The Market Impact of Trends and Sequences in Performance: New Evidence

GREGORY R. DURHAM, MICHAEL G. HERTZEL, and J. SPENCER MARTIN [*]

First version: September 3, 2002

This version: October 5, 2003

[*]Durham is at College of Business, Montana State University. Hertzel and Martin are at W. P. Carey School of Business, Arizona State University. This paper was written while Durham was at Arizona State University. We are grateful for the help and comments of S.P. Kothari, Mike Lemmon, and especially an anonymous referee and Rick Green. We also thank Arizona State brownbag participants for their comments.

The Market Impact of Trends and Sequences in Performance: New Evidence

ABSTRACT

This study contributes to the body of direct evidence testing behavioral finance theories, in particular evidence on market reactions to trends and patterns in performance data. Whereas Chan, Frankel, and Kothari (2003) find scant evidence that stock markets react in ways consistent with pervasive representativeness bias, Bloomfield and Hales (2002) find strong evidence that experimental market subjects are influenced by trends and patterns. We examine these issues using the football wagering market as our price laboratory. Sports betting markets have several advantages over traditional capital markets as an empirical setting, and commonalities with traditional markets allow for useful insights. The evidence in our market is mixed: over long performance horizons, bettor behavior is consistent with the experimental subjects in Bloomfield and Hales (2002); over shorter horizons, the results are more consistent with Chan, Frankel, and Kothari (2003). We also find evidence that investors in this market behave in a manner consistent with the shifting regimes model of Barberis, Shleifer, and Vishny (1998).

Introduction

Developed by Edwards (1968), Tversky and Kahneman (1974), and Kahneman and Tversky (1979), the prospect theory of behavior underlies a growing theoretical literature comprising numerous behavioral asset pricing models.[1] In this literature, deviations from rational expected utility maximization arise due to cognitive defects in human information processing. The representativeness heuristic, a tendency to mistake superficial similarity for deep similarity, is central [see Daniel, Hirshleifer, and Teoh (2001)] to many models that attempt to explain two important anomalies which have been the focus of a large empirical literature: momentum in returns and reversals in returns.[2] In this study we conduct simple experiments designed to detect the impact of the representativeness heuristic in action on market prices.

Existing empirical evidence bearing on behavioral models is limited, in part because the models make few directly testable predictions about the timing and duration of momentum and reversal effects. Direct tests in the stock market are especially difficult because of the many confounding factors involved. In a recent study, Chan, Frankel, and Kothari (2003) utilize patterns in past accounting performance as the means for operationalizing representativeness, and find little, if any, stock price evidence that investors extrapolate historical performance sequences over future horizons. Other stock price evidence comes from Hong, Lim, and Stein (2000), who find that, except for the smallest firms, momentum in asset prices is negatively correlated with analyst coverage, which is consistent with Hong and Stein (1999). Daniel and Titman (2003) find that predictability in stock returns lies solely in the component orthogonal to tangible accounting performance information.

The difficulty in using stock market prices is completely circumvented in Bloomfield and Hales (2002)

[1] See, e.g., Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999).

[2] The findings of long-run reversals in returns date to DeBondt and Thaler (1985), while shorter-run continuations in returns are documented in a body of work beginning with Jegadeesh and Titman (1993). Note that it is not at all necessary to have irrational agents in a model in order to generate these anomalies, as shown in recent models by Berk, Green, and Naik (1999), and Johnson (2002).

through use of experimental data. Experimental subjects observe a historical sequence of signed earnings surprises for a security and then assign a price to the security based upon expectations about the next observation in the sequence. Despite having the knowledge that earnings performance follows a random walk, participants consistently rely on the prevalence of past earnings trend reversals when predicting the likelihood of future reversals in earnings. Such participants behave in a manner consistent with Barberis, Shleifer, and Vishny (1998). In that model, a firm's earnings process is a random walk, with investors holding the flawed belief that the process is not a random walk but instead switches between a "reversal" regime (in which earnings changes tend to reverse themselves in sign) and a "continuation" regime (in which earnings changes are followed by changes of the same sign). In the model, investors look at the pattern of past performance to determine which regime they are in.

In this study, we choose a single market and conduct a broad set of simple experiments designed to detect the impact of the representativeness heuristic, among other biases, on market prices. Our first tests closely follow Chan, Frankel, and Kothari (2003), with particular emphasis on whether the most recent outcome confirms or contradicts previous performance. Next, we adapt the method of Bloomfield and Hales (2002) to infer whether investors are affected by short- or long-run reversals in performance. Finally, we investigate whether investor behavior in this market is consistent with sentiment effects due to regime-shifting beliefs of the sort delineated in the model of Barberis, Shleifer, and Vishny (1998). The setting for all of these tests is the legal wagering market for college football games in the U.S.

As noted by Avery and Chevalier (1999), sports betting markets have several advantages over traditional capital markets as an empirical laboratory; for instance, bets reach a perfectly observable terminal value in a relatively short period of time. This stands in contrast to stock markets, which have no obvious predefined moment of terminal payoff. Moreover, sports betting markets share many important features with stock markets: large volume, liquidity, and wide availability of information.

The remainder of the study proceeds as follows. Section I describes the market and provides further motivation for the study. Section II describes the sample. Section III describes the methodology and presents the results. Section IV offers specific directions for future research. Section V concludes.

I. The Market Setting

A. Advantages and Disadvantages of Various Market Settings

Measuring investor behavior and its corresponding effect on stock market prices is both difficult and imprecise in the U.S. setting, though several studies do match price movements with investor types.[3] The task remains difficult even in markets where regulators capture greatly detailed information about traders, such as in Finland.[4]

In contrast to real-world stock markets, experimental markets offer the researcher absolute certainty as to the identity of traders and to the stochastic processes that govern market fundamentals. This setting allows for powerful direct inferences about behavior, such as those in Bloomfield and Hales (2002). However, to extrapolate these inferences back to the real world is sometimes difficult because in the real world investors have their own wealth at stake with every trade and, more importantly, because the stochastic processes underlying market fundamentals are unknown and potentially unknowable.

Sports betting markets offer a useful "halfway house".[5] Compared to stock markets, they constitute an idealized laboratory setting; compared to experimental markets, they offer vast volumes of real money on

[3] See, for example, Dennis and Strickland (2002) and Griffin, Harris, and Topaloglu (2003).

