consistent with my conjecture. Moreover, there are undoubtedly stocks in the no announcement group experiencing value-relevant news as well, but this subset is unlikely to encompass the entire group. Extreme returns in the no announcement group are thus a more imprecise characterization of news than those in the announcement group. Stronger reversal and weaker drift in the no announcement group are therefore also consistent with my conjecture.

C. Cross-Sectional Regressions

In this section, I examine how the short-run return reversals are related to firm-specific news in a more general context. If (i) the reversals are solely due to microstructure issues and not to firm-specific news *per se* and (ii) there tends to be return continuation after firm-specific news, then I should be able to isolate a marginal positive effect of news on week *t*+1 returns. That is, controlling for total returns, the finding of a positive relation between news in week *t* and returns in week *t*+1 strongly supports the notion that reversals are microstructure driven and news persists in returns.

My proxy for firm-specific news is formed using the residual return from the market model

$$r_{it} = \alpha_i + \beta_i r_{Mt} + \varepsilon_{it} \qquad (1)$$

where r_{it} is the return on stock *i* in week *t*, α_i and β_i are coefficients, r_{Mt} is the return on the CRSP value-weighted index in week *t*, and ε_{it} is the firm-specific residual return. I estimate the market-model coefficients for each stock with a regression of weekly returns over the window [*t*-260, *t*-1], requiring a minimum of 104 observations over this time period. This is equivalent to the common practice of estimating coefficients over the prior five years and requiring at least 24 months of observations. I calculate the residual return in week *t* using the estimated coefficients as

$$\hat{\varepsilon}_{it} = r_{it} - \hat{\alpha}_i - \hat{\beta}_i r_{Mt}. \qquad (2)$$

My measure of firm-specific news is scaled residual (RES). RES_t is the residual return in week *t* scaled by the standard error of the residual return from the regression. Scaling the residuals serves to increase the signal-to-noise ratio since it accounts for the volatility of a given stock's return. Essentially, the scaled residuals identify the unusual residual returns, which better defines news than do total returns. This measure has the added advantage of not requiring the identification of specific news announcements.

Before testing for a marginal effect of news, I form portfolios based upon my measure of firm-specific news. The portfolios are long stocks with scaled residuals in week *t* greater than or equal to two and short stocks with scaled residuals less than or equal to negative two. In other words, the portfolios are long in good news and short in bad news. The profits are estimated as before. The results are equivalent to those for the total-return portfolios, and therefore are not tabulated. Again I see the short-run reversal in the first four weeks and again I see the persistent run-up in the profits from week five through fifty-two. Figure 2 displays the mean cumulative profits for these news portfolios. The conclusion is the same as the one for the total-return portfolios. There is no overreaction. To the contrary, the profits in the fifty-two weeks following the formation period are again significantly positive.

The finding of a short-run reversal in the news portfolio confirms that any positive effect news may have on future returns is, at least in the unconditional strategy, overcome by the strength of the immediate reversal. I now explicitly look for a marginal positive effect in week one. To this end, I estimate weekly cross-sectional regressions, similar to the method of Fama and MacBeth (1973). Each week I estimate the following regression across all available stocks,

$$r_{it} = \lambda_0 + \lambda_1 r_{i,t-1} + \lambda_2 RES_{i,t-1} + \xi_{i,t} \tag{3}$$

where r_{it} is the return on stock *i* in week *t*, λ_k is a coefficient for *k* = 0,1, and 2, $RES_{i,t-1}$ is the scaled residual from equation (2), and $\xi_{i,t}$ is an error term. The means of the weekly time-series of coefficients on prior return and prior news are reported in Table V along with the *t*-statistics.

The dependent variable in Panel A is raw return. In this regression, I see a marginal positive effect of last week's news controlling for last week's return. Also, as expected, raw return is negatively related to last week's return. I consider risk-adjusted returns in Panels B and C. The dependent variable in Panel B is the CAPM residual; Panel C uses the Fama and French (1993) residual. In both cases, the positive relation between last week's news and this week's return is positive and highly significant. Thus, the risk adjustments strengthen the main result. This finding strongly reiterates that the literature's conclusion of weekly reversals being due in part to an overreaction to news is misplaced. Even in week one, I find evidence of firm-specific news persisting.

