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

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ABSTRACT

Bloomfield and Hales (2002) find strong evidence that experimental market subjects are influenced by trends and patterns in a manner supportive of the shifting regimes model of Barberis, Shleifer, and Vishny (1998). We subject the model to further empirical scrutiny 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. We find scant evidence that investors behave in accordance with the model.

BARBERIS, SHLEIFER, AND VISHNY (1998) develop a model of investor sentiment that is consistent with two pervasive empirical anomalies that have been the focus of much research in finance: momentum in returns and reversals in returns.[1] The model is motivated by evidence documented by cognitive psychologists on two systematic biases that arise when people form beliefs, namely, conservatism and representativeness.[2] These biases are captured in a regime-shifting framework in which the earnings process follows a random walk, but investors hold the flawed belief that the process 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). A key feature of the model is that investors look at the frequency of past performance reversals to determine which regime currently governs performance.

A recent paper by Bloomfield and Hales (2002) reports results of laboratory experiments with MBA-student participants, which support the existence of

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[1] 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). 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).

[2] Conservatism refers to the tendency to underweight new evidence relative to prior beliefs and is suggestive of investor underreaction. Representativeness refers to the tendency to mistake superficial similarity for deep similarity and is suggestive of investor overreaction.

regime-shifting beliefs of the type theorized by Barberis, Shleifer, and Vishny. In the experiments, subjects observe historical sequences of signed earnings surprises for a security and then assign prices to the securities based upon expectations about the next observation in the sequence. Despite being told that earnings performance follows a random walk, participants consistently rely on the prevalence of past earnings performance reversals when assessing the likelihood of future reversals.

In this paper, we subject the Barberis, Shleifer, and Vishny assumptions to further empirical inspection using market data. Our tests are motivated in part by the suggestion in Barberis and Thaler (2003, p. 1118) that continued empirical scrutiny of assumed behavior is essential to validating the claims of behavioral finance theories: "If a theorist wants to claim that fact X can be explained by behavior Y, it seems prudent to check whether people actually do Y." Along similar lines, Hirshleifer (2001, p. 1577) suggests that "Routine experimental testing of the assumptions and conclusions of asset pricing theories is needed to guide modeling." Our tests are designed to determine whether the behavior hypothesized in the model and observed in the experimental laboratories extends to the marketplace.

The setting for our tests is the legal wagering market for college football games in the United States. As noted by Avery and Chevalier (1999), sports betting markets share many important features with stock markets (e.g., large volume, liquidity, wide availability of information), but have several advantages as an empirical laboratory. Particularly important for our tests is the feature 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 payoff.) Terminal values, measured as wins or losses against the spread, allow us to create signed historical performance sequences directly analogous to those shown to the experimental subjects of Bloomfield and Hales.

In our first set of tests, we examine market reactions following the identical set of eight-outcome historical performance sequences used in the Bloomfield and Hales (2002) experiment. We find that bettors do not react differently to low- and high-reversal historical sequences. Whereas experimental subjects appear to overreact to performances preceded by few reversals and underreact to performances preceded by many reversals, football bettors are insensitive to the number of recent reversals. The difference in outcomes might be due to differing information sets available to market participants versus laboratory subjects.

To maximize inferential power, we expand our analysis to include all 256 possible eight-outcome sequences and find similar results. Although tests that focus on longer historical sequences find some supportive evidence (with the 30-outcome sequences), overall it is hard to conclude that bettors fixate on the frequency of past performance reversals in a way that is consistent with Barberis et al. (1998).

We next refine the testing approach to examine another key prediction of the model that investors are more likely to expect a continuation in performance as the length of time since the most recent reversal increases. To investigate, we conduct a piecewise linear regression analysis of the intraweek change in point spread as a function of a team's current winning or losing streak against the spread. We find that spreads move in favor of teams that are on short winning streaks (i.e., streaks of three games or less), but move against teams that are on longer winning streaks. Contrary to the prediction of the Barberis, Shleifer, and Vishny model, this finding suggests that investors eventually expect a performance reversal as streak length grows.