[4] Grinblatt and Keloharju (2000) study momentum using a unique set of Finnish data which includes information on trader characteristics on both sides of every trade.

[5] A somewhat comparable market is the Iowa Political Market. For a detailed description, refer to Forsythe *et al.* (1992).

the line over lengthy time series. Avery and Chevalier (1999) point out that a useful feature of the football betting market is that bets reach a perfectly observable terminal value in a relatively short period of time. This stands in contrast to stock markets, which have no obvious predefined moment of terminal payoffs for stocks. The existence of a termination point is important for our study since it allows a measure of past performance that is reflective of true fundamental value. Without a clear settling up point, it is difficult to determine whether past performance reflects movements away from fundamental values due to sentiment.

Sports betting markets are also useful since they parallel securities markets in numerous ways. Like arbitrageurs and informed traders in capital markets, professional bettors attempt to seize any arbitrage opportunities that might arise in sports gambling markets. Information about spreads is nearly as widely disseminated as stock price information. Sports betting markets have their own version of expert stock pickers: so-called experts permeate the newspapers and gambling trade publications with their "wisdom." Finally, the bookmaker for sports bets has a near perfect analogue in the form of the market maker for securities.

B. Characteristics of the Football Market

The football betting markets are large and liquid, with a broad variety and volume of outlets for relevant information. Several dozen instruments trade each week of the 13-week college regular season. From a level measured at $1.8 billion in 1988,[6] total legal sports wagers in Nevada increased 50%, to $2.7 billion, by 1997.[7]

We follow Avery and Chevalier (1999) in concentrating on movements in point spreads as the variable of interest. Changes in point spreads, while markets are open for betting, can reflect either sentiment, or

[6] Hausch and Ziemba (1995), p. 549.
[7] Sinclair (1998), p. 17.

the arrival of new information, or both. Avery and Chevalier (1999) find that sentiment variables, which reflect information that is known at the time the opening line is set, are significant predictors of point-spread changes in the professional football wagering market. They conclude that some investors trade on sentiment and that this trading alters the path of prices. Our analysis focuses on determining whether point spreads move particularly in a fashion consistent with biased information processing resulting from investor reliance on the representativeness heuristic.

C. Football Market Tests

We begin by testing the conjecture by Chan, Frankel, and Kothari (2003) that an issue of particular importance is whether the most recent outcome confirms or contradicts the previous performance pattern. Using a data set consisting of point spreads and actual outcomes for a sample of college football games from 1991 through 1998, we find that the impact on prices (i.e., movements in point spreads) varies depending on whether the most recent outcome confirms or contradicts a prior trend. These results are different from the stock market results of Chan et al., who do not find evidence that investors formulate expectations about future performance by relying on past financial performance.

We next investigate whether the results of Bloomfield and Hales (2002) obtain in our market setting, by examining changes in point spreads following the identical set of historical sequences used in their experimental setting. We find that bettors do not react differently to low- and high-reversal sequences. Whereas experimental subjects appear to overreact to performances preceded by few reversals and underreact to performances preceded by many reversals, football betting market participants seem to be relatively insensitive to the number of recent reversals per se. Following Bloomfield and Hales, we also test whether bettors might be examining histories longer than eight games when formulating their expectations. We find that, when using 30-game histories, football betting market participants do react differently depending on the number of reversals in the historical sequences.

Finally, we are interested in whether investor behavior in this market is consistent with sentiment effects caused by regime-shifting beliefs of the sort delineated in the model of Barberis, Shleifer, and Vishny (1998). Using a piecewise regression analysis based on streaks in performance, we find that investors appear to believe in regime shifting. We find that spreads move in favor of teams that are on short winning streaks (i.e., streaks of three games or less) and move against teams that are on longer winning streaks. This evidence is consistent with bettors expecting performance to continue over the short term but to exhibit reversals over longer horizons.

II. Data

A. Source

This study uses eight years of data from the college football betting market. Specifically, the sample comprises every NCAA Division I-A game from 1991 through 1998 for which both opening and closing spreads were posted. For each of the 4584 game observations, the data set contains the following pieces of information: home team, visiting team, opening spread, closing spread, and each team's actual points scored. The data are compiled by Computer Sports World, which uses point spreads posted by the Stardust Casino Sportsbook.[8]

B. Market Conventions and Mechanics

It is critical to understand the quoting and cash-flow conventions of the football betting market; these conventions differ from those of stock markets, and from those of other betting markets such as parimutuel

[8] This data source is commonly used in academic studies of sports gambling markets. See, for example, Dare and MacDonald (1996).

wagering markets with variable odds. Football bet cash flows and odds are standardized, so instead of quoting odds, the market maker quotes a point spread such that bettors willingly enter both sides of the market at the standard odds, which state that for each $11 wagered, $21 is collected by a winner.[9] A bet wins if and only if the outcome of the game exceeds the spread that was quoted at the time the bet was placed.

Betting on a college football game usually commences each Sunday night, when the opening spreads are posted at the casinos; for a large majority of games, this is six days prior to the scheduled outcome the next Saturday. Bets on a game arrive during the week, and a game's spread changes any time the market maker needs to correct an order imbalance.[10] Once a game ends, its perfectly observable outcome can be compared with the point spread, and market participants can easily determine the value of their bets. All winning bettors can redeem their valuable asset for a payoff; all losing bettors are left holding an asset that is worthless.

C. Variables of Interest

From the initial data set, we construct the following variables for each observation: the intra-week change in spread, actual outcome, outcome against the (closing) spread, and historical performance (against the spread) for both the home team and away team. Historical game-by-game performance can then be used to identify particular performance patterns, as well as to identify winning streaks and losing streaks of various lengths.

The point spread is the mechanism by which the bookmaker manages the dollars bet on each team in the contest. The spread is also used in determining the terminal values of bets. To the extent that the spread for

[9] The market maker thus collects $1 out of every $22 bet, so transactions costs are a known, fixed 4.54 percent on each transaction.

