Asset Pricing and Sports Betting

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TOBIAS J. MOSKOWITZ*

ABSTRACT

Sports betting markets offer a novel laboratory to test theories of cross-sectional asset pricing anomalies. Two features of this market – no systematic risk and terminal values exogenous to betting activity – evade the joint hypothesis problem, allowing mispricing to be detected. Examining a large and diverse set of liquid betting contracts, I find strong evidence of momentum, consistent with delayed overreaction and inconsistent with underreaction and rational pricing. Returns are a fraction of those in financial markets and fail to overcome transactions costs, preventing arbitrage from eliminating them. An insight from betting also predicts value and momentum returns in U.S. equities.

*Yale University, AQR Capital, and NBER. Correspondence to: Tobias J. Moskowitz, Yale University, School of Management, and AQR Capital, 165 Whitney Ave., New Haven, CT 06511. E-mail: tobias.moskowitz@yale.edu. I have benefited from the suggestions and comments of Angie Andrikogiannopoulou, Nick Barberis, Antonio Bernardo, John Cochrane, Lauren Cohen, Josh Coval, Eugene Fama, Ken French, Xavier Gabaix, Bryan Kelly, Steve Levitt, Gregor Matvos, Stefan Nagel (the Editor), Lasse Pedersen, Amit Seru, Jesse Shapiro, John Shim, Richard Thaler, Kaushik Vasudevan, Rob Vishny, two anonymous referees and an Associate Editor, as well as seminar participants at NYU, Purdue, the SIFR conference in Stockholm, Sweden, the FRA meetings in Las Vegas, and the NBER Behavioral Finance meetings in Chicago. I also thank John Shim, Kaushik Vasudevan, and Brian Weller for outstanding research assistance and comments. Moskowitz thanks the Center for Research in Security Prices and the Initiative on Global Markets at the University of Chicago, Booth School of Business for initial financial support and Yale SOM for additional financial support. AQR Capital is a global investment firm that may or may not use the insights in this paper. The views expressed here are those of the author and not necessarily those of AQR Capital. I have read the *Journal of Finance's* disclosure policy and have no conflicts of interest to disclose.

The asset pricing literature is replete with predictors of financial market security returns, with much debate on their interpretation. Risk-based theories of rational asset pricing, behavioral theories of mispricing, and statistical explanations such as overfitting due to data mining provide three distinct views of these findings, with different implications for the broader role of asset pricing in the economy. Security characteristics that describe expected returns have become the focal point for discussions of market efficiency, risk sharing, resource allocation, and investment decisions, with debate centering on whether these variables represent compensation for bearing risk in an informationally efficient market, predictable mispricing in an informationally inefficient market (due perhaps to investor biases and market frictions), or a statistical fluke. Progress in resolving this debate is mired by the joint hypothesis problem (Fama (1970)), that is any test of efficiency is inherently a test of the underlying equilibrium asset pricing model, which leads to a host of theories to describe the same facts.

Financial market security prices provide a particularly difficult empirical laboratory to distinguish between these views of asset pricing because marginal utility and investor preferences are unobservable, and both rational and behavioral forces could operate simultaneously.[1] To circumvent the joint hypothesis problem, in this paper I analyze an alternative asset pricing laboratory – sports betting markets. The idea is simple. Two key features of sports betting markets provide a direct test of behavioral asset pricing that is distinct from, and not confounded by, any rational asset pricing framework: 1) sports bets are idiosyncratic and have no relation to risk premia in the economy, and 2) sports contracts reveal a terminal value that is (largely) independent from betting activity and preferences, where uncertainty is resolved, which allows mispricing to be detected.[2]

Importantly, I examine the *cross-section* of sports betting contracts, comparing betting lines across games at the same time and across bets on different outcomes of the same game. While aggregate risk preferences and changing risk premia in the economy could affect the entire betting market as a whole, they should have no bearing on the cross-section of games or the cross-section of contracts on the same game.[3] Hence, rational

[1] Complicating matters further is the role played by institutional, market, funding, trading, agency, and regulation frictions that may also affect prices and interact with rational and behavioral forces to exacerbate or mitigate return patterns.