Considering our evidence collectively, we conclude that our results are not supportive of investor behavior as theorized in Barberis et al. (1998). While there is some evidence that investors appear, over sufficiently long horizons, to rely upon the frequency of past reversals in predicting future reversals, our finding that investors come to expect that continuations in performance will reverse is inconsistent with a central feature of the model. This conclusion is not necessarily a reflection on the general importance of representativeness and conservatism in determining prices, but rather on the particular interaction of representativeness and conservatism that Barberis, Shleifer, and Vishny put forth in their regime-shifting framework.[3]

An alternative view is that the evidence we document is wholly consistent with the normal random variation in price changes that we should expect to see with efficient capital markets. However, to the extent that our findings reflect other behavioral biases (e.g., gambler's fallacy) or provide insight on relevant horizons, such can be incorporated in better models.

The remainder of the study proceeds in the following manner. Section I describes the market and provides further motivation for the study. Section II describes the sample. Section III describes the methodology and presents and discusses the results. Section IV discusses some possible implications of our findings and concludes.

I. The Market Setting

A. Betting Markets as a Useful Laboratory

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.[4] Direct tests in the stock market are especially difficult because of the many confounding factors involved. 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 (e.g., Dennis and Strickland (2002),

[3] Indeed, two recent working papers (Frieder (2004), Shanthikumar (2004)) using microstructure data find evidence that representativeness bias affects small traders in the stock market. The option price evidence of Poteshman (2001) is more supportive of the specific framework in the Barberis, Shleifer, and Vishny model.

[4] Hong, Lim, and Stein (2000) use analyst coverage data to find some support for the theory of Hong and Stein (1999).

Griffin, Harris, and Topaloglu (2003)). The task remains difficult even in markets in which regulators capture greatly detailed information about traders, such as in Finland.[5] Several papers avoid the behavior detection problem altogether and instead focus on the interaction between accounting fundamentals and subsequent market prices.[6]

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 of 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 middle ground. Compared to stock markets, they constitute an idealized laboratory setting; compared to experimental markets, they offer vast volumes of real money on the line over lengthy time series.[7] 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 feature stands in contrast to stock markets, which have no obvious predefined moment of terminal payoff. 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 point 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.[8]

[5] 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.

[6] Daniel and Titman (2003) find that predictability in stock returns lies solely in the component orthogonal to tangible accounting performance information. Chan, Frankel, and Kothari (2003) find little, if any, stock price evidence that investors extrapolate historical accounting performance sequences over future horizons. In contrast, Swaminathan and Lee (2000) report accentuation (attenuation) of postearnings announcement drift in stock prices when the most recent earnings signal contradicts (confirms) the prior earnings performance sequence.

[7] Another similar market is the Iowa Political Market. For a detailed description, see Forsythe et al. (1992).

[8] Researchers have also investigated whether sports betting markets suffer from certain behavioral biases. For instance, Gilovich, Vallone and Tversky (1985) find that although experimental subjects believe strongly in a "hot hand" effect, the outcomes of actual consecutive shots are effectively independent. Whether this aggregates market mispricing is less clear; see Camerer (1989), and Brown and Sauer (1993).

B. Characteristics of the Football Betting Market

The college football betting market is 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 (Hausch and Ziemba (1995), p. 549), total legal sports wagers in Nevada increased 50% to \$2.7 billion by 1997 (Sinclair (1998), p. 17).

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 sentiment, 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 investor belief in regime shifting.

II. Data

A. Source

This study uses 8 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 4,584 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. This data source is commonly used in academic studies of sports gambling markets (see, e.g., Dare and MacDonald (1996)).

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 also from those of other betting markets such as parimutuel 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. The market maker thus collects \$1 of every \$22 bet; so transactions costs are a known, fixed 4.54% on each transaction.