Viewing all results together, the market's response to the news in week *t* is anything but an overreaction. I find that abnormal returns are positive in the year following the formation week. Note that I extend the examination window of the extreme-return portfolios to three years (not in tables) and find no evidence of a reversal in the post-formation period. For the news portfolio, the profits in weeks *t*+1 to *t*+156

Table V
Cross-Sectional Regressions

Each week t, I regress return variables on lagged return (RET_{t-1}), lagged scaled residual (RES_{t-1}), and interactions with EXT. Scaled residual is constructed as follows: (1) I estimate a market model by regressing weekly return on the CRSP value-weighted index. (2) I compute one period ahead forecast errors. (3) Scaled residual is the forecast error scaled by the residual standard deviation from the market model estimation. The dependent variable in Panel A is raw return. Dependent variables in Panels B and C are out-of-sample CAPM and Fama-French residuals, respectively. I report the time-series means (multiplied by 100) and *t*-statistics for the regression coefficients.

Panel A: Dependent variable is raw return

Intercept	RET_{t-1}	RES_{t-1}	Average n	Average R^2
0.29	-6.52	3.06	2981	1.35
(6.76)	(-15.24)	(1.68)		

Panel B: Dependent variable is CAPM residual

Intercept	RET_{t-1}	RES_{t-1}	Average n	Average R^2
0.10	-7.38	6.54	3015	1.04
(4.51)	(-24.02)	(4.74)		

Panel C: Dependent variable is Fama French residual

Intercept	RET_{t-1}	RES_{t-1}	Average n	Average R^2
0.05	-9.14	12.07	3015	1.10
(3.85)	(-31.72)	(9.79)		

remain significantly positive, consistent with the literature on post-event continuation in returns.

D. Robustness Tests and Additional Analysis

D.1. Pre-Formation Performance

If the weekly strategy happens to select stocks that are already drifting prior to formation, then the holding period performance is not directly attributable to extreme weekly returns per se. In other words, return drift may simply be a characteristic of certain stocks both prior to and following the formation week. For example, researchers beginning with Jegadeesh and Titman (1993) have documented a robust momentum effect in stock returns – extreme winners defined over three to twelve months continue to outperform losers for up to one year. If weekly winners are already outperforming losers before portfolio formation, the drift documented in Table I is more a product of model misspecification than a continuation of weekly returns.

Table VI reports average profits in calendar time for various windows prior to the extreme return event. Average profit is insignificantly different from zero over weeks t-52 through t-5. This result is robust to both the CAPM and Fama-French adjustments. Thus, there is no evidence of pre-formation drift. In addition, profits in weeks t-4 through t-1 closely resemble those for weeks t+1 through t+4. Ball, Kothari, and Wasley (1995) attribute these "pre-formation reversals" to bid-ask bounce. It is known that formation week winners are more likely to have traded at the ask, which biases week one returns downward. Ball, Kothari, and Wasley note that formation week winners are also

Table VI
1-Week Total Return Strategy: Past Returns

I define Winners and Losers as in Table I. Using overlapping calendar-time portfolios, I calculate profits of the Winner – Loser zero-cost portfolio in the weeks prior to formation. The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

	Weeks -52 to -5	Weeks -4 to -1	Week -1
Mean Return	0.61	-61.58	-160.19
	(0.76)	(-24.73)	(-34.22)
CAPM Alpha	1.19	-61.08	-159.41
	(1.56)	(-24.33)	(-34.01)
FF Alpha	-0.04	-61.13	-160.26
	(-0.05)	(-24.74)	(-33.63)
Average n	355		

more likely to have traded at the bid in the prior week, which biases pre-formation returns downward as well. Pre-formation returns of losers are biased in the opposite direction.

D.2. Reversal and No Reversal Groups

During the year following portfolio formation, long-run return persistence dominates the immediate reversal yielding positive average weekly profits. My interpretation is that extreme weekly returns are not overreactions on average. However, what if the market overreacts to certain types of information and underreacts to others?[30] If so, one subset of stocks only reverses, while another subset only drifts. I address this concern here. Rather than attempting to pick the stocks that will ultimately reverse using only formation-week information, I impose a look-ahead bias and identify them directly. I then evaluate total return profits separately for stocks that do and do not reverse.