[2] I caveat "largely" here because there is no natural law stating that outcomes of sporting events are unrelated to betting activity, but this assumption seems likely to be true. For example, while illegal game fixing would violate this assumption, it does not appear to be a concern in the sample I study (see footnote 3). Perhaps more innocently, player effort may vary with how favored or heavily bet the team is, but to have an effect such variation would have to be unanticipated by bettors. If the market understands that players respond to betting activity, then prices would adjust accordingly. Game fixing, in contrast, would have to be unanticipated by markets for it be to successful. In both cases, the effect on market betting prices is likely negligible. Other stories may be concocted to link betting activity to outcomes, but they are not likely to have first-order effects. The point is that while no immutable law states that outcomes are independent of betting activity, this assumption seems reasonable and a good first-order description of how betting prices behave.

[3] For example, changing risk aversion and/or risk premia in the economy might affect betting behavior and prices for the entire football betting market as a whole – how much is bet, the willingness to bet, and perhaps betting odds in aggregate – but should have no impact on the betting prices of the Dallas versus New York game relative to the Washington versus Philadelphia

asset pricing theories have nothing to say about return predictability for the cross-section of sports contracts. In contrast, behavioral models, which are microfounded from evidence in psychology that pertain to generic risky gambles (Barberis and Thaler (2003), Barberis (2018)), should impact sports betting contracts just like any risky decision. Hence, the same behavioral biases that are claimed to drive the anomalous returns in financial security markets should be just as likely to affect the cross-section of sports betting contracts, providing a novel laboratory to directly investigate theories based on human cognitive biases. The setting can be thought of as an out-of-sample test of behavioral models in asset pricing.

Another key feature of sports betting contracts is that they have a known (and short) termination date, whereby uncertainty is resolved by outcomes (e.g., the game score) that are plausibly independent of investor behavior, beliefs, or preferences.[4] This feature is rarely observed in other security markets. While some financial assets also have finite terminal dates, such as fixed income and derivative contracts, they harbor risk premia and derive their terminal values from an underlying asset whose value itself may be affected by investor preferences and behavior. The terminal value of sports betting contracts being exogenous to investor behavior provides clean identification of mispricing and a stronger test of asset pricing theory. For example, if prices deviate from fundamental values due to cognitive biases or erroneous beliefs, they will be corrected on average by the game outcome that is exogenous to these biases or beliefs. Alternatively, market efficiency and rational pricing imply that information moves prices with no mispricing and therefore no return predictability (since there is no risk premium embedded in these contracts). The combination of both features – no risk premia and an exogenous finite terminal value – makes sports betting contracts a unique and useful laboratory for testing behavioral asset pricing theories. Furthermore, the direction of any price correction at the terminal date helps distinguish different sources of mispricing to test competing models. For example, investor overreaction implies a return reversal from the revelation of the terminal value, while underreaction

game happening at the same time. Nor can these aggregate risks have any effect on who wins a given contest or how many total points are scored in a game. Other systematic forces, like broad sentiment (Edmans, Garcia, and Norli (2007)) may affect betting markets and financial markets simultaneously, but are less likely to affect the cross-section of games that I study here. Hence, although systematic risk or sentiment could in principle affect betting markets and financial markets at the same time, the impact on the cross-section of contracts is likely inconsequential.

[4]As alluded to earlier, this assumption seems likely to be true or at least a good first-order description of price behavior. Unexpected behavior of players related to betting activity, such as game fixing or effort, seems implausible in my sample. While infamous cases of game fixing have arisen – the 1919 Chicago Black Sox in the World Series, the Dixie Classic scandal of 1961, the CCNY point-shaving scandal in 1950 to 1951, the Boston College basketball point-shaving scandal of 1978 to 1979, and the Arizona State point-shaving scandal of 1993 to 1994 – such cases are extremely rare, have typically involved obscure and illiquid games, and are often subject to debate as to how much "fixing" actually occurred. Bernhardt and Heston (2010) do not find evidence of game fixing or point shaving in a large cross-section of games. For the games analyzed in this paper, game fixing related to betting behavior should not be a concern given the depth of the sports markets analyzed, the attention and scrutiny paid to these contests, and the stakes and salaries of professional athletes over the sample period, which would make fixing games very expensive, consistent with the evidence in Bernhardt and Heston (2010). Also, for game fixing to affect interpretation of the results in this paper, it would have to be correlated with the cross-sectional return characteristics of momentum, value, and size.

models imply a return continuation. These distinct implications are not easily testable in financial markets because typically there is no known terminal value that is not confounded by the joint hypothesis problem.

