Identifying Investor Sentiment from Price Paths: The Case of Football Betting*

I. Introduction

The possibility that some participants in financial markets act irrationally has been suggested in the finance literature since at least the time of Keynes (1936). The proposition that these “noise traders” can affect asset prices has been frequently disputed. However, several recent articles show conditions under which rational arbitrageurs do not eliminate sentimental mispricing.1 Our particular interest in this article is in investor sentiment, which we define as any nonmaximizing trading pattern among noise traders that can be attributed to a particular exogenous motivation. We test the hypothesis that investor sentiment can affect both

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We examine the hypothesis that sentimental bettors can affect the path of prices in football betting markets. We hypothesize that sentimental traders follow the advice of false experts, believe excessively in momentum strategies, bet excessively on teams that are well known and covered in the media. We generate proxies for these sources of sentiment and show that point spreads move predictably over the course of the week, partially in response to variables known prior to the opening of betting. We show that a betting strategy of betting against the predicted movement in the point spread is borderline profitable.
average prices and the path of prices in an empirical analysis of football point-spread betting.

The football betting market offers several important advantages over traditional asset markets as an empirical setting. The first useful feature of the football betting market is that all bets reach a terminal value in a relatively short time. Betting on a particular set of games proceeds actively in the week prior to the games and then investments pay off or fail with the outcome of the games. The outcomes of those games provide a means for measuring the success of investments and, therefore, a means to determine if investors were indeed trading based on sentiment. In contrast, there is no "settling up" point for most assets in the stock market. The absence of a settling up point makes it difficult to ascertain whether assets have drifted away from their fundamental values due to sentiment.

The football point-spread market shares many important features with the stock market. In particular, while the football betting market is dominated by individual traders, there are many professional bettors who devote themselves to attempting to exploit mispricing. As in the stock market, information about prices is widely disseminated; Las Vegas point spreads are published in most newspapers. Finally, the wisdom of "experts" is in demand; picks are available from on-line services, newsletters, sports shows, newspaper columns, books, pay-per-view services, and 1-900 telephone numbers. Our goal in this article is to learn whether bettor sentiment drives the path of football point spreads (also called betting lines) to move in a systematic way from the opening of betting on a game to the closing of betting on that game 1 week later.

We consider three possible sources of sentiment for participants who bet on football games: (1) so-called expert opinions (which are actually uninformative), (2) a hot-hand bias, and (3) a bias toward prestigious teams. Each of these sources of sentiment has a natural analogue in the stock market. We use the published predictions of sportswriters to represent expert opinions and we use recent game outcomes as a proxy to represent sentiment due to the hot hand. We use performance from the past year and conference membership as measures of prestige for each team.

Our article is distinct from previous studies of betting markets because it studies the path of point spreads during betting. Most previous articles have concentrated solely on the accuracy of the final betting line in various sports (see Gander et al. 1988 for many more references; see also Brown and Sauer 1993a; Woodland and Woodland 1994; and Gray and Gray 1997). Much of the previous literature has focused on

2. Most tests for the efficiency of the final point spread for football games have been inconclusive. One limitation of these tests is that a range of prices eliminate arbitrage since
the possibility that individuals systematically overbet on the favorite team or the home team, with the exception of several articles that test for a hot-hand bias (Camerer 1989; Brown and Sauer 1993b). Our goal in this article is to restrict our attention to examining possible sources of mispricing that have natural analogues in the stock market.

The only other articles, of which we are aware, that compare the final point spread to the initial point spread are Gandar et al. (1988, 1998). These articles test for the presence of sentiment in the football and basketball betting lines by comparing the predictive power of the final point spread to that of the initial point spread. Both articles find that the final point spread is more accurate than the opening point spread. As we will show, this test may not have high power as a test of betting line efficiency because changes from the opening to the closing point spread can reflect either sentiment or new information.\(^3\) Thus, in our article, we attempt to uncover the source of point-spread changes over the course of the week, distinguishing between changes that reflect new information and changes that can be predicted from information known prior to the start of betting.

In our 12-year sample of games from 1983 to 1994 (excluding the strike season of 1987), we find that each set of sentiment variables serves as a significant predictor of point-spread movements, but not of actual game outcomes. These results suggest that some investors trade on sentiment and that this trading alters the path of prices. This demonstrates a clear inefficiency in the point-spread market: it should not be possible to predict point-spread movements from information already known at the time the line was set. We also find that movements in the line that cannot be predicted from sentiment variables are strongly predictive of game outcomes. Thus, changes in the betting line during the week do indeed reflect two separate effects. One component of changes in the betting line is due to new information that arrives during the course of the week; another component of changes in the betting line is distortion due to sentiment. We also find evidence that Las Vegas incorporates sentiment in setting its opening point spread, creating two sources of bias in the point spread due to sentiment: the opening point spread is biased because of sentiment and there is a small but systematic increase in that bias during the week of betting. The strategy derived from our study, betting against the predicted sentiment in the point spread, is borderline profitable even after the casino’s commission is

there is a transactions cost to betting. We believe that following the path of the point spread during the week provides a much cleaner means for testing the efficiency of the market.

3. Gandar et al. (1998) argue that changes in the basketball point spread are less likely to reflect new information than changes in the football point spread because the period of betting is shorter for basketball than for football games. Gandar et al.’s conclusion that initial point spreads for basketball games are chosen poorly is by no means clear, since information may arrive at different rates for different sports.
paid. If there are no transactions costs to trading, then arbitrage in the form of contrarian strategies should eliminate pricing imperfections due to sentiment.

The article proceeds as follows: Section II considers how sentiment might affect price paths in football betting. Section III describes some institutional aspects of the football betting market. Section IV describes the data. Sections V–VII present an empirical analysis of the efficiency of the football betting market. Finally, Section VIII concludes.

II. Theoretical Background to the Problem

This section discusses the conditions under which sentiment will be identifiable from price movements. Clearly, sentiment will only have an effect on price levels in an asset market if sentiment is correlated across investors—that is, at a price equal to the asset's true fundamental value, the aggregate demand of noise traders is nonzero. In considering the effect of sentiment on the path of prices, we distinguish between anticipated sentiment, which can be predicted in advance of trading of the new asset, and unanticipated sentiment, which only becomes known during the period of trading. For simplicity, throughout this section, we will consider the case in which the aggregate demand of sentimental investors favors buying.

A. Unanticipated Sentiment

We consider the case in which sentiment arrives during the course of trading as an unanticipated demand shock. This shock will lead to an observable trend in prices whenever it distorts the equilibrium price from the true expected value of the asset. The previous literature on investor sentiment (see, e.g., DeLong, Shleifer, Summers, and Waldmann 1990; Shleifer and Vishny 1997) has shown that, under certain circumstances, investor sentiment can distort the market price. This literature has not focused on deriving the minimal set of conditions that are required for sentiment to affect equilibrium asset prices. However, these conditions can easily be derived. Each of the four conditions required for unanticipated sentiment to affect price paths are:

1. The aggregate demand due to noise traders is nonzero (in expectation) at a price equal to the expected value of an asset;\(^4\)
2. there is some transactions cost to arbitrage: it is costly to enter the market as a trader or to acquire information;
3. there is residual uncertainty in the value of the asset conditional on the (aggregate) private information held by informed traders; and
4. informed traders are risk averse.

\(^4\) In a rational expectations equilibrium, the expected value of the asset is conditional on trading information.
Investor Sentiment

Requirement 1 simply states that sentiment is in favor of buying or selling so that it could affect the average asset price without a response from informed traders to offset sentiment. Requirement 2 simply guarantees that the entry of new traders in response to pricing inefficiencies only produces limited demand from arbitrageurs. Requirements 3 and 4 combine to limit the response of informed traders to sentiment. If the asset value is known with certainty after trading or if informed traders are risk neutral, then the informed traders will buy as many shares as possible for any price less than the expected asset value. An alternative version of requirement 4, which would also produce the same result, is that informed traders are risk neutral but strategic. A finite set of risk-neutral informed traders who consider the effect of their trades on the price will not trade sufficiently to completely offset the effect of sentiment in the price.