The reversal (no reversal) group contains stocks selected by the total return strategy whose week t and t+1 market-adjusted returns are of opposite (same) sign. Table VII evaluates these strategies beginning in week t+2. The no reversal group (Panel A) shows a brief reversal going forward. This is presumably due to bid-ask bounce as the winners all had positive market-adjusted returns in week t+1 and losers had negative market-adjusted returns. Persistence beginning in week five is strong and significant. Thus, this group has strong drift and, by construction, no week t+1 reversal. The reversal group (Panel B) has strong positive profits in week t+2, also likely due to

[30] Overreacting and underreacting to different types of information is a key concept in the behavioral theory of Barberis, Shleifer, and Vishny (1998).

Table VII
Reversal and No-Reversal Groups

Stocks selected by the total return strategy in week *t* are grouped according to their week *t*+1 market-adjusted returns. The no reversal group (Panel A) contains stocks with week *t* and week *t*+1 returns of the same sign. The reversal group (Panel B) contains stocks with week *t* and week *t*+1 returns of opposite sign. Overlapping calendar-time portfolios with weekly rebalancing are considered over various horizons. Numbers in the table represent the performance of these portfolios, in basis points, over the specified holding period week(s). The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

Panel A: No Week 1 Reversal

	Week 2	Weeks 2-4	Weeks 5-52	Weeks 2-52
Mean Return	-126.02	-56.38	10.62	6.39
	(-23.32)	(-14.08)	(6.53)	(3.87)
CAPM Alpha	-122.95	-54.09	10.81	6.71
	(-23.90)	(-14.55)	(6.78)	(4.19)
FF Alpha	-123.11	-54.59	11.46	7.50
	(-23.26)	(-13.63)	(6.90)	(4.48)
Avg. n (winners)	149			
Avg. n (losers)	168			

Panel B: Week 1 Reversal

	Week 2	Weeks 2-4	Weeks 5-52	Weeks 2-52
Mean Return	27.98	15.28	3.93	4.76
	(7.29)	(7.83)	(7.60)	(9.20)
CAPM Alpha	28.67	15.75	4.07	4.91
	(7.53)	(8.18)	(7.95)	(9.67)
FF Alpha	29.03	14.95	4.19	4.86
	(7.39)	(7.57)	(8.06)	(9.26)
Avg. n (winners)	206			
Avg. n (losers)	187			

throughout the year. So even by selecting stocks that reverse immediately, I am unable to eliminate the return persistence.

The fact that the drift in the no reversal group is much stronger than that in the reversal group is not surprising. These stocks have stronger return shocks – positive returns over the formation period are reinforced by positive returns in the subsequent week. In fact, the average return of the spread portfolio in week one is about 10%. On the other hand, the stocks in the reversal group experience strong returns in week one that are in the opposite direction of their formation week returns. Average week one return of this spread portfolio is about -10%. The average *net* return shock of the spread portfolio is still positive over the first two weeks, but it is much smaller than that for the no reversal group. To the extent that the size of the drift is related to the magnitude of the net return shock over weeks t and t+1, we should expect greater drift for the no reversal group.

D.3. Subsample Results

In this section, I discuss the robustness of my prior findings for the total-return portfolios across size, time periods, and trading volume. I first split the sample at the thirtieth and seventieth percentiles of market capitalization using NYSE stocks only to identify the breakpoints. This produces three subsets of stocks: small, medium, and large. Table VIII shows that the short-run reversals are decreasing in size, and the profits across weeks five to fifty-two are also decreasing in size. Both the brief reversal and the subsequent continuation in returns are significant even in the large-cap stocks.

Table VIII
Size Subsamples

I form Winner and Loser portfolios as in Table I within three size groups. The small subsample, presented in Panel A, considers stocks with market capitalization below the 30th NYSE percentile at the time of portfolio formation. The medium subsample, presented in Panel B, considers stocks with market capitalization between the 30th and 70th NYSE percentiles. The large subsample, presented in Panel C, considers stocks with market capitalization greater than the 70th NYSE percentile. Overlapping calendar-time portfolios with weekly rebalancing are considered over various horizons. Numbers in the table represent the performance of these portfolios, in basis points, over the specified holding period week(s). The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

Panel A: Small Stocks (Winners – Losers)