Betting on college football games 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. 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. 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 intraweek 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 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

$$SPREAD_{i,w,t} = E_t[HOMEPTS_{i,w} - AWAY\,PTS_{i,w}], \tag{1}$$

where $HOMEPTS_{i,w}$ is the home team's points scored and $AWAY\,PTS_{i,w}$ is the visiting team's points scored. In this study, for all games, only the opening and closing spreads are of interest, where $OPEN_{i,w}$ denotes the opening spread and is measured at the time betting commences, and $CLOSE_{i,w}$ 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 intraweek 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,

$$CHANGE_{i,w} = CLOSE_{i,w} - OPEN_{i,w}. \tag{2}$$

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; that is, for each game i in each week w, the outcome is

$$OUTCOME_{i,w} = HOMEPTS_{i,w} - AWAY\,PTS_{i,w}, \tag{3}$$

where $HOMEPTS_{i,w}$ is the home team's points scored and $AWAY\,PTS_{i,w}$ is the visiting team's 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:

$$OUTCATS_{i,w} = \begin{cases} 1, & \text{if } OUTCOME_{i,w} > CLOSE_{i,w} \\ 0, & \text{if } OUTCOME_{i,w} = CLOSE_{i,w} \\ -1, & \text{if } OUTCOME_{i,w} < CLOSE_{i,w}, \end{cases} \tag{4}$$

where $OUTCATS_{i,w}$ equals 1, 0, or -1, depending on whether the home team covered the spread, "pushed" (i.e., tied), 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

$$HLGnATS_{i,w} = \begin{cases} OUTCATS_{j,w-n} & \text{if home team played at home } n \text{ games ago in game } j \\ -OUTCATS_{j,w-n} & \text{if home team played away } n \text{ games ago in game } j, \end{cases} \tag{5}$$

and

$$ALGnATS_{i,w} = \begin{cases} OUTCATS_{j,w-n} & \text{if away team played at home } n \text{ games ago in game } j \\ -OUTCATS_{j,w-n} & \text{if away team played away } n \text{ games ago in game } j. \end{cases} \tag{6}$$

These lagged performance variables can then be used to classify teams' historical performance patterns into specific categories. Alternatively, they can be used to calculate teams' streaks (either winning or losing) against the spread, another useful historical performance measure. We define a team's current winning streak against the spread (*HW STREAK* for the home team, *AW STREAK* for the away team) as the number of consecutive times the team has covered the spread—up through its most recent game. A team's current losing streak against the spread (*HL STREAK*, *AL STREAK*) is similarly defined as the number of consecutive failures to cover spreads. If a given team pushes against 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.

The streak-against-the-spread variables are, in effect, measuring abnormal performance. However, bettors could fixate on raw team performance, the team's winning (or losing) streak per se, in their attempt to discern the governing regime. Thus, in unreported results we perform all of the tests in Section III using raw performance variables. We find little evidence that bettors fixate on raw winning or losing streaks. These findings are consistent with some evidence on the relation between stock market anomalies and abnormal performance. For instance, Grundy and Martin (2001) show that extreme abnormal stock returns are associated with more momentum than extreme raw stock returns are.

D. Summary Statistics

The average intraweek change in spread is indistinguishable from zero. Therefore, instead of simple averages and variances, 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% chance of beating the spread in any given game. This observation invites a more formal random walk test.

Toward 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, that is, the hypothesis of a random walk. For 105 of 113 teams in the entire sample, the hypothesis that performance follows a random walk cannot be rejected at the 5% significance level. None of the individual Z-scores falls outside the critical Bonferroni threshold for 5% joint significance, which is an absolute value of 3.51. 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. Frequency of Performance Reversals and Its Effect on Expectations

The central feature of the behavioral model of Barberis et al. (1998) is the assumption that although earnings follow a random walk, investors falsely believe that the earnings process shifts between two regimes. As a result of this belief, investors examine the pattern of past performance reversals to assess the likelihood of which regime governs earnings. Bloomfield and Hales (2002)

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 the 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 chi-square 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 chi-square value is 0.8618.)

Streak Length	Home Team	Relative Frequency	Visiting Team	Relative Frequency
−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	1,182	25.79	1,120	24.43
1	1,152	25.13	1,157	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

devise a set of laboratory tests meant to examine the validity of this assumption and its implication that investors are more likely to expect reversals after a high rate of recent reversals. In this subsection, 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.