[10] Following standard practice in the sports wagering literature, we presume that the bookmaker's objective is to balance the amounts of dollars bet on both teams in a contest.

a game represents the expected outcome of that game, the spread for game i, in week w at any given time t during the week, can be expressed as

$$SPREAD_{i,w,t} = E_t \left[HOMEPTS_{i,w} - AWAYPTS_{i,w} \right],$$

where $HOMEPTS_{i,w}$ is the home team's points scored and $AWAYPTS_{i,w}$ is the visiting team's points scored. In this study, for all games, only the opening and closing spreads are of interest. $OPEN_{i,w}$ denotes the opening spread and is measured at the time betting commences. $CLOSE_{i,w}$ is the closing spread, measured at the time betting ceases. The spread variables are ordered such that they represent a difference between the home team's score and the visiting team's score. For example, a spread equal to $+8$ indicates that the home team is favored to win the contest by eight points; a spread of -5 suggests that the home team is a five-point underdog.

The intra-week change in a game's spread is the difference between the closing spread and the opening spread. That is, for each game i in each week w,

$$CHANGE_{i,w} = CLOSE_{i,w} - OPEN_{i,w}.$$

A positive change in the spread means that the home team became either a heavier favorite or a lesser underdog; a negative change in the spread implies the opposite.

The actual outcome equals the difference between the home team's and visiting team's points scored; i.e., for each game i in each week w, the outcome is:

$$OUTCOME_{i,w} = HOMEPTS_{i,w} - AWAYPTS_{i,w},$$

where $HOMEPTS_{i,w}$ is the home team's points scored and $AWAYPTS_{i,w}$ is the visitors' points scored. A positive value for the outcome suggests that the home team won the game; a negative value indicates that the visiting team was victorious. Of particular interest from a wagering perspective is a game's outcome relative to the corresponding spread. If the favored team wins the game by an amount larger than the spread (i.e., if the outcome is greater than the spread), the favorite is said to have won against (or covered) the spread. If the underdog either loses the game by an amount less than the spread or wins the game outright, the underdog is said to have won against (or covered) the spread. For each game i in each week w, we calculate the indicator variable $OUTCATS_{i,w}$ (outcome against the spread) by transforming the difference between the outcome and the closing spread:

$$OUTCATS_{i,w} = \begin{cases} 1, & \text{if } OUTCOME_{i,w} > CLOSE_{i,w} \\ 0, & \text{if } OUTCOME_{i,w} = CLOSE_{i,w} \\ -1, & \text{if } OUTCOME_{i,w} < CLOSE_{i,w} \end{cases}.$$

$OUTCATS_{i,w}$ equals 1, 0, or -1, depending on whether the home team covered the spread, "pushed," or failed to cover the spread.

Since our study focuses heavily on the possibility that bettors evaluate teams' historical performance against the spread when predicting future performance, we create lagged relative performance variables for each team in each game. For each game i in each week w, we identify the historical outcomes against the spread for the home team and away team. That is, the home and visiting teams' lagged-n outcomes against the spread are:

$$HLGnATS_{i,w} = \begin{cases} OUTCATS_{j,w-n} & \text{if home team was home in its prior game } j \text{ in week } w-n \\ -OUTCATS_{j,w-n} & \text{if home team was away in its prior game } j \text{ in week } w-n \end{cases},$$

and

$$ALGnATS_{i,w} = \begin{cases} OUTCATS_{j,w-n} & \text{if away team was home in its prior game } j \text{ in week } w-n \\ -OUTCATS_{j,w-n} & \text{if away team was away in its prior game } j \text{ in week } w-n \end{cases} .$$

These lagged performance variables can then be used to classify teams' historical performance patterns into specific categories. Or, they can be used to calculate teams' streaks (either winning or losing) against the spread, another useful historical performance measure.[11] We define a team's current winning streak against the spread ($HWSTREAK$ for the home team, $AWSTREAK$ for the away team) as the number of consecutive times that the team has covered the spread up through its most recent game. A team's current losing streak against the spread ($HLSTREAK$, $ALSTREAK$) is similarly defined as the number of consecutive failures to cover spreads.

D. Summary Statistics

The average intra-week change in spread is indistinguishable from zero. Instead of simple averages and variances, then, Table I reports the distribution of streak lengths against the spread for all teams. A quick glance suggests that the frequencies fall by half or slightly more than half at each step, which would be consistent with teams having nearly a 50 percent chance of beating the spread in any given game. This invites a more formal random walk test.

To this end, we perform a runs test for each team in the sample. The runs test is a simple indicator of deviations from random walk behavior. The observed number of runs in the time-series performance against the spread is compared to the expected level under the null hypothesis, i.e., the hypothesis of random

[11] If a given team "pushes" against (i.e., ties) the spread in a particular game, the push is not considered to be a termination of that team's existing streak. Instead, a push is interpreted to simply maintain the team's current winning or losing streak against the spread.

walk. For 105 out of 113 teams in the entire sample, the hypothesis that performance follows a random walk cannot be rejected at the five percent significance level. Table II shows the results for a 35-team subsample; these results are representative of the overall 113-team sample.

III. Methodology and Results

A. Trends and Sequences as Indicators of Representativeness Bias

Following the observation by Chan, Frankel, and Kothari (2003) that patterns in past performance are the best way to operationalize representativeness, we investigate price changes (intra-week point spread changes) as a function of patterns in performance of past bets. In measuring the impact of behavioral biases on pricing, we harness the result of Avery and Chevalier (1999) that point spread changes during the week reflect expression of investor sentiment.

We measure the pattern of past performance by calculating the trend in a team's performance. Each week for eight weeks, we assign an indicator value of $+1$ to weeks when the team beat the spread, and -1 to weeks when the team failed to beat the spread. We define the *prior trend* as the sum of the seven indicators directly preceding the most recent outcome. For instance, a team beating the spread six times and failing to do so once would have a prior trend of $+5$.