It is important to note that many models of trading fail to satisfy the requirements for sentimental investors to affect the equilibrium price. For example, Glosten and Milgrom (1985) study a market in which prices are set by competitive and risk-neutral market makers. In their model, the price equals the expected value of the asset conditional on public information and the current trade; sentiment cannot distort the expected trading price. Viewing Glosten and Milgrom's market makers as additional traders, it is clear that sentiment cannot affect prices because requirements 2 and 4 above do not hold. As risk-neutral traders, the market makers in the Glosten and Milgrom model offset any trading imbalance due to sentiment without affecting the price. Further, free entry into the market-making sector is inconsistent with requirement 2, that there are transactions costs to entering the market. The existence of a limited number of risk-averse market makers is required for sentiment to affect equilibrium prices. Thus, for unanticipated sentiment to affect the path of prices in football betting markets, it would have to be the case that both bettors and market makers (casinos) face transactions costs to enter the market, and that both bettors and casinos are risk averse, or behave as if they are risk averse. The regulatory hurdles required to start a sports book insure that there is not free entry in the legal sports book market. As discussed in Section III, casinos (appear to) behave as if they are risk averse, though this behavior may stem from factors other than literal risk aversion on the part of the casinos.

B. Anticipated Sentiment

While unanticipated sentiment alters the path of prices in a wide variety of situations, we find that more specialized conditions are necessary

5. In contrast, one implication of the Diamond and Verrecchia (1991) study of disclosure and liquidity is that risk-averse market makers will adjust the price on average to account for sentiment.
for fully anticipated sentiment to alter price paths. This should not be surprising since anticipated sentiment merely shifts the position of the demand curve in a manner that is known before trading occurs. In general, one might expect that the full effect of anticipated sentiment should be captured in the initial market clearing price, so that there is an equal distortion in the price across all periods of trading. That intuition holds in many, but not all, circumstances. Circumstances under which anticipated sentiment can affect the path of prices are described below.

1. Dynamic uncertainty. Dynamic uncertainty can lead to trends in price paths, but the direction of the trend is ambiguous. For example, suppose that there is uncertainty about the realized volume of sentimental demand, but that sentimental demand will be the same throughout the period of trade. Ordinarily, a monopolist market maker would increase the price from the true expected value of the asset in response to sentiment. Given the uncertainty about realized sentiment, the monopolist faces two separate risks.

First, if realized sentiment is in favor of selling rather than buying, the monopolist could end up taking a buy position but at an unfavorable price in initial trading.

Second, if realized sentiment is even more in favor of buying than was expected, the monopolist could end up taking a larger selling position then expected in initial trading. These risks lead to countervailing incentives. The monopolist can protect against the first risk by reducing the price initially so that it is closer to the true expected value, but this also leads to a (further) imbalance of buy orders on average and exacerbates the second risk. Since these risks have opposite implications for initial pricing, it is not possible to make an absolute prediction about the influence of dynamic risk considerations for pricing. The introduction of competition, additional demand uncertainties, and the arrival of further information over time complicate the analysis without clarifying the results.

2. Market composition and price discrimination. Simple price discrimination can produce price trends if the distribution of traders changes over time. Holding commissions fixed, imperfectly competitive market makers will always mark up the price from the expected asset value to take advantage of sentimental traders. Holding other trading conditions fixed, these market makers will choose the largest mark-ups when the ratio of sentimental traders to maximizing traders is the greatest. If sentimental traders are most important toward the end of trading, then prices will move in the direction of sentiment, increasing over time in a market with sentimental buying.

In our context of football betting, we suspect that sentimental traders tend to arrive late in the week rather than early in the week. A large fraction of the sentimental bettors are probably tourists who are likely
to be most prevalent on the weekend. Since the betting week runs from Monday through Sunday, there is probably a greater proportion of sentimental bettors at the end of the week than there is at the beginning of the week. Further, sentimental bettors may be those who co-consume the placing of the bet and watching of the game. Those bettors, who may (illegally) place bets with a local bookie who clears the bet in the legal market, may also be more likely to bet at the end of the week.

There is some evidence that the proportion of sentimental to rational investors fluctuates predictably in other asset markets. For example, recent literature has examined long-run price drifts following initial public offerings (IPOs) (Ritter 1991; Loughran and Ritter 1995), stock splits (Ikenberry, Rankine, and Stice 1996), seasoned equity offerings (Loughran and Ritter 1995), and equity repurchases (Ikenberry, Lakonishok, and Vermaelen 1995). It is quite possible that major events such as equity purchases, equity sales, or stock splits generate large inflows or outflows of sentimental investors. Further, Lakonishok and Maberly (1990) document that the composition of individual versus institutional investors varies systematically during the course of the week and argue that these compositional changes cause pricing anomalies.

3. Myopic pricing. Sentiment can influence the path of prices with perfectly competitive market makers if those market makers are risk averse and compete myopically during the period of trade.

In a market with sentimental buying outweighing sentimental selling, the market makers will tend to build an inventory of buy orders. Then their risk premium for further buy orders increases during the period of trade. If the market makers compete in a myopic Bertrand fashion, they will compete to the point where they receive zero utility from the trades in each period. In this case, the price will increase from period to period on average to reflect the growing risk premium faced by each market maker for accepting another buy order. Prices should be stationary, however, if market makers recognize the possibility of dropping out of the market in early trading in order to avoid taking on an inventory of sentimental trade orders and to gain a profit in yet subsequent trading.

4. Market maker irrationality. Fully anticipated sentiment could move the line systematically over the course of the week if casino line-setters systematically underestimate the degree of sentiment present in the market. At first glance, one might be reluctant to accept such an explanation, as the profits of bookmakers presumably rely on both their understanding of the true probabilities of game outcomes and their understanding of investors’ misperceptions of those probabilities. However, persistent underestimation of the degree of sentiment is closely related to “the curse of knowledge,” a psychological phenomenon described in Camerer, Loewenstein, and Weber (1989). Camerer, Loewenstein, and Weber examine a situation in which an agent is as-
signed the task of reproducing the judgment of a less-well-informed agent. Although the agent who possesses private information knows the information set of the less-well-informed agent, experimental subjects systematically incorporate some of their private information into their assessment of the less-well-informed agent’s judgment. That is, in predicting the judgments of others, an agent is typically unable to ignore additional information that he alone possesses. Camerer, Loewenstein, and Weber examine whether market forces, learning from feedback, and financial incentives reduce the magnitude of the curse. They find that the bias persisted in experiments with market dynamics, but it was half as large as the bias in individual judgments.

Bookmakers have good information about the maximum likelihood game outcome. If they suffer from the curse of knowledge, they might set lines as if the bettors were almost as well informed. Thus, they would systematically underestimate the amount of misinformed sentiment to incorporate into the line and be forced to update the line when excess betting built up on one side.6

C. Testable Hypotheses

Our discussion of the theoretical possibilities leads to the following set of testable hypotheses:

HYPOTHESIS 1. Betting lines will move in the direction of investor sentiment.

HYPOTHESIS 2. Movements in the line caused by sentiment will not predict game outcomes.

HYPOTHESIS 3. Market makers (e.g., the casinos) will adjust the opening betting line to account for sentiment, but (due to hypothesis 1) the opening betting line will not incorporate sentiment to the same degree as the closing betting line.

HYPOTHESIS 4. The effect of sentiment on prices is bounded by the marginal transactions cost that would be incurred by an arbitrageur attempting to profit by trading against sentiment.

HYPOTHESIS 5. Changes in the betting line, which could not be predicted as the result of sentiment, are informative about the game outcome.

We test these predictions based on a set of selected variables that proxy for popular sentiment about the likely outcome of professional football games. The null hypothesis is that the sentiment variables neither affect the path of point spreads nor are they predictive about game

6. This particular explanation for the results most closely matches the impressions of Joe Lupo, the sports book manager at the largest sports book in Nevada, Stardust Casino. In a telephone interview in May 1998, Lupo characterized the bookmaker’s goal as trying to incorporate predicted sentiment fully in the opening line but ascribed our results to that process being an “imperfect science.”
outcomes given the closing point spread. Our alternate hypotheses are hierarchical: first, that unanticipated sentiment variables satisfy hypothesis (1) to hypothesis (5) and, second, that all sentiment variables do so. We study unanticipated and anticipated sentiment separately because, as noted above, a stronger set of assumptions about market behavior is required for fully anticipated sentiment to affect the path of prices.