The tests here, and throughout the rest of the paper, focus on price changes (intraweek point spread changes) as a function of patterns in the performance of past bets. In measuring the impact of behavioral biases on pricing, we harness

Table II

Excerpted Observations from Team-by-Team Runs Tests

This table contains observations for 35 teams among the 113 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). The normal numbers of runs and the Z-scores are calculated as described by Campbell, Lo, and MacKinlay (1997, Ch. 2, pp. 40–41). The Z-scores include a continuity correction as per Wallis and Roberts (1956).

Team	Total Number of Games	Total Number of Runs	Runs as % of Total	Normal Number 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
North 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

the result of Avery and Chevalier (1999) that point-spread changes during the week reflect the expression of investor sentiment. Absent behavioral biases, in an efficient market one pattern of prior outcomes should have no different impact from any other pattern on current price changes. Put even more strongly, in an efficient market the expected change in point spread during the week prior to the game is zero.

A.1. Eight-Week Horizons

We begin, in Table III, by simply recreating the eight specific eight-outcome performance history sequences (and their mirror images) used in the experiment of Bloomfield and Hales (2002). For each sequence, the table shows the mean change in spread during the week of betting preceding a 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. These findings are evidence against the model, but may be the result of small samples in each group.

To further investigate the hypothesis that the frequency of past reversals affects investor expectations, and to maximize inferential power, we expand our

Table III

Mean Changes in Spread for Specific Eight-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 game's outcome against the spread. Associated p-values are reported in parentheses.

Performance Sequence	Number of Reversals	N	Mean Change in Spread	Summary by Reversal Frequency
A: W-W-W-W-W-W-W-W	0	60	0.15000	
L-L-L-L-L-L-L-L			(0.2895)	
B: L-W-W-W-W-W-W-W	1	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	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	64	0.18750	
W-W-W-W-W-L-L-L			(0.2570)	
E: L-L-L-W-L-L-L-W	3	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	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	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	51	0.53922	(0.1973)
W-L-W-L-W-L-W-L			(0.3146)	(N = 118)

Table IV

Changes in Spread for All Eight-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 game's 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	1,187	0.11205	
		(0.0550)	
3	1,989	0.14555	Moderate:
		(0.0423)	0.12978
4	1,871	0.08445	(0.0237)
		(0.0429)	(N = 6,303)
5	1,256	0.18909	
		(0.0539)	
6	412	0.13350	High:
		(0.0937)	0.17819
7	51	0.53922	(0.0904)
		(0.3146)	(N = 463)

analysis of mean changes in spreads to include all 256 possible eight-outcome sequences. The results are shown in Table IV, classified by the number of reversals (0–7) in each sequence. In reaction to low-reversal (0–1), moderate-reversal (2–5), and high-reversal (6 or 7) 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 nonzero, nor is the difference in means. The evidence in Table IV strongly contradicts the prediction of the model; indeed, the findings are consistent with a scenario in which agents believe that the underlying process is a random walk.

In contrast to 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.

A.2. Sixteen-Week and 30-Week Horizons

We next test whether bettors might be examining histories longer than eight games when formulating their expectations about 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 0–3 reversals as being "low reversal"; sequences with 4–7 reversals are "high reversal." The number of reversals present in 16-outcome histories in our sample ranges from 1 through 14. We classify historical sequences with 1–7 reversals as being "low reversal"; sequences with 8–14 reversals are "high reversal." Similarly, for 30-game histories, "low reversal" constitutes numbers of reversals in the lower half of the sample range (6–14 reversals) and the "high reversal" category includes the rest (15–23 reversals). The results appear in Table V.

The first line in Table V indicates that the mean change in spread following eight-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. Similarly, investors do not appear to react differently to low-reversal and high-reversal sequences when examining 16-game histories. Both sets of results are evidence against the model.