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-158.74	-57.96	7.73	2.20
	(-31.94)	(-22.94)	(8.13)	(2.18)
CAPM Alpha	-156.57	-56.26	8.02	2.62
	(-32.08)	(-23.90)	(8.73)	(2.71)
FF Alpha	-156.95	-56.70	8.07	2.98
	(-32.04)	(-22.51)	(8.35)	(2.99)
Average n	213			

Panel B: Medium Stocks (Winners – Losers)

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-109.04	-38.42	5.64	1.95
	(-23.54)	(-13.83)	(4.97)	(1.70)
CAPM Alpha	-106.80	-36.70	5.79	2.23
	(-23.68)	(-14.10)	(5.16)	(2.00)
FF Alpha	-106.64	-37.36	6.00	2.63
	(-23.46)	(-13.38)	(5.09)	(2.22)
Average n	94			

Table VIII: continued

Panel C: Large Stocks (Winners – Losers)

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-77.73	-25.03	3.60	1.24
	(-16.85)	(-9.25)	(3.14)	(1.09)
CAPM Alpha	-75.94	-23.76	3.48	1.22
	(-16.65)	(-9.16)	(3.01)	(1.07)
FF Alpha	-77.56	-24.82	4.39	2.09
	(-16.57)	(-8.81)	(3.82)	(1.81)
Average n	48			

The large-cap profits across weeks one to fifty-two though only show evidence of being positive using the Fama-French alphas.

Table IX gives the portfolio profits dividing the sample into two subperiods from 1963 to 1982 and from 1983 to 2001. The brief reversals and the subsequent continuations remain evident across both subperiods. The finding that the profits are significantly positive in the year following the formation week is strong in the latter subperiod. The fifty-two week post-formation profits are positive in the former subperiod only in the Fama-French alphas. The profits in the first subperiod are, however, never negative. So the conclusion that the formation-week returns are not overreactions is robust across subperiods.

I also observe how the profits change with trading volume (per share). The interest here is in furthering our empirical understanding of the complex relation between volume and returns. Volume-return theories recognize that the motivations for trading can imply particular effects on future returns. As noted by Llorente et al. (2002), a high volume of liquidity trading should result in price pressure that will be reversed, while a high volume of informed trading should diminish the reversal since the private information is positively related to future returns. Llorente et al. provide a thorough discussion of the work on returns and volume, and I refer interested readers there. Llorente et al. use size as a proxy for information asymmetry and argue that high-volume returns in small stocks should display less of a reversal as the trades are more likely to be informed trades. They find supporting evidence.

Table IX
Subperiods

I evaluate the strategies in Table I over two subperiods. The early subperiod, presented in Panel A, covers 1963 to 1982. The late subperiod, presented in Panel B, covers 1983 to 2001. Overlapping calendar-time portfolios with weekly rebalancing are considered over various horizons. Numbers in the table represent the performance of these portfolios, in basis points, over the specified holding period week(s). The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

Panel A: 1963 to 1982

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-131.82	-53.25	5.81	0.60
	(-23.97)	(-19.18)	(5.29)	(0.51)
CAPM Alpha	-130.38	-52.50	5.98	0.83
	(-24.29)	(-20.28)	(5.71)	(0.75)
FF Alpha	-129.57	-51.22	6.61	2.00
	(-23.34)	(-18.87)	(6.29)	(1.86)
Average n	272			

Panel B: 1983 to 2001

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-134.67	-40.00	8.25	4.56
	(-20.20)	(-9.83)	(4.98)	(2.72)
CAPM Alpha	-130.86	-37.20	8.39	4.90
	(-19.95)	(-10.01)	(5.10)	(2.99)
FF Alpha	-132.69	-39.80	8.30	4.61
	(-20.72)	(-9.66)	(4.70)	(2.57)
Average n	440			

I separate the stock universe into those stocks whose volume increases in week *t* relative to week *t*-1 and those stocks whose volume decreases in week *t*. I then form total return portfolios as before using all available stocks and then using the small-cap, medium-cap, and large-cap subsets. Table X reports the portfolios' profits and the test for a difference in profits across the increasing-volume and decreasing-volume portfolios. Short-run reversals are stronger for the extreme-return stocks with increasing volume in week *t*. This holds for all stocks except the large-cap stocks (Panel D). Volume however has no effect on the continuations in weeks five to fifty-two; the return continuations are significant in each subsample but not different across the volume categories. Although not in the tables, the fifty-two week post-formation performance is never negative in any of the subsamples considered. There is never evidence of overreaction.