III. Institutional Details: The Football Betting Market

In this section, we briefly describe the football betting market and mention the links between our hypotheses and the institutional details of the market. Betting on football games is based on point spreads rather than odds. In Super Bowl XXX, played in January 1996, Dallas was favored over Pittsburgh by 13.5 points, meaning that a bet on Dallas required Dallas to win by more than 13.5 points, while a bet on Pittsburgh required them to lose by less than 13.5 points or to win outright. Had Dallas won by exactly 13.5 (impossible in the given circumstance because scores are in integral increments), all bets would have tied, with no money changing hands. Bets on Pittsburgh were successful, even though Pittsburgh lost the game, because the winning margin was less than the point spread. Since bets on Pittsburgh were winning bets, it is said that Pittsburgh won against the point spread (or “covered the point spread”) and that Dallas lost against the point spread (or “failed to cover the point spread”).

Point spreads may change during the week prior to the game. However, bettors receive the point spread in effect at the time at which they placed their bets. Point spreads move in 1/2 point increments. If the point spread is not at an integral value, as in this example, then each bet wins or loses, for it is impossible for the game outcome to match the point spread.

Legal betting on the National Football League (NFL) is coordinated by Las Vegas casinos, which act as market makers, setting prices and accepting bets on either team competing in a given game. Rather than setting a bid-ask spread, the casinos take a 10% commission (known as vigorish or juice) on any losing bet. For example, for a $10 bet, the bettor pays $11 and wins either $21 or $0. Therefore, one must win a proportion of 11/21 or 52.4% of bets to break even (see Gandar et al. 1988; and Root 1989, chap. 4, for further details).

The casinos do not necessarily set the initial point spread to their assessment of the median in the distribution of game outcomes, which would make a bet on either team equally likely to win or to lose. Instead, they choose a point spread to try to balance the betting on each team. With balanced betting on both teams, the casino is assured of making money on the game through commissions, regardless of which team wins against the spread.
The point spreads offered at each casino may change over the course of the week for two reasons. First, a casino may change its point spread when relevant information is released. For example, a casino might change a line when an announcement is made about a player’s injury status. Second, and more important for our analysis, the point spread may change because the casino is receiving more bets on one side of a game than it is receiving on the other side.

We know that sentimental betting should not affect prices in the football betting market if casinos are willing to take large positions against sentimental bettors. However, most accounts of the market emphasize the propensity of casinos to set and alter the line over time to balance betting even if the casino does not believe that the new point spread predicts the game outcome more accurately than the original point spread (Gandar et al. 1988; Root 1989). Indeed, the casinos appear to behave as if they are risk averse in their choice of the lines or as if they have other costs from maintaining an unbalanced book. One explanation for why the casinos balance betting even if there is predictable sentimental betting on one side could be because the casinos are literally risk averse. A more attractive possibility is that the casinos balance betting because they do not want bettors or regulators to believe that the casino has an incentive to try to fix a game. A further possibility is that the casino forces the sports book manager to maintain a balanced book in response to the agency problem between the sports book manager and the casino. If the book manager was allowed to maintain implicit bets on behalf of the casino, the book manager would presumably share in the gains if the casino won the implicit bets but, at worst, could lose his job if the casino lost the implicit bets. Thus, forcing a balanced book may be an alternative to an explicit incentive scheme that attempts to control the book manager’s risk-taking behavior. This explanation is consistent with evidence in trading markets for other commodities. The maximum size of a trader’s overnight open position is typically set by trading firms (see Lyons 1996, p. 194, for details).

IV. Data

Point spreads for each professional football game played in the National Football League are published daily during the season in newspapers throughout the United States. There were 28 teams and thus

7. Casinos typically have a stake in the outcome only for games that are played out before the bettor using regulated equipment (e.g., card games, baccarat, slot machines, etc.).

8. Joe Lupo confirms that the casino sets a maximum net position allowed for each game. However, Lupo notes that some increase in that budget would typically be allowed when a clear case of bettor sentiment can be made. However, he characterized such increases as limited by the fact that, ultimately, “the book has to respect the money.”
8–14 games took place each week between 1976 and 1994; the NFL expanded to 30 teams in 1995. The majority of the games take place on Sunday afternoon, although one game per week is played on Monday night and there are occasional games at other times (generally Thursday and Sunday nights).

There is no official Las Vegas line because the casinos may have slightly different lines on a given game, notably if the imbalance of betting has not been consistent at each casino (Root 1989, ch. 4). Most newspapers subscribe to a syndicate that provides point spreads that are representative of the current betting lines in Las Vegas. For example, the Boston Globe publishes lines provided by Sports Features Syndicate.

We collected point-spread data from three newspapers, USA Today (1983–94), the Boston Globe (1983–94), and the Dallas Morning News (1992–94). Our primary data source was the USA Today betting lines; these are provided to the newspaper by Danny Sheridan, a noted betting expert. We studied point spreads for all regular season games from 1982 to 1994, excluding 1987, which was disrupted by a player’s strike.

We checked for systematic errors in the USA Today point spreads in two ways. First, we compared the set of USA Today point spreads against the point spread quoted for each game in the Friday Boston Globe. We also recomputed our results for the 1992–94 period using a different betting line created by Michael “Roxy” Roxborough, an independent consultant who supplies the Las Vegas casinos with suggested point spreads for each sports event. It is said that up to 70% of the casinos use the Roxborough line as their baseline point spread. We collected Roxborough’s point spreads from the Sunday edition of the Dallas Morning News over the period 1992–94. The results for the Roxborough point spreads are remarkably similar to the results using the USA Today point spreads for 1992–94.

Every regular season game in the National Football League is played at a home site provided by one of the teams. For a given game, the point spread in our sample is represented with respect to the home team. A point spread of -7 indicates that the home team is favored by 7 points. A point spread of -7 indicates that the visiting team is favored by 7 points.

9. From 1983 to 1989, each team played once per week in a 16-week season. From 1990 to 1994, each team had 1 week off during a 17-week season, with the exception of 1993 when each team had 2 weeks off during an 18-week season.

10. USA Today began publishing in 1982, but that season was also abbreviated due to a players' strike. In 1982, due to the strike, only seven regular-season games were played and 16 teams advanced to the playoffs, more than in any other season in our sample.

11. Dare and MacDonald (1996) study the effect of alternate methods for indexing the point spread.
### TABLE 1 Distribution of Point-Spread Changes during the Week

<table>
<thead>
<tr>
<th>Movement in Point Spread</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Cumulative Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3 or less</td>
<td>24</td>
<td>.010</td>
<td>.010</td>
</tr>
<tr>
<td>-2.5</td>
<td>28</td>
<td>.012</td>
<td>.0220</td>
</tr>
<tr>
<td>-2</td>
<td>42</td>
<td>.018</td>
<td>.040</td>
</tr>
<tr>
<td>-1.5</td>
<td>91</td>
<td>.038</td>
<td>.078</td>
</tr>
<tr>
<td>-1</td>
<td>236</td>
<td>.100</td>
<td>.178</td>
</tr>
<tr>
<td>-.5</td>
<td>431</td>
<td>.182</td>
<td>.360</td>
</tr>
<tr>
<td>No change</td>
<td>705</td>
<td>.298</td>
<td>.658</td>
</tr>
<tr>
<td>+.5</td>
<td>376</td>
<td>.159</td>
<td>.817</td>
</tr>
<tr>
<td>+1</td>
<td>253</td>
<td>.107</td>
<td>.924</td>
</tr>
<tr>
<td>+1.5</td>
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<td>17</td>
<td>.007</td>
<td>.992</td>
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<tr>
<td>+3 or more</td>
<td>18</td>
<td>.008</td>
<td>1.00</td>
</tr>
<tr>
<td>Total</td>
<td>2,366</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

**Note.**—Point-spread change is computed by the difference between Sunday’s point spread and the effective opening point spread.