We further observe whether the most recent outcome confirms or contradicts the prior trend; confirmation occurs when a team with a positive (negative) prior trend wins (loses) against the spread in the most recent game. Similarly, a contradictory outcome occurs when a team with a positive (negative) prior trend loses (wins) against the spread in the most recent game. Absent behavioral biases, in an efficient market the price behavior following contradicting events should be no different than the price behavior following confirming events.[12] Alternatively, in the presence of the representativeness heuristic confirming events would be succeeded by momentum (continuation of prior trend), and contradicting events would be succeeded by correction (reversal of prior trend).[13]

A.1. Outcomes That Confirm/Contradict Prior Trends

Table III shows mean changes in spread following both negative trends and positive trends, with the results further sub-grouped depending on whether the most recent outcome in an eight-game sequence confirms or contradicts the prior trend in performance. Starting with confirming events, we note that when a team loses against the spread following a negative prior trend, the average change in spread *during* the week of betting preceding the team's next game is -0.10096; i.e., the spread moves against that team by 0.10096 points. Similarly, when a positive trend is confirmed by the current outcome, the subsequent week's mean change in spread averages $+0.10456$ points. Both of these changes, as well as the difference of $+0.20552$, are statistically significant. Given this price behavior, investors appear to believe that a confirming event is an indication that a team's performance trend will continue.

For most recent outcomes that contradict their prior trends, the mean change in spread is $+0.15131$ when a negative trend is contradicted and is -0.15420 when a positive trend is contradicted. Both of these changes, as well as the difference of -0.30551, are statistically significant. These results are consistent with bettors believing that a single-game performance that contradicts a prior trend is an indication that the trend, either negative or positive, will be reversed.

There is a clear pattern in these results consistent with the behavioral alternative hypothesis that momentum follows confirming events and reversal follows contradicting events. We also note that the magnitudes of the contradicting event average impacts are approximately 50 percent larger than the magnitude of the

[12] Put even more strongly, in an efficient market the expected change in point spread during the week prior to the game is zero.
[13] This implication is derived in Chan, Frankel and Kothari (2003, p. 15).

confirming event average impacts, albeit not statistically significantly different.

A.2. Does Trend Size Matter?

In Table IV, observations are sorted into four trend categories of roughly equal numbers of observations: prior trend less than or equal to -3, prior trend equal to -1, prior trend equal to $+1$, and prior trend greater than or equal to $+3$. This arrangement accommodates the observation of Chan, Frankel, and Kothari (2003) that market reactions may be dependent on both the consistency as well as the magnitude of prior performance.

Adapted to our data, their observation implies that the market impact following any given game should be weaker, the more consistent the prior trend. Stronger prior trends proxy for more consistent past performance. Due to the operation of representativeness, events that confirm stronger prior trends should be afforded less marginal importance by bettors— in other words, there should be more impact following events that confirm weak positive and negative trends than following events that confirm strong positive and negative trends, respectively. Likewise, the reaction to trend-contradicting events should be weaker when prior trends are stronger because such contradictions are de-emphasized by investors.

To illustrate Table IV, suppose a team loses against the spread after a strong negative prior trend. This is a confirming outcome. On average, during the week of betting preceding that team's next game, the spread moves against it by 0.09120 points. Before turning to the question of whether trend size matters, we note that these categorized results confirm Table III much more strongly for contradicting events than for confirming events. For all four types of prior trend (strong minus, weak minus, weak plus, and strong plus), the market impact following contradicting events is significant: 0.14878, 0.15326, -0.16087, and -0.14618 points, respectively. In contrast, the market impact following confirming events is significant for only one trend type (weak plus).

Table IV also provides evidence, albeit weak, that the size of the trend does matter, in the sense of being concordant with the implications of representativeness. The magnitudes in Table IV show a consistent pattern of stronger prior trends being followed by weaker market impacts. For confirming events, post-strong trend impacts are 0.09120 and 0.07541 versus post-weak trend impacts of 0.10874 and 0.12848 for negative and positive prior trends, respectively; and for contradicting events, post-strong impacts are 0.14878 and 0.14618 versus post-weak impacts of 0.15326 and 0.16087 for negative and positive prior trends, respectively. None of these individual differences is statistically significant; however, the null hypothesis that all four differences are equal and zero can be rejected.

A.3. Summary

On balance, our findings suggest that bettors do consider whether a team has recently been in a positive or negative performance trend, and whether the most recent observation confirms or contradicts the preceding trend. The results in Tables III and IV are largely inconsistent with those of Chan, Frankel, and Kothari (2003), who do not find evidence consistent with investors formulating expectations about future performance by relying on past financial performance. The difference might be explained by the relative structural simplicity of the wagering market, or it might be that stock investors are less susceptible to behavioral biases.

B. Frequency of Performance Reversals and Its Effect on Expectations

The tests of Chan, Frankel, and Kothari (2003) are able to detect broad effects of representativeness bias, which could be consistent with any of several behavioral models. In contrast, Bloomfield and Hales (2002) devise a set of tests meant to examine the validity of one particular assumption associated with the behavioral model of Barberis, Shleifer, and Vishny (1998). In this section, we adapt their experimental tests to determine whether investors in the football market condition their expectations about future performance upon the prevalence of past performance reversals.

B.1. Eight-Week Horizons

We begin, in Table V, by simply recreating the eight specific 8-outcome performance history sequences used in the experiment of Bloomfield and Hales (2002).[14] For each sequence, the table shows the mean change in spread during the week of betting preceding the team's next game. In turn, the sequences are grouped according to the prevalence of performance reversals: sequences A through D are in the low reversal group, sequences E and F are in the moderate reversal group, and sequences G and H are in the high reversal group. In the low reversal group, the mean change in spread is 0.05378, compared to a mean change of 0.21610 following series of high reversals. Neither mean is significantly different from zero, nor is the difference in means, but this may be due largely to small samples in each group.[15]

To further investigate the hypothesis that the frequency of reversals matters, and to maximize inferential power, we expand our analysis of mean changes in spreads to include all 256 possible 8-outcome sequences. The results are shown in Table VI, classified by the number of reversals (zero to seven) in each sequence. In reaction to low-reversal (zero or one), moderate-reversal (two to five), and high-reversal (six or seven) performance sequences, the mean changes in spread are 0.06328, 0.12978, and 0.17819, respectively. The mean reactions to the low- and high-reversal histories are not statistically significantly non-zero, nor is the difference in means.

In contrast with the experimental subjects, bettors do not exhibit oppositely signed reactions for the low and high reversal sequences. Whereas experimental subjects appear to overreact to performances preceded by few reversals and underreact to performances preceded by many reversals, football market participants seem to be relatively insensitive to the number of recent reversals *per se*.

[14] Each of the eight sequences A through H contains results for a pair of mirror image shapes.

[15] In unreported results we obtain similar findings for subsamples conditioned on the most recent outcome being a win against the spread or a loss against the spread.