The finding of stronger short-run reversals in small stocks with increasing volume is inconsistent with the predictions and the findings of Llorente et al. (2002), who use daily returns, a different testing method, and a different stock sample. My finding that conditioning on volume only has an impact on the short-run returns further indicates that higher volume in my sample is more associated with inducing temporary price pressure than with identifying more informed trading. My findings also disagree with those of Cooper (1999) who examines various contrarian strategies on large-cap stocks conditioning on return and volume filters. My findings are more generally supportive of those of Conrad, Hameed, and Niden (1994) who examine NASDAQ stocks only. They also find that reversals are greater in high-volume returns. As

Table X
Share Turnover Subsamples

I divide the sample into two subsamples based on changes in share turnover during the formation week. Within each subsample, I form Winner and Loser portfolios as in Table I. Panel A presents results separately for firms with increasing and decreasing share turnover during the formation week. Panels B – D present the share turnover subsample results within each of size groupings used in Table II. Overlapping calendar-time portfolios with weekly rebalancing are considered over various horizons. Numbers in the table represent the performance of these portfolios, in basis points, over the specified holding period week(s). The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

	Week 1			Weeks 5-52		
	Increasing Turnover	Decreasing Turnover	Difference	Increasing Turnover	Decreasing Turnover	Difference
Panel A: All Stocks (Winners – Losers)						
Mean Return	-159.61	-137.48	-22.13	7.81	5.17	2.64
	(-32.43)	(-30.47)	(-4.88)	(5.43)	(3.78)	(1.36)
CAPM Alpha	-157.57	-135.23	-22.35	7.47	6.06	1.41
	(-32.55)	(-30.64)	(-4.95)	(5.20)	(4.94)	(0.77)
FF Alpha	-157.79	-135.81	-21.99	8.09	6.21	1.88
	(-32.09)	(-31.99)	(-4.93)	(5.80)	(5.89)	(1.33)
Average n	146	155				
Panel B: Small Stocks (Winners – Losers)						
Mean Return	-211.68	-169.00	-42.68	8.42	6.75	1.67
	(-34.26)	(-31.92)	(-6.59)	(6.10)	(5.04)	(0.86)
CAPM Alpha	-209.81	-166.67	-43.14	8.05	7.86	1.91
	(-34.38)	(-31.97)	(-6.70)	(5.84)	(6.60)	(0.10)
FF Alpha	-209.63	-167.42	-42.21	8.81	7.17	1.64
	(-33.73)	(-33.40)	(-6.51)	(6.48)	(6.69)	(1.07)
Average n	82	87				

Table X: Continued

	Week 1 Increasing Turnover	Week 1 Decreasing Turnover	Week 1 Difference	Weeks 5-52 Increasing Turnover	Weeks 5-52 Decreasing Turnover	Weeks 5-52 Difference
Panel C: Medium Stocks (Winners – Losers)						
Mean Return	-120.39	-109.43	-10.97	6.25	5.32	0.93
	(-21.27)	(-20.97)	(-2.10)	(3.94)	(4.09)	(0.54)
CAPM Alpha	-118.46	-107.40	-11.06	5.83	6.16	-0.34
	(-21.25)	(-21.02)	(-2.13)	(3.68)	(5.19)	(-0.21)
FF Alpha	-118.11	-106.95	-11.16	6.51	5.85	0.66
	(-21.06)	(-21.12)	(-2.13)	(4.09)	(4.98)	(0.46)
Average n	41	43				
Panel D: Large Stocks (Winners – Losers)						
Mean Return	-73.27	-74.97	1.70	4.35	2.39	1.96
	(-12.90)	(-14.14)	(0.32)	(2.81)	(2.22)	(1.38)
CAPM Alpha	-72.12	-73.52	1.40	3.95	2.65	1.30
	(-12.88)	(-14.18)	(0.27)	(2.54)	(2.49)	(0.93)
FF Alpha	-73.17	-75.45	2.28	5.11	3.58	1.53
	(-12.52)	(-14.71)	(0.42)	(3.45)	(3.35)	(1.22)
Average n	23	24				

Llorente et al. point out, the return-volume dynamics are quite complicated and current models do not capture all aspects. They argue that their model is sufficient though to link return-volume patterns to the underlying motives of trade. If this is so, then trading motives change across stocks and across time.