For each game, we collected the opening lines listed on Monday, the lines on Tuesday and Thursday during the week, and the closing lines listed on the following Monday.\(^{12}\) We also collected Wednesday lines for games involving teams that played on Monday night, after the publication of the initial line for the next week’s games. Whenever a team plays a Monday night game, we take Wednesday’s betting line as the opening line for that team’s next game, as that is the first time that we are certain that the betting line incorporates the result of the Monday night game. Similarly, when either team has played on Sunday night, we take the Tuesday line as the opening line. Our initial sample consists of 2,464 games. As mentioned above, we eliminated nine games for which there is a large discrepancy between the *USA Today* line and the *Boston Globe* line.

We eliminated 11 games for which the opening line is missing,\(^{13}\) and 78 games for which the closing (Sunday) line is missing, leaving a total of 2,366 games in our sample.

Table 1 gives the distribution of point-spread changes during the week. The point spread changed from the initial point spread in 79.1% of the games. Most point-spread changes are fairly small. A change of

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12. When one of these lines is missing from *USA Today*, we replace it with the next day’s line.

13. If Monday’s point spread is missing, we take Tuesday’s point spread as the opening line. If both are missing, we eliminated the game from the sample.
at least one point occurred in 36.1% of the games. The average change in point spread across all games (including those where there was no change) was 0.68 points.¹⁴

V. Sentiment and Movements in the Point Spread

Most of the sentiment variables that we examine, such as recent performances of the teams, are observable at the start of the week. Any systematic pricing effect due to these variables could be predicted when the opening point spread is set. These variables represent anticipated sentiment. We have also collected data on expert predictions for the games that are published in the Friday *Boston Globe*. We take expert predictions to represent unanticipated sentiment because these predictions are potentially not known at the start of trading. Our goal in choosing sentiment variables was to examine variables that have natural analogues in other asset markets.

A. Unanticipated Sentiment: Expert Opinions

We collected expert predictions published in the Friday edition of the *Boston Globe*. Each of the six experts, generally Boston sportswriters, predict the outcome of each game against the spread.¹⁵

These experts are known to varying degrees outside of Boston; Will McDonough is particularly well known as a commentator for the national networks ESPN and NBC. In addition to the six local experts, we collected the predictions of two syndicated writers, Gerald Strine and Jeff Sagarin, whose predictions are published in many newspapers. Strine predicts only a few games each week, which he describes as the best bets of that week. Sagarin does not explicitly make picks but instead publishes an alternate betting line.

For all of the experts except Sagarin, we measure the expert opinions as simple categorical variables: 1 if the expert picked the home team, −1 if the expert picked the visiting team to beat the spread, and 0 if the expert made no pick. We represent Sagarin’s predictions as the difference between his betting line and the Vegas opening line: SAG = actual Sagarin line − opening point spread.

Table 2 lists the experts who predicted games in our sample period along with their success rates. Their success rates are shown relative to the betting line published in the *Boston Globe* on the day that the

¹⁴. There is a small, but statistically significant, negative drift of .016 points per game from the opening point spread to the closing point spread in our sample.

¹⁵. However, the expert predictions are made earlier in the week on Wednesday or Thursday. Thus, the predictions are technically picks against the spread prevailing on Wednesday. Sagarin is the exception to this: his picks are first published on Tuesday.
TABLE 2  Expert Predictions

<table>
<thead>
<tr>
<th>Expert</th>
<th>Years</th>
<th>Record vs. Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Michael Madden</td>
<td>1983–94</td>
<td>1130-1123 (.502)</td>
</tr>
<tr>
<td>Ron Borges</td>
<td>1983–94</td>
<td>1121-1133 (.497)</td>
</tr>
<tr>
<td>Will McDonough</td>
<td>1983–94</td>
<td>1122-1132 (.498)</td>
</tr>
<tr>
<td>Jim McCabe</td>
<td>1989–94</td>
<td>548-573 (.489)</td>
</tr>
<tr>
<td>Vince Dorla</td>
<td>1983–88</td>
<td>540-527 (.506)</td>
</tr>
<tr>
<td>Leigh Montville</td>
<td>1983–88</td>
<td>497-525 (.486)</td>
</tr>
<tr>
<td>Fred delAppa</td>
<td>1990–94</td>
<td>368-368 (.500)</td>
</tr>
<tr>
<td>Mark Blaudschun</td>
<td>1988–89</td>
<td>215-206 (.511)</td>
</tr>
<tr>
<td>Harry Eisenberg</td>
<td>1983–84</td>
<td>198-226 (.467)</td>
</tr>
<tr>
<td>Mike Freeman</td>
<td>1990</td>
<td>43-35 (.551)</td>
</tr>
<tr>
<td>Gerald Strine</td>
<td>1983–94</td>
<td>384-373 (.507)</td>
</tr>
<tr>
<td>Jeff Sagarin</td>
<td>1983–94</td>
<td>1022-1045 (.494)</td>
</tr>
</tbody>
</table>

NOTE.—The table shows the periods over which each expert made predictions and the expert's record with the success rate in parentheses. Records versus the spread are calculated assuming that a bet was placed at the Boston Globe betting line on the day that the predictions were published. Freeman and delAppa each predicted games for only half of 1990. Montville missed 3 weeks in 1988 and Strine predicts only a few games each week. In this and all subsequent tables a betting strategy or expert is profitable if it achieves a success rate higher than 52.4%. Freeman and delAppa each predicted games for half of 1990. Montville missed 3 weeks of 1988. Strine predicts only a few games each week. Sagarin's predictions were computed from a comparison of his point spread to the Boston Globe spread.

The results suggest that expert predictions are not themselves informative. None of the experts is significantly better than random in their success, and no one who picked more than 100 games beat the 52.4% level of success necessary for a profit. Table 2 shows that success is not a prerequisite for longevity in the expert market. Thus, if prices move with expert predictions, that is suggestive that some bettors trade on the basis of sentiment rather than new information.

Expert opinions can represent sentiment in two different ways if they do not provide information beyond that contained in the point spread. First, expert opinions can influence the betting decisions of the public if they are widely disseminated and believed. Previous literature has emphasized the role of trading on the advice of false experts as an explanation for why we might observe noise traders betting on one side of the market (see, e.g., Black 1986; and DeLong et al. 1990).

A second possibility is that investors do not follow the advice of experts made their predictions. The results suggest that expert predictions are not themselves informative. None of the experts is significantly better than random in their success, and no one who picked more than 100 games beat the 52.4% level of success necessary for a profit. Table 2 shows that success is not a prerequisite for longevity in the expert market. Thus, if prices move with expert predictions, that is suggestive that some bettors trade on the basis of sentiment rather than new information.

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16. We wish to be cautious in concluding that the labor market for experts is inefficient. This table considers the success rates of experts employed by newspapers. The newspaper may be more concerned with providing entertainment rather than advice. It is quite possible that experts who are paid directly by bettors are less likely to survive if they do poorly.
experts, but rather the predictions given by experts reflect the consensus of public feeling about a particular game. In this case, even if no bettors were informed about the predictions of the experts, we would find that the predictions of experts affected market prices.

It is also possible that variables that are observable prior to the start of trading influence the experts’ picks. It is only necessary that some component of the expert opinions could not be anticipated at the start of the week to distinguish the expert opinions from our other sentiment variables that are all calculated from information published at the same time as the opening point spread. According to our model, this unanticipated sentiment could affect the path of betting lines even if anticipated sentiment does not affect the path of betting lines.

Table 3 examines the effects of expert predictions on changes in the line. The results in column 1 show that, in general, investors are betting on the same teams that the experts are picking. The coefficient for the expert prediction is positive in all cases except for John Carney and Mark Blaudschun. The coefficients are positive and statistically significant at the 0.01 level for McDonough, Strine, Sagarin, and Jim McCabe. It is encouraging that this particular set of experts has the largest, most statistically significant, coefficients, since Strine and Sagarin are the most widely published of the experts, and McDonough appears frequently on television.