B.2. Sixteen-Week and Thirty-Week Horizons

We next test whether bettors might be examining histories longer than eight games when formulating their expectations about a performance continuation or reversal. Differences in mean reactions to low- and high-reversal sequences are examined for 8-, 16-, and 30-game histories. The number of reversals present in eight-outcome performance histories ranges from 0 through 7, and we classify historical sequences with zero to three reversals as being "low-reversal"; sequences with four to seven reversals are "high-reversal." The number of reversals present in sixteen-outcome histories in our sample ranges from one through 14. We classify historical sequences with one to seven reversals as being "low-reversal"; sequences with eight to 14 reversals are "high-reversal." Similarly, for 30-game histories "low reversals" constitutes numbers of reversals in the lower half of the sample range (six to 14 reversals) and the "high reversals" category includes the rest (15 to 23 reversals). The results appear in Table VII.

The first line in Table VII indicates that the mean change in spread following 8-game histories is not significantly different across low-reversal (0.12384) and high-reversal (0.13315) histories. We infer that investors do not react differently to the frequency of prior reversals when examining teams' most recent eight games. Likewise, investors do not appear to react differently to low-reversal and high-reversal sequences when examining 16-game histories. However, the results suggest that when examining 30-game histories to assess performance, investors do react differently depending on the number of reversals in historical performance sequence. The mean change in spread following low-reversal performance sequences is 0.17427, and the mean change in spread following high-reversal performance sequences is 0.04979. The difference is a statistically significant 0.12448.[16]

[16] In unreported results, we find that it does not matter whether the team's most recent outcome was a win against the spread or a loss against the spread. The statistically significant differences in mean reactions are confirmed in both sub-samples.

C. Further Evidence on Regime-Shifting

Within the framework of Barberis, Shleifer and Vishny (1998), investors are more likely to expect reversals after seeing many reversals, and are more likely to anticipate continuations after seeing fewer reversals. The previous section tests for evidence of both of these kinds of expectations, with the result that the number of past reversals has little effect at all at the short (8-week) horizon.

In this section, we examine the issue of recent past performance more closely. We refine the testing approach with a piecewise regression analysis based upon a team's current winning or losing streak against the spread. Since a team's current winning or losing streak against the spread is really a measure of the distance in time to the most recent reversal, a streak-based test allows us to focus purely on the effect of continuations in performance without confounding effects from observed reversals.

C.1. Regime-Shifting Beliefs and Representativeness Bias

The representativeness heuristic is the motive force underlying the continuation regime (Model 2) of Barberis, Shleifer, and Vishny (1998), but the model also relies upon a conservatism bias to produce overreaction. Conservatism means that investors are slow to change their beliefs in the face of new evidence, and thus conservatism bias is the driving force underlying the reversal regime.[17]

It is possible that the results in the previous section obtain because bettors, as compared to other investors, have a lesser tendency to be affected by conservatism bias. The focus on current performance streak diminishes as much as possible any effects of conservatism, and also allows for maximal complementarity with the representativeness results from III.A above.

[17] In a Bayesian sense, conservatism results from the tendencies to underutilize relevant new statistical information and to rely too heavily on the less useful information employed to form priors. Alternatively, overconfidence about prior beliefs, or biased self-attribution, could also lead to a conservative response to new information.

C.2. Methodology

To test for evidence on bettors' beliefs in performance regimes, we run a piecewise linear regression where $SLENGTH$ denotes the streak-length threshold:

$$\begin{aligned} CHANGE = \alpha &+ \beta_1 HWSTREAK_1 + \beta_2 HWSTREAK_2 + \beta_3 AWSTREAK_1 \\ &+ \beta_4 AWSTREAK_2 + \beta_5 OPEN + \epsilon, \end{aligned}$$

where

$$HWSTREAK_1 = \begin{cases} HWSTREAK & \text{if } HWSTREAK < SLENGTH \\ SLENGTH & \text{if } HWSTREAK \geq SLENGTH \end{cases},$$

and

$$HWSTREAK_2 = \begin{cases} 0 & \text{if } HWSTREAK < SLENGTH \\ HWSTREAK - SLENGTH & \text{if } HWSTREAK \geq SLENGTH \end{cases}.$$

The remaining explanatory variables ($AWSTREAK_1$, $AWSTREAK_2$, $HLSTREAK_1$, $HLSTREAK_2$, $ALSTREAK_1$, and $ALSTREAK_2$) are defined similarly. We include the opening spread ($OPEN$) as a control variable.

The dependent variable in this analysis is $CHANGE$, the intra-week change in spread. Under the null hypothesis that only the arrival of new information moves the spread, all variables based on prior performance should fail to explain current spread changes. Under a regime-shifting alternative, bettors could be expected to move the spread in favor of (against) a team on a winning (losing) streak of $SLENGTH$ games or fewer, and against (in favor of) a team on a longer winning (losing) streak.[18]

[18] Because the turning point is not *ex ante* apparent, we utilize a one-dimensional grid-search technique, as described in Greene

Table VIII shows the results of our piecewise linear regression of the intra-week change in spread on the streak variables. Column 1 shows the results of the regression of change in spread on the winning streak variables, an intercept term, and the opening spread. The coefficient on $HWSTREAK_1$ (short winning streak indicator) is positive and statistically significant. The positive coefficient on $HWSTREAK_1$ is consistent with bettors expecting the home team's short-term performance to continue; e.g., the spread moves in the direction of the home team that is on a winning streak of three games or less. The negative coefficient on $HWSTREAK_2$ suggests that bettors expect that performance of teams on longer streaks will reverse. This coefficient is marginally significant. An identical interpretation applies to the statistically significant away-team winning-streak variables; streaks of three games or less attract bets on continuation, and streaks longer than three games attract bets on reversal (n.b. the Away team streak coefficients have signs opposite of the Home team coefficients due to the quoting convention of the data that positive is always the from the viewpoint of the home team.).

The specification in column 2 includes the losing-streak variables, with an intercept term and the opening spread. The coefficient on $HLSTREAK_1$ is significantly positive; following short losing streaks, the subsequent spread change is negative (since $HLSTREAK$ lies between -1 and -3, against the home team; i.e., bettors expect the losing streak to continue. The $HLSTREAK_2$ coefficient is significantly negative, and so bettors expect home teams' longer losing streaks to reverse. For the away team, the significantly negative $ALSTREAK_1$ coefficient suggests bettors expect short-term losing streaks to continue; the coefficient on $ALSTREAK_2$ is insignificant.[19]

(2003, p. 934). We search for the turning point that maximizes the model's adjusted R^2 value, settling on a value of $SLENGTH$ = 3 as the threshold where investors shift expectations.