When examining 30-game histories to assess performance, we find that investors do react differently depending on the number of reversals in the historical performance sequence. The mean change in spread following low-reversal performance sequences is a significant 0.17427, and the mean change in spread following high-reversal performance sequences is an insignificant 0.04979. The

Table V

Short versus 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 eight-game histories, the number of reversals ranged from 0 through 7. Thus, the low-reversals category includes all sequences with 0–3 reversals and the high-reversals category includes all sequences with four 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. Associated 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 = 3,658)	(N = 3,590)	
16-game histories	0.14014	0.12203	0.01811
	(0.0351)	(0.0351)	(0.7154)
	(N = 2,840)	(N = 2,946)	
30-game histories	0.17427	0.04979	0.12448
	(0.0436)	(0.0429)	(0.0419)
	(N = 1,928)	(N = 1,908)	

difference is a statistically significant 0.12448. It is hard to attribute this to investor fixation on past performance reversals. That is, if investors do not condition on what happened over the most recent 8- and 16-week horizons, why would the least recent 14 weeks within a 30-game horizon be pivotal in shifting regime expectations? One possibility is that compared to experimental subjects, bettors need a sufficiently longer sequence of high-reversal performance to affect expectations about subsequent performance. Still, at best this is weak evidence in support of the model.

B. Streak-Based Tests

In the previous section, we examine whether the rate of reversals in historical sequences of fixed length affect investor expectations of future reversals in performance. In this section, we refine the testing approach with a piecewise regression analysis of the intraweek change in spread 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, in effect, a measure of the distance in time to the most recent reversal, a streak-based approach allows a test of another implication of the Barberis, Shleifer, and Vishny model: Investors are ever less likely to expect a reversal in performance, as the time since the most recent reversal increases. As Barberis et al. (1998, p. 310) put it, "when a positive earnings surprise is followed by another positive surprise, the investor raises the likelihood that he is in the trending regime, whereas when a positive surprise is followed by a negative surprise, the investor raises the probability that he is in the mean-reverting regime."

The regression we estimate is as follows:

$$CHANGE = \alpha + \beta_1 HWSTREAK_1 + \beta_2 HWSTREAK_2 + \beta_3 AWSTREAK_1 + \beta_4 AWSTREAK_2 + \gamma OPEN + \epsilon, \tag{7}$$

where

$$HWSTREAK_1 = \begin{cases} HWSTREAK & \text{if } HWSTREAK < SLENGTH \\ SLENGTH & \text{if } HWSTREAK \geq SLENGTH, \end{cases} \tag{8}$$

and

$$HWSTREAK_2 = \begin{cases} 0 & \text{if } HWSTREAK < SLENGTH \\ HWSTREAK - SLENGTH & \text{if } HWSTREAK \geq SLENGTH, \end{cases} \tag{9}$$

where *HWSTREAK* denotes the home team's current winning streak and *SLENGTH* denotes a streak-length threshold value.[9] The remaining

[9] Because no turning point in sentiment is ex ante apparent, we utilize a one-dimensional grid-search technique, as described in Greene (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.

explanatory variables ($AW\,STREAK_1, AW\,STREAK_2$) are defined similarly using the away team's current winning streak, $AW\,STREAK$. We also include the opening spread ($OPEN$) as a control variable.

The dependent variable in this analysis is $CHANGE$, the intraweek 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 the current change in spread. Under this hypothesis, none of the streak length variable coefficients should be significant such that $\beta_i = 0\ \forall i$. Under the regime-shifting alternative of Barberis et al. (1998), investors bet on continuation of past streaks, a hypothesis that implies $\beta_i > 0, i \in \{1, 2\}$, and $\beta_i < 0, i \in \{3, 4\}$. We note that the away-team streak coefficients have signs opposite of the home-team coefficients due to the quoting convention by which spreads are always stated from the perspective of the home team.

Table VI shows the results of our piecewise linear regression of the intraweek change in spread on the streak variables. Column one 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 $HW\,STREAK_1$ (short winning streak indicator) is positive and statistically significant. This finding is consistent with bettors expecting the home team's short-term performance to continue; for example, the spread moves in the direction of a home team that is on a winning streak of three games or less. The negative coefficient on $HW\,STREAK_2$ suggests that bettors expect that the 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.