Each expert’s coefficient represents the predicted change in the spread when the expert selects a team to win. Thus, for example, when Strine selects a team, the regression predicts a 0.32 point increase or decrease in the point spread. The other experts have much less of a predicted effect on the point spread. The coefficient on Sagarin’s prediction should be interpreted differently from the coefficients on the predictions of other experts. The Sagarin prediction is the difference between his prediction and the opening betting line. Thus, for each one point difference between the Sagarin line and the opening betting line, the regression predicts a 0.04 point increase or decrease in the point spread.

There are several caveats in interpreting the results of these regressions. Most important, because the expert predictions are made during the course of the week, they are subject to an important endogeneity: they may be a function of betting early in the week and not predictive of anything thereafter. Second, any relationship between expert predictions and line movements need not be causal. Expert predictions could simply reflect the opinions of other bettors in the market. Columns 2 and 3 of table 3 tests for the possibility that the expert opinions predict changes in the betting line only because the experts pick the team on Wednesday or Thursday, which was favored in betting earlier in the week. If such an endogeneity is to explain the effect of the experts in
**TABLE 3** Regression Estimates for Point-Spread Changes

<table>
<thead>
<tr>
<th>Expert</th>
<th>Full Week (1)</th>
<th>Monday–Thursday (2)</th>
<th>Thursday–Sunday (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opening line</td>
<td>.0063* (.0037)</td>
<td>-.0034 (.0036)</td>
<td>.0054 (.0028)</td>
</tr>
<tr>
<td>McDonough</td>
<td>.0763*** (.0201)</td>
<td>.0525*** (.0194)</td>
<td>.0338** (.0150)</td>
</tr>
<tr>
<td>Madden</td>
<td>.0862*** (.0206)</td>
<td>.0411** (.0200)</td>
<td>.0352** (.0154)</td>
</tr>
<tr>
<td>Borges</td>
<td>.0093 (.0206)</td>
<td>-.0312 (.0200)</td>
<td>.0162 (.0154)</td>
</tr>
<tr>
<td>Strine</td>
<td>.3227*** (.0347)</td>
<td>.1934*** (.0334)</td>
<td>.1635*** (.0257)</td>
</tr>
<tr>
<td>Montville</td>
<td>.0294 (.0303)</td>
<td>.0359 (.0294)</td>
<td>-.0044 (.0226)</td>
</tr>
<tr>
<td>McCabe</td>
<td>.0907*** (.0286)</td>
<td>.0573*** (.0277)</td>
<td>.0671*** (.0213)</td>
</tr>
<tr>
<td>Carney</td>
<td>-.0036 (.0236)</td>
<td>-.0382* (.0226)</td>
<td>.0348** (.0174)</td>
</tr>
<tr>
<td>del Appa</td>
<td>.0496 (.0342)</td>
<td>.0746** (.0330)</td>
<td>.0100 (.0254)</td>
</tr>
<tr>
<td>Eisenberg</td>
<td>.0875* (.0452)</td>
<td>.0381 (.0434)</td>
<td>.0496 (.0334)</td>
</tr>
<tr>
<td>Dorla</td>
<td>.0144 (.0290)</td>
<td>.0385 (.0280)</td>
<td>-.0116 (.0216)</td>
</tr>
<tr>
<td>Blaudschun</td>
<td>-.0276 (.0458)</td>
<td>-.0175 (.0436)</td>
<td>-.0156 (.0336)</td>
</tr>
<tr>
<td>Sagarin Line</td>
<td>.0357*** (.0065)</td>
<td>.0395*** (.0066)</td>
<td>.0644*** (.0051)</td>
</tr>
<tr>
<td>Constant</td>
<td>-.0929*** (.0229)</td>
<td>-.0247 (.0224)</td>
<td>-.0644*** (.0173)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,366</td>
<td>1,622</td>
<td>1,622</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.08</td>
<td>.06</td>
<td>.06</td>
</tr>
</tbody>
</table>

**NOTE.**—The dependent variable is the change in the point spread for the given period. In the first column, the period is the full week. In the second column, the period is Monday–Thursday, while in the third column, the period is Thursday–Sunday. Standard errors are in parentheses. Monday–Thursday and Thursday–Sunday regressions exclude Thursday games and games in which Monday was not the opening line.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

the point spread regressions from column 1 of table 3, then these expert predictions should be insignificant in predicting changes from Thursday to Sunday.

Column 2 demonstrates the effect of each expert from Monday to Thursday and column 3 demonstrates the effect from Thursday to Sunday. With the exception of Sagarin, each expert (Strine, Madden, McDonough, McCabe), whose predictions are significant at the 0.01 level for the full regression, is significant at the 0.05 level in the Thursday to Sunday regression. The results clearly show that we cannot conclude that the entire expert effect stems from readers betting on the
experts’ predictions. This is not surprising, since the predictions in the *Boston Globe* are not publicized to a national audience. Rather, it is likely that some component of the expert opinions simply reflect strong opinions that happen to be shared by a large fraction of the betting public. However, it is interesting that Sagarin is the lone expert to have a strong effect on betting early in the week but no measurable effect on betting later in the week. Sagarin differs from the others in that he is widely published earlier in the week (his picks appear on Tuesdays in some newspapers), and because he uses a mathematical model based on past performance to predict game outcomes. Both of these factors suggest that “the Sagarin effect” should not play much of a role later in the week.

The movements in the betting line suggest that the path of market prices comove with expert opinions. This fact, combined with the evidence that expert opinions are uninformative, is strongly suggestive that investor sentiment is present in football betting. We cannot definitively conclude from our results that readers follow the advice of experts directly. However, if this were the case, the relationship between line movements and expert predictions would not be very surprising because the expert opinions would not be fully anticipated and, therefore, could not have been incorporated in the opening line. However, in the next section, we will examine the possibility that even fully anticipated sources of sentiment create price movements.

### B. Anticipated Sentiment

In this section we consider the possibility that even fully anticipated sentiment may create movements in the line. We consider two categories of sentiment variables that are fully observable at the start of the week. Each category of variables corresponds to a behavioral strategy that investors have been alleged to follow in the stock market. Our hot-hand measures are designed to capture the possibility that individuals prefer to bet on past winners. A hot-hand betting strategy in the football market is very similar to a momentum investment strategy in the stock market. Our prestige variables are designed to capture the possibility that individuals bet on teams that they have heard a lot about in the media.

Prestige effects in football betting parallel the possibility that individual investors in the stock market buy shares of companies that make products that are used by many investors or have been prominently featured by the media. Investor recognition has been examined in the stock market context by Merton (1987) and, most recently, by Falkenstein (1996).

1. **Hot-hand effects.** The results of recent games could create a hot-hand bias if fans prefer to bet on teams that have been performing well. The outcomes of previous games are common knowledge at the time
the opening line is set. Thus, if movements in the betting line covary with the results of past games, then the bettors are overbetting on the hot hand or the casino is not appropriately considering the role of hot hands in predicting game outcomes. In either case, the betting market is inefficient.

We calculate four variables that measure how "hot" a team has been in the recent past. First, for both the home team and the visitor we calculate 1-week and 2-week lags of performance relative to the spread. The variables in our regression equation, LAG1 and LAG2, are the difference between the home team and the visiting team's lagged performance, that is, LAG_k = (the home team's actual score minus its opponent's score k weeks ago - the predicted score difference for that game [closing betting line]) - (the visiting team's actual score minus its opponent's score k weeks ago - the predicted score difference for that game).

We also calculate a measure of which team is on a better streak, WINSTREAK. This variable is the difference between a streak measure for the home team and a streak measure for the visiting team. The streak measures the number of games, including the most recent previous game, for which the games had the same outcome as the most recent previous game. The streak variable is positive for teams that won last week and is negative for teams which lost last week. So, for example, the streak measure for a team that won for the last 3 weeks, but lost 4 weeks ago is +3.

If bettors tend to bet on teams that have done well in the recent past relative to their opponents, the movement in the line during the week will covary positively with LAG1, LAG2, and WINSTREAK. If bettors bet on poor performers, the movement in the line will covary negatively with LAG1, LAG2, and WINSTREAK.