[19] For robustness, we also performed additional regression analyses besides those shown in Table VIII; the additional specifications included various sentiment variables that were found to exhibit explanatory power in both the NFL betting market (Avery and Chevalier (1999)).

IV. Conclusion

Stock price evidence on momentum and reversals suggests that investors have varying tendencies to underreact and overreact to new information. One possible explanation for such tendencies is that investors rely upon a representativeness heuristic when formulating expectations about future outcomes and that this heuristic leads to biases in investors' information processing. In particular, the representativeness heuristic can cause individuals to detect patterns in performance, even if performance is actually governed by a random process. Using point spreads and actual outcomes for a sample of college football games from 1991 through 1998, we perform various experiments in an attempt to measure the impact of representativeness bias on prices (or point spreads) in the college football wagering market.

As suggested by Chan, Frankel, and Kothari (2003), the impact of representativeness on prices might also depend on whether the most recent outcome confirms or contradicts the previous performance pattern. Inconsistent with the findings of Chan et al., we find that the impact on prices does, indeed, depend on whether the outcome confirms or contradicts a prior trend.

Using the same eight historical sequences used in Bloomfield and Hales' (2002) experimental setting, we find that bettors do not react differently to low- and high-reversal sequences. Our findings are similar when we expand our sample to include all possible eight-game historical performance patterns, rather than just the eight specific patterns used by Bloomfield and Hales. Our results differ from those of Bloomfield and Hales, who found their experimental subjects to overreact to performances preceded by few reversals and to underreact to performances preceded by many reversals. We then expand the historical performance horizon to include 16, and then 30, games and we find that investors appear to react differently depending on the number of reversals in 30-game performance histories.

Our paper concludes with tests for evidence consistent with a behavioral model developed by Barberis, Shleifer, and Vishny (1998). Our evidence that investors believe in regime-shifting comes from a piecewise linear regression analysis of the effects of past performance against the spread on changes in point spreads during betting. We find that spreads move in favor of teams that are on short winning streaks (i.e., streaks of three games or less) and move against teams that are on longer winning streaks. This evidence is consistent with bettors expecting performance to continue over the short term but to exhibit reversals over longer horizons. Although we find qualitatively similar results for our analysis based on losing streaks against the spread, the findings are not as statistically strong in some specifications. Differential attitudes towards "winners" and "losers" as documented by earlier researchers may be one avenue worthy of further investigation.

Finally, according to Barberis, Shleifer and Vishny, investors who update their beliefs in Bayesian fashion are more likely to expect reversals after seeing many reversals, and are more likely to anticipate continuations after seeing fewer reversals. Our findings are consistent with this only up to a point; i.e., continuations are expected to be more likely following short runs in performance. We do find, however, that reversals are expected to be more likely following longer runs (i.e., fewer reversals) in performance. This suggests that regime-shifting models taking this feature into account may prove more successful in predicting investor behavior.

REFERENCES

Avery, Christopher, and Judith Chevalier, 1999, Identifying investor sentiment from price paths: The case of football betting, *Journal of Business* 72, 607–36.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–43.

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1608.

Bloomfield, Robert, and Jeffrey Hales, 2002, Predicting the next step of a random walk: Experimental evidence of regime-shifting beliefs, *Journal of Financial Economics* 65, 397–414.

Campbell, John Y., Andrew Lo, and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton Press).

Chan, Wesley S., Richard Frankel, and S.P. Kothari, 2003, Testing behavioral finance theories using trends and sequences in financial performance, The 2003 Journal of Accounting & Economics Conference on: Research on Market Efficiency, Valuation, and Mispricing: Risk, Behavioral, and Alternative Explanations.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839–86.

Daniel, Kent, David Hirshleifer, and Siew Hong Teoh, 2001, Investor psychology in capital markets: Evidence and policy implications, *Journal of Monetary Economics* 49, 139–209.

Daniel, Kent, and Sheridan Titman, 2003, Market reactions to tangible and intangible information, Working Paper, Kellogg School of Business.

Dare, William H., and S. Scott MacDonald, 1996, A generalized model for testing the home and favorite team advantage in point spread markets, *Journal of Financial Economics* 40, 793–808.

DeBondt, Werner, and Richard Thaler, 1985, Does the stock market overreact? *Journal of Finance* 40, 793–808.

Dennis, Patrick, and D. Deon Strickland, 2002, Who blinks in volatile markets, individuals or institutions? *Journal of Finance* 57, 1923–49.

Edwards, Ward, 1968, Conservatism in human information processing, in Benjamin Kleinmutz, ed.: *Formal Representation of Human Judgment* . pp. 17–52 (John Wiley and Sons).

Forsythe, Roberrt, Forrest Nelson, George Neumann, and Jack Wright, 1992, Anatomy of an experimental political stock market, *American Economic Review* 82, 1142–61.

Greene, William H., 2003, *Econometric Analysis* (Prentice Hall).

Griffin, John M., Jeffrey H. Harris, and Selim Topaloglu, 2003, The dynamics of institutional and individual trading, *Journal of Finance* 58, 411–35.

Grinblatt, Mark, and Matti Keloharju, 2000, The investment behavior of various investor types: A study of Finland's unique data set, *Journal of Financial Economics* 55, 43–67.

Hausch, Donald B., and William T. Ziemba, 1995, Efficiency of sports and lottery betting markets, in Robert Jarrow, Vojislav Maksimovic, and William T. Ziemba, ed.: *Handbooks in Operations Research and Management Science, Volume 9, Finance* . pp. 545–80 (Elsevier Science B.V.).

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143–84.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Johnson, Timothy C., 2002, Rational momentum effects, *Journal of Finance* 57, 585–607.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–91.

Sinclair, Sebastian, 1998, The 1997 United States gross annual wager: A new entitlement, *International Gaming and Wagering Business* 19, 17.

Tversky, Amos, and Daniel Kahneman, 1974, Judgment under uncertainty: Heuristics and biases, *Science* 185, 1124–31.