D.4. Seasonality

I consider seasonal variation in the performance of the portfolios. Table XI reports January and non-January trading profits separately. Immediate reversals are present in both January and non-January months, with January reversals being visibly stronger. Seasonal differences do exist in longer holding periods. In the year following formation, average January profit is negative. However, non-January profits are reliably positive. This result is similar to that of the Jegadeesh and Titman (1993) momentum strategy. Authors such as Grinblatt and Moskowitz (2004) have attributed such seasonal patterns to tax loss selling behavior.

E. Discussion and Fit

The evidence presented in this dissertation is inconsistent with a market that systematically overreacts to new information. The fact that weekly returns persist for a full year suggests that if there is any misreaction at all, it is an underreaction. So why, then, do weekly returns reverse? The leading contender offered in the literature is market microstructure issues. Measuring such issues however has proven to be a daunting task. A novelty of my approach is that it need not directly measure these issues.

Table XI
January Seasonality of Total Return Profits

I evaluate the Total Return Strategy in January and non-January months separately. Panel A reports January results. Panel B reports non-January results. Overlapping calendar-time portfolios with weekly rebalancing are considered over various horizons. Numbers in the table represent the performance of these portfolios, in basis points, over the specified holding period week(s). The average number of firms in each side of the strategy is also provided. I calculate heteroskedasticity and autocorrelation consistent *t*-statistics (in parentheses) as in Gallant (1987) using four lags.

Panel A: January

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-155.75	-81.79	-14.97	-21.55
	(-10.94)	(-10.15)	(-2.86)	(-4.05)
CAPM Alpha	-150.55	-78.35	-13.30	-19.46
	(-10.44)	(-10.00)	(-2.79)	(-4.06)
FF Alpha	-134.56	-56.75	-4.36	-8.30
	(-8.74)	(-7.49)	(-0.97)	(-1.86)
Average n	352			

Panel B: Non-January

	Week 1	Weeks 1-4	Weeks 5-52	Weeks 1-52
Mean Return	-1.31	-43.45	8.97	4.74
	(-29.30)	(-17.21)	(9.52)	(4.94)
CAPM Alpha	-1.29	-42.31	9.10	4.95
	(-29.60)	(-17.91)	(9.80)	(5.32)
FF Alpha	-1.30	-43.55	9.20	5.04
	(-29.75)	(-17.08)	(9.77)	(5.25)
Average n	355			

By offering evidence against the overreaction story, I indirectly implicate market microstructure as a driving force behind short-run reversals.

Importantly, the continuation of weekly returns unifies the short-run predictability literature with other bodies of research that previously appeared disjoint. Consider first studies that document drift following specific news events. Earnings surprises, stock splits, seasoned equity offerings, dividend initiations and omissions, repurchases, and merger announcements are all associated with some degree of return persistence for up to one year following the event.[31] These studies find results of a completely different tenor than those in the short-run predictability literature, which has fixated on reversals. I have shown here that, in concert with findings in the event literature, extreme weekly returns in fact persist. In other words, there is no inconsistency between the two literatures. Furthermore, the return persistence in both cases seems related to news.

Second, the momentum literature documents continuation of intermediate-term returns. To provide continuity with the short-run reversal literature, momentum researchers implicitly argue that a stock must have extreme returns for a longer period of time (say, three to six months) in order for the returns to persist. This, however, is not the case according to the evidence presented here. Momentum is not simply an intermediate-term phenomenon. The same effect occurs even with very short formation periods.

[31] The measurement and robustness of this drift, however, is still contested.

Granted, trading profits documented in the momentum literature are larger than the profits of my strategies. However, this is not a function of the *length* of the formation period. It is a function of the *size* of the formation period return. Consider the following. A six-month winner minus loser portfolio generates profits of about 12% (annualized) over the following year after skipping the first month. Unreported tests reveal an average return to the spread portfolio of roughly 100% during the formation period. The drift is therefore about twelve percent of the initial extreme return. The weekly total return strategy has an average formation period return of 20%, which is followed by an annualized profit of about 3.5% in weeks five through fifty-two. In this case, the drift is over seventeen percent of the initial extreme return.[32] Along these lines, the strength of weekly return continuation is in the same ballpark as traditional momentum. Thus, the persistence of weekly returns and momentum are remarkably similar and appear to be a manifestation of the same phenomenon.