The results reported in column 2, based on losing streaks, are qualitatively similar. This specification includes losing streak variables instead of winning streak variables, together with an intercept term and the opening spread. These variables, $HL\,STREAK_1$, $HL\,STREAK_2$, $AL\,STREAK_1$, and $AL\,STREAK_2$ are defined in the same manner as the winning streak variables, except that a losing streak is negative and so the turning point, $SLENGTH$, is negative as well. The estimated coefficient on $HL\,STREAK_1$ (short losing streak indicator) is positive and statistically significant; this finding is consistent with bettors expecting the losing streak to continue. The $HL\,STREAK_2$ coefficient is significantly negative, suggesting that bettors expect the performance of home teams on longer losing streaks to reverse. For away teams, the significantly negative $AL\,STREAK_1$ coefficient suggests bettors expect short-term losing streaks to continue; the coefficient on $AL\,STREAK_2$ is insignificant.[10]

Overall, the piecewise regression results are not consistent with the Barberis, Shleifer, and Vishny prediction that investors are more likely to believe they

[10] For robustness, we also perform additional regression analyses besides those shown in Table VI; the additional specifications include various sentiment variables that are found to exhibit explanatory power in the National Football League betting market (Avery and Chevalier (1999)). The streak length results are qualitatively the same when these control variables are included.

Table VI

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 three and the home team's winning streak length. $HWSTREAK_2$ is equal to the minimum of zero and the home team's winning streak minus three. 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	4,583	4,583
R^2	0.0231	0.0214

are in a continuation regime, the longer the time since the most recent reversal. Rather, as streak length increases, investors behave as if they expect the streak to reverse. While this could be considered regime shifting of a sort, it is not the kind envisioned by the model.

IV. Conclusion

Bloomfield and Hales (2002) report results of laboratory experiments with MBA-student participants who observe historical sequences of signed earnings surprises for a security and then assign a price based upon expectations about the next observation in the sequence. As hypothesized by Barberis et al. (1998), participants consistently rely on the prevalence of past earnings performance reversals when assessing the likelihood of future reversals. In this paper, we conduct a market test in which participants are exposed to the very same sequences of surprises, and measure their reactions. Whereas the MBA students show consistent overreliance on perceived patterns of recent reversals in performance, football bettors are relatively insensitive to the frequency of recent performance reversals.

Our conflicting findings may be due to differences in experimental setting. For example, in our market setting, bettors learn by observing random walk sequences over long periods, whereas in the laboratory setting, participants are specifically told that the observed sequences follow a random walk. Bloomfield and Hales consider altering their experimental setting to conform with this feature of the marketplace: "An alternative would be to provide no such information, but allow participants to learn the nature of the time series by observing patterns of outcomes for a long time. We doubt, however, that this alternative approach would yield substantially different results." One possibility is that laboratory participants are not convinced of the underlying process when it is simply communicated by the experimenter.

Our tests revealing that bettors come to expect a reversal in performance as streak length grows are in contradiction to the model's implication that investors become more certain that they are in the continuation regime as the number of periods since the last reversal increases. Alternatively, this finding could be viewed as consistent with behavior induced by the well-documented psychological phenomenon known as the gambler's fallacy.[11] The classic example is where, after a string of reds at the roulette wheel, bettors expect that a "black is due." Our finding that longer streaks lead to greater expectations for a reversal is in keeping with this phenomenon. As the gambler's fallacy represents a departure from Bayesian reasoning in situations in which individuals know that sequences follow a random walk, it is in conflict with the world of Barberis, Shleifer, and Vishny, in which individuals are rational Bayesian updaters using the wrong sequence-generating model.

It is difficult to draw inferences from our results that would be applicable to other prominent behavioral theories such as Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). One view of the evidence we document here is that it contributes to the interaction and feedback between theory and empirics, which is especially important in developing new and challenging paradigms. In many respects behavioral finance is in its infancy and still faces what Fama (1998) refers to as the "daunting task" of replacing market efficiency with better, more specific models of price formation. This task is

[11] Studies that present evidence on the gambler's fallacy include Tversky and Kahneman (1971), Metzger (1985), Bar-Hillel and Wagenaar (1991), Rapoport and Budescu (1992), Clotfelter and Cook (1993), Terrell (1994), and Burns and Corpus (2004). See Rabin (2002) for a recent review of the evidence on belief in the law of small numbers.

made all the more difficult by the broad range of judgment biases that have been documented in the cognitive psychology literature. To the extent that the gambler's fallacy is present in the behavior of market participants, incorporation of its effects may prove useful in developing both improved laboratory experiments and improved models.

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