Wallis, W. Allen, and Harry V. Roberts, 1956, *Statistics: A New Approach* (New York: Free Press).

Table I

Distribution of Streak Lengths

This table shows the distribution of streak lengths, for both home teams and away teams. A team's current winning streak, against the spread, is defined as the number of consecutive times that team has covered the spread up through its most recent game; a team's current losing streak against the spread is similarly defined by consecutive failures to cover spreads. (The χ^2 value for a test of differences between the home-team distribution and the expected binomial distribution is 0.8684; for the same test for the away-team distribution, the χ^2 value is 0.8618.)

Streak Length	Home Team	Relative Freq.	Visiting Team	Relative Freq.
-15	0	0.00	1	0.02
-14	1	0.02	0	0.00
-13	0	0.00	1	0.02
-12	1	0.02	1	0.02
-11	1	0.02	1	0.02
-10	3	0.07	2	0.04
-9	4	0.09	7	0.15
-8	6	0.13	8	0.17
-7	12	0.26	19	0.41
-6	27	0.59	35	0.76
-5	56	1.22	69	1.51
-4	133	2.90	135	2.95
-3	271	5.91	283	6.17
-2	563	12.28	574	12.52
-1	1182	25.79	1120	24.43
1	1152	25.13	1157	25.24
2	569	12.41	552	12.04
3	272	5.93	278	6.06
4	135	2.95	151	3.29
5	72	1.57	71	1.55
6	31	0.68	37	0.81
7	14	0.31	17	0.37
8	9	0.20	7	0.15
9	4	0.09	4	0.09
10	2	0.04	1	0.02
11	1	0.02	1	0.02
12	1	0.02	0	0.00
13	0	0.00	1	0.02
Totals		100.00		100.00

Table II

Excerpted Observations from Team-by-Team Runs Tests

This table contains observations for 35 representative teams among the 108 teams in our sample. For each team, the following are reported: total number of games played from 1991 through 1998, the total number of time-series performance runs, number of runs as a percentage of total number of games, the normal number of runs (as a percentage of total number of games), and the Z-score for the difference between the observed number of runs (as a percentage) and the normal number of runs (as a percentage) are reported. The normal numbers of runs and the Z-scores are calculated as described by Campbell, Lo, and MacKinlay (1997, Ch. 2, pages 40-41). The Z-scores include a continuity correction as per Wallis and Roberts (1956).

Team	Tot. # of Games	Tot. # of Runs	Runs as % of Total	Normal # of Runs	Z-score
Alabama	95	48	50.5%	48.0	0.2052
Arizona	93	48	51.6%	47.0	0.4148
Arizona State	90	40	44.4%	45.5	-0.9487
Arkansas	90	47	52.2%	45.5	0.5270
Auburn	83	39	47.0%	42.0	-0.4391
Baylor	91	44	48.4%	46.0	-0.2097
Boston College	92	45	48.9%	46.5	-0.1043
California	90	44	48.9%	45.5	-0.1054
Clemson	84	44	52.4%	42.5	0.5455
Colorado	94	44	46.8%	47.5	-0.5157
Duke	87	48	55.2%	44.0	1.0721
Florida	101	53	52.5%	51.0	0.5970
Florida State	96	55	57.3%	48.5	1.5309
Georgia	90	53	58.9%	45.5	1.7920
Georgia Tech	86	46	53.5%	43.5	0.7548
Illinois	90	45	50.0%	45.5	0.1054
Indiana	90	47	52.2%	45.5	0.5270
Iowa	92	36	39.1%	46.5	-1.9809
Iowa State	83	46	55.4%	42.0	1.0976
Kansas	88	42	47.7%	44.5	-0.3198
Kansas State	87	38	43.7%	44.0	-1.0721
Louisiana State	90	49	54.4%	45.5	0.9487
Maryland	84	40	47.6%	42.5	-0.3273
Miami (FL)	88	45	51.1%	44.5	0.3198
Michigan	98	56	57.1%	49.5	1.5152
Michigan State	93	47	50.5%	47.0	0.2074
Minnesota	88	40	45.5%	44.5	-0.7462
Mississippi	86	49	57.0%	43.5	1.4018
Mississippi State	91	50	54.9%	46.0	1.0483
Missouri	88	42	47.7%	44.5	-0.3198
Nebraska	98	51	52.0%	49.5	0.5051
No. Carolina State	89	46	51.7%	45.0	0.4240
North Carolina	92	45	48.9%	46.5	-0.1043
Northwestern	91	42	46.2%	46.0	-0.6290
Notre Dame	97	58	59.8%	49.0	2.0307

Table III

Change in Spread Following Confirming vs. Contradicting Events

This table shows mean changes in spread following events that either confirm or contradict the preceding trend. A team's trend is measured using lagged performance over first seven of a team's most recent eight games, and is calculated by subtracting the number of losses against the spread from the number of wins against the spread over that horizon. A team's most recent outcome confirms the trend either if the trend is negative and the lag-1 outcome against the spread is a loss or if the trend is positive and the lag-1 outcome against the spread is a win. Otherwise, a team's most recent outcome against the spread contradicts the trend. N is simply the number of observations for each category; t-statistics for the mean changes are also reported. Differences in means, and their corresponding p-values, are also reported for the "Confirming"and "Contradicting" categories.

	Confirming Events			Contradicting Events			Difference in Means
	N	Change	t-stat.	N	Change	t-stat.	(p-value)
Negative Trend	1768	-0.10096	-2.21	1877	0.15131	3.53	-0.25227
							(<0.00001)
Positive Trend	1758	0.10466	2.30	1845	-0.15420	-3.52	0.25886
							(<0.00001)
Difference in Means		0.20563			-0.30551		
(p-value)		(0.00150)			(<0.00001)		

Table IV

Change in Spread After Confirming vs. Contradicting Events, by Trend Type

This table shows mean changes in spread following events that either confirm or contradict the preceding trend. A team's trend is measured using lagged performance over first seven of a team's most recent eight games, and is calculated by subtracting the number of losses against the spread from the number of wins against the spread over that horizon. A team's most recent outcome confirms the trend either if the trend is negative and the lag-1 outcome against the spread is a loss or if the trend is positive and the lag-1 outcome against the spread is a win. Otherwise, a team's most recent outcome against the spread contradicts the trend. N is simply the number of observations for each category; t-statistics for the mean changes are also reported.