The timing of games within a season creates an inconsistency in all of these variables. There is no recent performance data for any of these teams at the beginning of the season because we do not carry any outcome information from season to season.17 Thus, we do not include data from the first 2 weeks of the season in our regression. However, in addition, each team was idle for 1 or 2 weeks per season from 1990 to 1994. In any case where a team did not play k weeks ago, lagged k results are all reported as zero. The streaks are calculated by ignoring weeks in which the team did not play.

We also consider the possibility that bettors attach special significance to previous matchups of the same pair of teams. This could be important for two reasons. First, if team A beat team B last time, bettors

17. We do not carry these streaks across seasons not only because a considerable amount of time has elapsed between seasons but also because key personnel changes tend to occur in the off-season.
could feel confident that team A will beat team B again. Second, it is possible that, if team A beat team B last time, bettors could believe that team B "is due" or will "seek revenge." For approximately 25% of the games in our sample, the two teams played each other previously in the season. We construct a variable PREVMATCH. The variable PREVMATCH takes the value of one if the home team won the teams' prior matchup in the season. PREVMATCH takes the value of $-1$ if the visiting team won the teams' prior matchup in the season. PREVMATCH equals zero for games for which the two teams have not met previously in the season.

2. Prestige variables. The general popularity of a given team and the extent to which it is mentioned in the media may also be a source of sentimental trading.

We measure the general prestige of each team with three categories of variables. Our first set of prestige variables classifies teams according to their performances in the previous year under the assumption that more successful teams tend to be more popular. We create dummy variables to measure whether the home and visiting teams made the playoffs in the previous year. Our variable PLAYOFF equals the playoff dummy for the home team minus the playoff dummy for the visiting team. From 1983 to 1989, 10 teams made the playoffs; in 1990, the playoffs were expanded to 12 teams. Similarly, we measure bad performance from the previous year by creating dummy variables for teams that finished in last place in each of the six divisions of the league. The variable in our specifications, LASTPLACE, is the last place dummy for the home team minus the last place dummy for the visitor. If bettors tend to bet on teams that did well last year, we expect the coefficient of PLAYOFF to be positive, while the coefficient of LASTPLACE will be negative.

Our second type of prestige variable classifies teams according to their conference affiliation. The NFL is divided into two conferences, the American Football Conference (AFC) and the National Football Conference (NFC). The conference champions play for the league championship each year in the Super Bowl. There are several reasons to believe that the NFC was a more prestigious conference for the duration of our sample period. From 1984 to the present, the NFC representative has defeated the AFC representative in the Super Bowl, winning by an average score of 38 to 17 in those 12 years. Two 1988 polls cited by the Football Encyclopedia concluded that NFC teams surpassed AFC teams in "charisma" and "star quality," with each poll citing the NFC's advantage over the AFC in Super Bowl games. The NFC also had a stronger foothold in the major television markets during 18. We also considered division winners, Super Bowl participants, and actual records from the previous year. These yield similar but less predictive results.
### TABLE 4

<table>
<thead>
<tr>
<th></th>
<th>Full Sample without WINSTREAK (1a)</th>
<th>Full Sample with WINSTREAK (1b)</th>
<th>1984–89 (2)</th>
<th>1990–94 (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opening line</td>
<td>-.0043 (.0048)</td>
<td>.0102* (.0055)</td>
<td>.0127* (.0081)</td>
<td>.0075 (.0076)</td>
</tr>
<tr>
<td>Lag 1</td>
<td>.0071*** (.0012)</td>
<td>.0109*** (.0014)</td>
<td>.0106*** (.0019)</td>
<td>.0115*** (.0022)</td>
</tr>
<tr>
<td>Lag 2</td>
<td>.0062*** (.0012)</td>
<td>.0080*** (.0013)</td>
<td>.0074*** (.0016)</td>
<td>.0090*** (.0020)</td>
</tr>
<tr>
<td>WINSTREAK</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PLAYOFF</td>
<td>.1313*** (.0408)</td>
<td>.1302*** (.0405)</td>
<td>.0879 (.0576)</td>
<td>.1760*** (.0584)</td>
</tr>
<tr>
<td>LASTPL</td>
<td>-.1178** (.0447)</td>
<td>-.1083** (.0444)</td>
<td>-.0718 (.0583)</td>
<td>-.1456** (.0678)</td>
</tr>
<tr>
<td>PREVMATCH</td>
<td>-.1535*** (.0456)</td>
<td>-.1444*** (.0453)</td>
<td>-.1372*** (.0611)</td>
<td>-.1516** (.0673)</td>
</tr>
<tr>
<td>CONF</td>
<td>-.1404 (.0472)</td>
<td>-.1360*** (.0469)</td>
<td>-.0239 (.0634)</td>
<td>-.2426*** (.0692)</td>
</tr>
<tr>
<td>Constant</td>
<td>-.0042 (.0264)</td>
<td>-.0567 (.0280)</td>
<td>-.0751 (.0384)</td>
<td>-.0368 (.0410)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,907</td>
<td>1,907</td>
<td>960</td>
<td>947</td>
</tr>
<tr>
<td>R²</td>
<td>.05</td>
<td>.06</td>
<td>.06</td>
<td>.08</td>
</tr>
</tbody>
</table>

**NOTE.**—The dependent variable is the closing line minus the opening line. Nonzero coefficients for any variables indicate that the betting line moves in a predictable manner over the course of the week. Standard errors are in parentheses.

* *p < .10.
** **p < .05.
*** ***p < .01.

the sample period; its marquee teams were in Washington, Dallas, New York, Chicago, San Francisco, and Los Angeles. We include a conference dummy variable, CONF, which takes the value +1 if the home team is an AFC team and the visiting team is an NFC team, 0 if both teams are in the same conference, and −1 if the home team is an NFC team and the visiting team is an AFC team. If sentiment is in favor of NFC teams relative to AFC teams, then we expect changes in the point spread to be negatively correlated with the conference variable.

### C. Anticipated Sentiment and Changes in the Line

We now test hypothesis 1 of our theoretical section for the anticipated sentiment variables by examining whether changes in the betting line over the course of the week are correlated with recent past performance, last year’s performance, or conference membership.

Table 4 contains the results of linear regressions with the final (Sunday) point spread minus the opening point spread as the dependent variable. We exclude games from 1983 and the first 2 weeks of the
Investor Sentiment

season from study because lags are not calculable. Thus, we have a total of 1,907 observations for these specifications.

Column 1 examines the relationship between the change in the betting line and the anticipated sentiment variables. Columns 1a and 1b perform the same regression with and without the winning streak variable.

In either case, all of the hot-hand measures are significant at the .01 level in predicting the movement in the betting line. Bettors bet on teams that performed well in the past 2 weeks. Interestingly, the coefficient for the winning streak variable is negative, suggesting that bettors bet against teams on longer winning streaks. But, when this variable is included in a regression without the two lag variables, its coefficient is positive. Similarly, as shown in column 1a, the coefficients on the two lag variables remain positive and significant at the .01 level without the inclusion of the streak variable. Thus, the negative coefficient of WINSTREAK could be interpreted to suggest that bettors bet against teams that have won their recent games, but only just barely. Finally, if the two teams have played each other previously during the season, bettors bet against the team that won last time.

While the hot-hand variables are statistically significant, their magnitudes are not huge. Consider a game between two teams, each of which won last week and lost the week before that. Thus, the value of WINSTREAK is zero. Suppose that the home team beat the spread by eight points in each of the past 2 weeks, while the visiting team failed to cover the spread by eight points in each of the past 2 weeks. The regression coefficients indicate that we would expect to see the line move to favor the home team by approximately a third of a point over the course of the week.

The results for the prestige variables are similarly suggestive. Bettors bet on teams that made it to the playoffs last year and bettors bet against teams in last place in their division the previous years. Bettors bet significantly on teams that are members of the National Football Conference. Each of these variables is significant at the .01 level in both of the regressions in columns 1a and 1b with the exception of LASTPLACE, which is significant at the .05 level with the inclusion of WINSTREAK and at the .01 level without the inclusion of WINSTREAK.

To examine the possibility that bettors or Vegas learned over time, we estimate separate regressions for the 1984–89 period and the 1990–94 period. These are shown in columns 2 and 3 of table 4. The coefficients on the sentiment variables all take the same signs in each period.