[32] Even if the first four weeks are considered, annualized average profit is about seven percent of the formation period return.

V. CONCLUSION

Since the early 1990s, reversal has been the stylized fact associated with weekly individual stock returns. Much attention has been devoted to identifying the source of this reversal pattern. Some argue market microstructure effects such as bid-ask bounce, nonsynchronous trading, temporary price pressure, or specialists' inventory concerns are to blame but have been unsuccessful in establishing a complete empirical link. Controlling for these issues, others have argued reversals are driven by the market overreacting to information. In this dissertation, I provide an alternate vantage point for the debate and show extreme weekly returns actually persist over the following year. In other words, weekly winners continue to outperform losers for a full year in spite of the brief reversal. This suggests some of the attention on explaining reversals has been misplaced

The immediate implication is that short-run *correctional* reversals do not exist. If categorized as misreactions to information, extreme weekly returns are underreactions – not overreactions. This serves as indirect evidence that brief reversals are market microstructure driven. The predictability is also greater when news is more credibly identified. For example, return persistence is stronger when accompanied by the specific news found in earnings announcements. More generally, after controlling for total return, my measure of firm-specific news is positively related to future return as early as the next week. These findings contribute to a growing body of work to show return continuation following news is ever-present at various horizons and seems to be a pervasive feature of the price formation process.

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APPENDIX I

This appendix follows Appendix I from Daniel, Hirshleifer, and Subrahmanyam (1998), which lists news events associated with event-date and long-run abnormal performance of the same sign. I provide references of studies (if they exist) that document whether or not brief reversals also follow the events.

A. Evidence of No Immediate Reversal

- Stock splits: Grinblatt, Masulis, and Titman (1984)
- Tender offers and open market repurchases: Ikenberry, Lakonishok, and Vermaelen (1995)
- Analyst recommendations: Womack (1996)
- Dividend initiations and omissions: Healy and Palepu (1988)
- Earnings Surprises: Bernard and Thomas (1989)

B. Indeterminate

- Seasoned equity offerings: Asquith and Mullins (1986) find significant 2-day average abnormal returns of -2.7% around the announcement of equity offerings. They report in their Table 2 average abnormal returns of .5% in the first four days after the announcement, but provide no information on the statistical significance for this return window.

- Public announcement of previous insider trades: Seyhun (1998) finds abnormal stock returns for a full year following insider trades. His analysis, which is based on monthly returns, does not report market reactions on the days surrounding the revelation of insider trades.

Table A-I
Quick Reference for Main Methodology

This is a step-by-step instruction for creating the dataset and forming and evaluating the trading strategy from Table I.

Step 1*: *Calculate weekly returns. For all stocks listed in the daily CRSP files from 1963 to 2001, calculate weekly returns as the return from Wednesday's close to the following Wednesday's close.

Step 2*: *Create the main sample. From the weekly return dataset, retain the returns of all primary shares traded on the NYSE, AMEX, and NASDAQ exchanges whose prices exceed five dollars at the end of the previous week.

Step 3*: *Identify extreme returns. Each week, rank stocks into deciles based on their prior week's return. Define the top return decile as the winners and the bottom return decile as the losers. This week (week t) is referred to as the formation week.

Step 4*: *Form trading strategy. Each week, create an equal-weighted portfolio of the prior week's winners and an equal-weighted portfolio of the prior week's losers. The total return strategy is a zero investment strategy taking a long position in the winner portfolio and a short position in the loser portfolio. For the total return strategy, the winner and loser portfolios each contain an average of 355 stocks across time.

Step 5*: *Evaluate trading strategy. Use overlapping calendar-time portfolios to evaluate the strategy in weeks $t+k_1$ through $t+k_2$. In a given calendar week τ, there are k_2-k_1+1 open strategies formed in weeks $\tau-k_2, \tau-k_2+1, \ldots, \tau-k_1-1, \tau-k_1$, respectively. The profit in week τ is the mean profit across these cohort portfolios. This procedure generates a single time series of profits representing the $t+k_1$ through $t+k_2$ window. Average raw profit is the mean of the time series. Average risk-adjusted profit is the alpha from a time series regression of strategy profits on risk factors (e.g., market returns or the Fama and French (1993) factors).

VITA

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