	Confirming Events			Contradicting Events		
Trends	N	Change	t-stat.	N	Change	t-stat.
-7, -5, -3	784	-0.09120	-1.35	820	0.14878	2.26
-1	984	-0.10874	-1.75	1057	0.15326	2.70
1	969	0.12848	2.14	1007	-0.16087	-2.65
+3, +5, +7	789	0.07541	1.08	838	-0.14618	-2.31

Table V

Mean Changes in Spread for Specific 8-Game Performance Histories

Reactions to each pattern and its mirror image are bundled together. Thus, the change in spread is signed according to the prior games outcome against the spread. (p-values are reported in parentheses.)

Performance Sequence	Number of Reversals	Trend	N	Mean Change In Spread	Summary by Reversal Frequency
A: W–W–W–W–W–W–W–W	0	8	60	0.15000	
L–L–L–L–L–L–L–L				(0.2895)	
B: L–W–W–W–W–W–W–W	1	6	58	-0.04310	Low:
W–L–L–L–L–L–L–L				(0.2318)	0.05378
C: L–L–L–L–W–W–W–W	1	0	69	-0.07246	(0.1307)
W–W–W–W–L–L–L–L				(0.2643)	(N=251)
D: L–L–L–L–L–W–W–W	1	-2	64	0.18750	
W–W–W–W–W–L–L–L				(0.2570)	
E: L–L–L–W–L–L–L–W	3	-4	47	-0.26596	Moderate:
W–W–W–L–W–W–W–L				(0.2664)	-0.09615
F: W–W–W–L–W–W–L–W	4	4	57	0.04386	(0.1573)
L–L–L–W–L–L–W–L				(0.1849)	(N=104)
G: W–L–L–W–L–W–L–W	6	0	67	-0.02985	High:
L–W–W–L–W–L–W–L				(0.2496)	0.21610
H: L–W–L–W–L–W–L–W	7	0	51	0.53922	(0.1973)
W–L–W–L–W–L–W–L				(0.3146)	(N=118)

Table VI

Mean Changes in Spread for All 8-Game Performance Histories By Reversal Frequency

Reactions to each pattern and its mirror image are bundled together. Thus, the change in spread is signed according to the prior games outcome against the spread. Associated p-values are reported in parentheses.

Number of Reversals	N	Mean Change In Spread	Summary by Reversal Frequency
0	60	0.15000	Low:
		(0.2895)	0.06328
1	422	0.05095	(0.0901)
		(0.0945)	(N = 482)
2	1187	0.11205	
		(0.0550)	
3	1989	0.14555	Moderate:
		(0.0423)	0.12978
4	1871	0.08445	(0.0237)
		(0.0429)	(N = 6303)
5	1256	0.18909	
		(0.0539)	
6	412	0.13350	High:
		(0.0937)	0.17819
7	51	0.53922	(0.0904)
		(0.3146)	(N = 463)

Table VII

Short vs. Long Performance Histories By Reversal Frequency

Reactions to each category of reversals and their mirror images are bundled together. Thus, the change in spread is signed according to the prior game's outcome against the spread. Across all 8-game histories, the number of reversals ranged from 0 through 7. Thus, low-reversals category includes all sequences with 0-3 reversals and the high-reversals category includes all sequences with 4 or more reversals. Across all 16-game histories, the number of reversals ranged from 1 through 14. Thus, 16-game histories with 1-7 reversals are included in the low-reversals category and histories with 8-14 reversals are considered to have a high level of reversals. Similarly, for 30-game histories, sequences with 6-14 reversals are categorized as low-reversal sequences, while sequences with 15-23 reversals are high-reversal sequences. (p-values are reported in parentheses.)

Performance History Length	Low Reversals	High Reversals	Difference
8-game Histories	0.12384	0.13315	-0.00931
	(0.0314)	(0.0315)	(0.8342)
	(N=3658)	(N=3590)	
16-game Histories	0.14014	0.12203	0.01811
	(0.0351)	(0.0351)	(0.7154)
	(N=2840)	(N=2946)	
30-game Histories	0.17427	0.04979	0.12448
	(0.0436)	(0.0429)	(0.0419)
	(N=1928)	(N=1908)	

Table VIII

Piecewise Regressions of Change in Spread on Streak Lengths

This table contains the results from the OLS regression of $CHANGE$ on various streak-length variables, the opening spread ($OPEN$), and an intercept term. The change in spread ($CHANGE$) is equal to the difference between the closing point spread and the opening point spread. Streak-length variables ($HWSTREAK_1$, $HWSTREAK_2$, $AWSTREAK_1$, $AWSTREAK_2$, $HLSTREAK_1$, $HLSTREAK_2$, $ALSTREAK_1$, and $ALSTREAK_2$) are transformations of the home and away teams' discrete winning- and losing-streak variables. For example, $HWSTREAK_1$ equals the minimum of 3 and the home team's winning streak length. $HWSTREAK_2$ is equal to the minimum of 0 and the home team's winning streak minus 3. Then, $AWSTREAK_1$ and $AWSTREAK_2$ are constructed in identical fashion, using visiting team's winning streaks instead. Finally, $HLSTREAK_1$, $HLSTREAK_2$, $ALSTREAK_1$, and $ALSTREAK_2$ are similarly constructed, using teams' losing streaks. (Associated t-statistics are reported beneath the corresponding estimated coefficients.)

	Model Coefficient Estimates	
Variable	(1)	(2)
$HWSTREAK_1$	0.1313	
	(4.43)	
$HWSTREAK_2$	-0.0914	
	(-1.69)	
$AWSTREAK_1$	-0.1582	
	(-5.36)	
$AWSTREAK_2$	0.1353	
	(2.50)	
$HLSTREAK_1$		0.1149
		(3.88)
$HLSTREAK_2$		-0.1880
		(-3.48)
$ALSTREAK_1$		-0.1245
		(-4.27)
$ALSTREAK_2$		0.0353
		(0.74)
$OPEN$	0.0148	0.0150
	(7.52)	(7.60)
Intercept	-0.0965	-0.1424
	(-2.19)	(-3.21)
N	4583	4583
R-squared	0.0231	0.0214