19. We did not want to use sentiment variables based on the previous year’s performance for 1983 because of the severe distortions caused by the player’s strike in 1982. We did use the performance variables from the strike season of 1987 because that strike was short and did not affect the playoff system.
as they do in the full regression. The hot-hand variables are significant at the .01 level in each period. The prestige variables are somewhat more predictive of changes in the point spread in the 1990–94 period. In the 1990–94 period, two of the four variables are significant at the .01 level and two variables are significant at the .05 level, whereas three of the four variables are not significant at the .05 level in the 1984–89 period.

VI. Are These Movements in the Line Predictive?

The results of the previous section show that the Vegas line moves during the week to favor NFC teams and teams that were relatively successful in the previous weeks and in the past year. This result confirms hypothesis (1) of our theoretical section and in itself clearly indicates that the market is inefficient. Either investors are overbetting on teams that are hot or prestigious or Vegas is underweighting the importance of recent performance or popularity in determining the opening line. In this section, we examine whether the movements in the line, which we identified in the previous section, are caused by bettors causing an inefficiency in the line or by bettors correcting an inefficiency in the line.

One natural test that one might consider is similar to that of Gandar et al. (1988, 1998), who test whether the closing line is a better or worse predictor of game outcomes than the opening line. However, a simple comparison of the opening and final lines is not very powerful because two effects are intermingled in the movement from the opening line to the closing line. The first effect is the one of interest: sentiment may cause the closing line to be a worse predictor of the game outcome than the opening line.

However, new information about injuries and weather arrive during the course of the week. The incorporation of this information in the line should cause the closing line to be a better predictor of the game outcome than the opening line. In this section, we separate movements in the line over the course of the week into two parts: movements in the line that are predictable from our sentiment variables and movements in the line that are not predicted from our sentiment variables. Our results show that point-spread changes that are predicted by our sentiment variables are either pure noise or negative predictors of game outcomes. In particular, the part of the movement of the line that is predictable based on the hot-hand variables is a movement in the wrong direction. However, the unpredicted part of the movement in the line is a significant predictor of game outcomes. Together, these results suggest that the point spread adjusts during the week to reflect both sentiment and new information.
A. Ordered Probit Specifications for Point-Spread Changes

We construct an ordered probit to test whether our sentiment variables are accurate predictors of game outcomes. The dependent variable takes the value of one if the home team covered the closing spread, zero if all bets tied, and -1 if the visiting team covered the closing spread. The independent variables are the opening line, the hot-hand variables, and the prestige variables.

We test whether the probability of covering the spread is related to the hot-hand and prestige variables described above. If the hot-hand and prestige variables have zero coefficients in the regression, then the closing line optimally includes all relevant information about recent performance. If the variables have coefficients of the opposite signs as their signs in the line change regressions, then bettors moved the opening line away from an unbiased estimate of the game outcomes. If they have the same coefficients as their signs in the line change regressions, then bettors moved the opening line toward an unbiased estimate of game outcomes but did not move the line enough to make the closing line an unbiased predictor of game outcomes.

The results from this specification are shown in table 5. These results are mixed. Column 1 shows the results for the full time period. The coefficients for the lag variables and streak variable have the opposite sign from their coefficient in the line change regression, suggesting that the predictable movement in the point spread due to these variables tended to move the line in the wrong direction. The coefficients for each of the lag variables are statistically significant at the 15% level, while the coefficient for the streak variable is statistically different from zero at the 5% level. However, the playoff, last place, conference, and previous matchup coefficients in column 1 have the same sign as in the line change regression, suggesting that the predictable movement in the point spread due to these variables tended to move the line in the correct direction. The coefficient for the last place variable is significant at the 12% level. Thus, the results support the hypothesis that investors overbet on the hot hand but that the closing line did not sufficiently reflect the abilities of the prestigious teams.

In columns 2 and 3 of table 5, we examine the possibility that the investors improved their strategies over the time period of the sample. In fact, we find just the opposite. The significance of the lag variables and the streak variable in the full-sample specification are derived entirely from their significance in the post-1990 period.\(^{20}\)

These results suggest that, in the post-1990 period, the pattern of

\(^{20}\) Using somewhat different independent variables, Gray and Gray (1997) conclude that hot-hand effects are negatively predictive of game outcomes in a probit analysis for a sample of games from 1976 to 1994.
| TABLE 5 Predicting Game Outcomes vs. the Final Point Spread: Ordered Probit Specifications |
|-----------------------------------------------|----------------|----------------|----------------|
|                                               | Full Sample    | 1984–89        | 1990–94        |
|                                               | (1)            | (2)            | (3)            |
| Opening line                                  | -.153**        | -.0170         | -.0165*        |
|                                               | (.0070)        | (.0109)        | (.0092)        |
| Lag 1                                          | -0.026         | .0005          | -.0063**       |
|                                               | (.0018)        | (.0025)        | (.0027)        |
| Lag 2                                          | -0.0023        | -.0015         | -.0036         |
|                                               | (.0016)        | (.0022)        | (.0024)        |
| WINSTREAK                                      | .0237**        | .0051          | .0427***       |
|                                               | (.0107)        | (.0150)        | (.0154)        |
| PLAYOFF                                        | .0178          | .0972          | -.0326         |
|                                               | (.0511)        | (.0770)        | (.0703)        |
| LASTPL                                         | -.0884         | -.1555**       | -.0175         |
|                                               | (.0562)        | (.0779)        | (.0817)        |
| PREVMatch                                      | -.0447         | -.0187         | -.0681         |
|                                               | (.0572)        | (.0815)        | (.0812)        |
| CONF                                           | -.0578         | -.0723         | -.0329         |
|                                               | (.0592)        | (.0846)        | (.0833)        |
| Break 1                                        | -.0609         | -.0317         | -.1000         |
|                                               | (.0356)        | (.0515)        | (.0498)        |
| Break 2                                        | -.0107         | .0077          | -.0385         |
|                                               | (.0356)        | (.0515)        | (.0497)        |
| Observations                                   | 1,907          | 960            | 947            |
| Log likelihood                                 | -1,476         | -728           | -743           |

NOTE.—The dependent variable takes the value of one if the home team beat the final point spread, zero if the teams tied the spread, and minus one if the visiting team beat the final point spread. A nonzero coefficient for any variable indicates the presence of a systematic bias in the closing line. Standard errors are in parentheses.

* p < .05.
** p < .01.
*** p < .001.

betting on the hot hand moved the line significantly in the wrong direction. The subsample results also suggest that in the 1984–89 period, the closing line did not fully incorporate the poor prospects of teams that were in last place last year. Investors moved the line in the correct direction over the course of the week but not enough to eliminate the bias in the closing line. For 1990–94, the last place variable is insignificant in the ordered probit shown in table 5. The combination of these results suggests that Vegas improved its choice of the opening line over time.

B. The Accuracy of Point-Spread Changes: Betting Strategies
The most direct way to test whether bettors moved the line in the “correct” direction is to examine the profitability of taking bets against investor sentiment. Our strategy calls for a bet against the favored team if the regression predicts that the point spread will increase during the
TABLE 6  Betting against Predicted Point-Spread Changes

<table>
<thead>
<tr>
<th>Cutoff</th>
<th>Overall</th>
<th>1984–89</th>
<th>1990–94</th>
</tr>
</thead>
<tbody>
<tr>
<td>All movements</td>
<td>944-925 (.505)</td>
<td>445-500 (.471)</td>
<td>499-425 (.540)</td>
</tr>
<tr>
<td>.5 SD</td>
<td>598-551 (.520)</td>
<td>300-308 (.493)</td>
<td>298-243 (.551)</td>
</tr>
<tr>
<td>1 SD</td>
<td>313-285 (.523)</td>
<td>163-155 (.513)</td>
<td>150-130 (.536)</td>
</tr>
<tr>
<td>1.5 SD</td>
<td>131-122 (.518)</td>
<td>64-72 (.471)</td>
<td>67-50 (.573)</td>
</tr>
</tbody>
</table>

NOTE.—The table shows the records and success rates (in parentheses) of betting strategies based on betting at the closing line against the part of movements in the line over the course of the week that were ex ante predictable.

week or for a bet for the (initially) favored team if the regression predicts that the point spread will decline during the week.

We can also try to improve on this strategy by only taking bets for which there is a clear prediction about the movement of the line. If the predicted movement of the line is greater than a specified cutoff (some number of standard deviations in the mean line movement), our strategy calls for a bet on the opponent of the team predicted to be favored by sentiment. Note that it should be more desirable to make these bets at the closing line rather than the opening line because the closing line includes the effects of sentiment from previous betting.

Table 6 reports the results of the trading strategy. We estimate predicted movements in the line, estimating the coefficients using the whole data sample. Column 1 shows the results for the whole sample. Column 2 shows the results for the 1984–89 subsample and column 3 gives the results for the 1990–94 subsample. In order to be profitable after taking the casino’s commission into account, a trading strategy must have a winning ratio of 52.4%.

As table 6 shows, betting against predicted movement in the line is only profitable in the late period. This matches the results of the ordered probits in table 5.

The fact that the betting strategy is profitable in the full sample, but is not very far from the arbitrage bound, does suggest that rational arbitrageurs in the market may be functioning to correct most of the mispricing.

Notice that the strategy used was to bet against the predicted move-

21. Notice that the trading strategy is not implementable. We do not present it in order to suggest that readers exploit the strategy in the future, but rather as an efficiency test. An implementable trading strategy would estimate the line change coefficients in the first half of the sample and implement the trades in the second half of this sample. Such a strategy is more profitable than any of the betting strategies we have presented. However, we think that table 6 provides a more complete overall view of market efficiency.

22. Table 5 suggests further that most of the profits from our betting strategy should be due to the hot-hand effect. A strategy of betting against movements in the point spread that are predicted by the hot-hand variables alone is slightly more profitable than the strategy presented in Table 6.
TABLE 7  
Betting against Actual Point-Spread Changes

<table>
<thead>
<tr>
<th>Cutoff</th>
<th>Overall</th>
<th>1984–89</th>
<th>1990–94</th>
</tr>
</thead>
<tbody>
<tr>
<td>All changes</td>
<td>651-688 (.486)</td>
<td>321-334 (.490)</td>
<td>330-354 (.482)</td>
</tr>
<tr>
<td>.5 SD</td>
<td>334-375 (.471)</td>
<td>160-181 (.469)</td>
<td>174-194 (.473)</td>
</tr>
<tr>
<td>1 SD</td>
<td>158-163 (.492)</td>
<td>80-69 (.537)</td>
<td>78-94 (.453)</td>
</tr>
<tr>
<td>1.5 SD</td>
<td>68-82 (.453)</td>
<td>31-36 (.463)</td>
<td>37-46 (.446)</td>
</tr>
</tbody>
</table>

NOTE.—The table shows the records and success rates (in parentheses) of a betting strategy of betting against the actual movement in the line over the course of the week.

ments in the line, not the actual movements in the line. The actual movement in the line includes the part of the line movement that is motivated by information about injuries, weather, and so on that becomes known during the course of the week. The actual movement in the line may also, of course, reflect the fact that bettors might correct any mistake that the sports book managers might have made in setting the initial line. The results of betting against actual movements in the line are shown in table 7. Betting against the actual movement in the line typically yields a winning percentage of less than 50% for both the early and late subsamples. This result indicates that the unpredicted part of the movement in the line is a good predictor of the game outcome.23

VII. Does the Opening Line Reflect Sentiment?

In this section, we turn to the question of whether the market maker sets the opening price to partially reflect predicted sentiment. As mentioned earlier, the curse of knowledge might be one possible explanation for bookmakers’ failing to incorporate sentiment fully in setting the opening line. In particular, in this section, we test whether the Vegas opening line is skewed away from the maximum-likelihood prediction of the game outcome in order to capture investor sentiment. One way to test the hypothesis that Vegas skews the line is to create a betting strategy.

Above, we considered betting against the predicted movement in the line by placing bets at the closing line. Here, we consider placing bets against the predicted movement in the line at the opening line. If such betting is profitable, then the opening line is skewed in the direction of sentiment.

23. We confirmed that unpredicted changes in the line are strongly predictive of game outcomes in a separate two-stage regression: a one point change in the line during the week, which was not predicted by sentiment, leads to a predicted change of 1.38 points in the game outcome. This coefficient for the effect of unpredicted changes in the line in predicting game outcomes is significant at the 1% level.
TABLE 8  Betting against the Opening Line

<table>
<thead>
<tr>
<th>Cutoff</th>
<th>Overall</th>
<th>1984–89</th>
<th>1990–94</th>
</tr>
</thead>
<tbody>
<tr>
<td>All movements</td>
<td>939-924 (.504)</td>
<td>444-497 (.472)</td>
<td>495-427 (.537)</td>
</tr>
<tr>
<td>.5 SD</td>
<td>592-555 (.516)</td>
<td>298-309 (.491)</td>
<td>293-246 (.544)</td>
</tr>
<tr>
<td>1.0 SD</td>
<td>312-290 (.518)</td>
<td>165-156 (.514)</td>
<td>147-134 (.523)</td>
</tr>
<tr>
<td>1.5 SD</td>
<td>127-126 (.502)</td>
<td>63-73 (.463)</td>
<td>64-53 (.547)</td>
</tr>
</tbody>
</table>

Note.—The table shows the records and success rates (in parentheses) of betting strategies in which bets are placed at the opening line against predicted movements in the line.

The results of this betting strategy are shown in table 8. Betting against the predicted movement in the spread is profitable in the full sample. As expected, however, betting against the predicted movement in the spread at the opening line is somewhat less profitable than betting against the predicted movement in the spread at the closing line. This would be expected because our analysis of line changes shows that there is more sentiment embedded in the closing line than in the opening line. However, the small difference in profitability between the two trading strategies suggests that Vegas attempts to capture most of the sentiment effect in its setting of the opening line. Columns 2 and 3 show that the success of this trading strategy derives entirely from its success in the later period.

Columns 2 and 3 indicated that Vegas exploited sentiment in setting the line more in the later period. This might seem surprising: given the estimated $2 billion dollars at stake each year in football betting, it may seem natural to conclude that Las Vegas oddsmakers are expert in choosing profit-maximizing point spreads. Historically there have been a series of prominent oddsmakers, beginning with Jimmy "The Greek" Snyder, with each ascending to prominence by exploiting systematic flaws in the odds. Given this pattern in the labor market for oddsmakers, it is perhaps not surprising that we find that the betting line has improved over time.

We could also test whether Vegas skewed the line against expert predictions. However, we are uncomfortable undertaking this analysis because expert predictions are not generally known at the time that the opening line is set.

VIII. Conclusion

Much of the previous literature on betting lines has focused on the question of whether betting lines efficiently predict game outcomes.

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24. Michael "Roxy" Roxborough, who supplied the odds to a majority of Las Vegas casinos in the early 1990s, first became known for utilizing weather conditions to make money betting on the total number of runs scored in baseball games.
The goal of this article is to expand that mission by examining possible sources of betting line inefficiencies and by looking at the role of sentiment in generating a predictable path of betting lines over the course of the week.

We examine the hypothesis that bettors bet on past winners, follow the advice of experts, and bet on teams with name-recognition or prestige. We focus on these strategies because these have been alleged to be important sources of sentimental trading in the stock market. We show that bettors do, to some extent, have the hypothesized betting proclivities and that these proclivities lead to predictable movements in the betting line. Our evidence is less convincing on the question of whether the inefficiency stems from bettors moving the line in the “wrong” direction or whether bettors correct Vegas’s systematic errors in setting the opening line. However, we show that a betting strategy designed to exploit the sentiment-induced mispricing of the betting line is borderline profitable in our sample.

Previous work on investor sentiment has not focused so much on predictable price movements in asset markets but rather has focused on distortion in average prices. This article illustrates that prices in the football point-spread betting markets move in a predictable manner over the course of the 1-week betting cycle in response to both potentially unanticipated and fully anticipated sentiment.

References

Glosten, L. R., and Milgrom, P. R. 1985. Bid, ask, and transaction prices in a specialist