To connect the broader asset pricing literature to the sports betting laboratory, I focus on three cross-sectional predictors of returns that have received the most attention in financial markets: size, value, and momentum.[5] I do not consider other biases or characteristics specific to sports betting markets, such as home-team bias or favorite-longshot bias, because the aim is to focus on behavioral asset pricing models that generate implications for the characteristics pertaining to size, value, and momentum that pervade financial securities markets, but I do control for these other effects in the analysis. The goal of the paper is not to provide a comprehensive study of the efficiency of sports betting markets across all possible signals, although my findings have something to say about efficiency. Rather, the goal is to examine the three asset pricing factors most commonly used in financial markets in a unique setting, in which I can test behavioral asset pricing theories not contaminated by systematic risk. A key objective, therefore, is to derive analogous measures of characteristics for sports contracts. Momentum, measured by past performance, is the least controversial and most easily applied to sports betting contracts. Value is captured by a variety of proxies for "cheapness" following the broad conceptual framework of Asness, Moskowitz, and Pedersen (2013). Size is captured by the market value of the team or the size of the local market in which it resides. While there are many other cross-sectional predictors of returns in financial markets, most do not apply to sports betting contracts, and momentum, value, and size are the most prominent characteristics in the literature.[6]

Using the opening and closing betting lines from the most comprehensive betting data set to date, I test whether price movement from the opening to the close of betting is related to the three characteristics, and if so, whether that price movement has any predictive content for the return from the close of betting to the game's outcome. Looking at these two return horizons (open-to-close and close-to-end of game) helps distinguish various behavioral models. For example, an overreaction model predicts that open-to-close movement will reverse from the close to the game's outcome, while an underreaction model predicts a return

[5] Abundant evidence exists that size, value, and momentum explain the cross-section of returns in many markets and time periods. For recent syntheses of this evidence and its application to other markets, see Fama and French (2012) and Asness, Moskowitz, and Pedersen (2013). The behavioral and risk-based asset pricing models also focus predominantly on these three characteristics; see Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) for behavioral models and Gomes, Kogan, and Zhang (2003), Belo (2010), Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2007) for risk-based explanations.

[6] For example, the financial markets literature on anomalies also includes carry (Koijen, et al. (2018)), profitability (Novy-Marx (2013)), investment (Hou, Xue, and Zhang (2015), Fama and French (2015)), accruals (Sloan (1996)), and defensive or low-risk strategies (such as Frazzini and Pedersen's (2014) betting against beta strategy or quality measures from Asness, Frazzini, and Pedersen (2019)) that are not analyzed here. Many of these other variables are not applicable to sports betting contracts. For example, carry, as defined by Koijen, et al. (2018), is the return an investor receives if prices do not change, which is literally zero for all sports betting contracts. Most accounting-based anomalies, like profitability and accruals, do not apply either, nor do investment-related anomalies. Moskowitz and Vasudevan (2021) analyze low-risk strategies in sports betting and compare the results to financial market low-risk anomalies.

continuation. These tests are novel to the sports betting literature and are more powerful and direct tests of behavioral pricing models.

My unique data come from the largest Las Vegas and online sports gambling books across four U.S. professional sports leagues: the National Basketball Association (NBA), National Football League (NFL), Major League Baseball (MLB), and National Hockey League (NHL), with multiple contracts per game that allow for bets on who wins, by how much, and total points scored, covering more than 100,000 contracts spanning three decades. Across all contracts and all sports considered, I find that price movements from the open to the close of betting react strongly to momentum and weakly to value signals in a manner consistent with evidence from financial markets. Size exhibits no return predictability, also consistent with more recent evidence in stock markets (Asness et al. (2018), Alquist, Israel, and Moskowitz (2018)). I also find that these price movements are fully reversed by the game's outcome. The evidence suggests that bettors follow momentum (and to a lesser extent, value) signals that push prices away from fundamentals, which then get fully reversed by the game's outcome. These results are most consistent with overreaction pricing models and extrapolative beliefs (Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis and Shleifer (2003), and Barberis, et al. (2015, 2018)) and are inconsistent with underreaction models or rational pricing.

The patterns that I document above hold across a variety of specifications and measures, both for each of the four sports and for separate betting contracts on the same game. The remarkably consistent patterns across sports and across contracts, where betting outcomes are independent, implies that the results are not likely due to chance and helps mitigate concerns related to confounding factors. For instance, finding the same results for contract bets on the *total points* scored by both teams and for contract bets on a particular team winning rules out team-specific explanations such as favorite-longshot or home-team biases.

The findings support the view that momentum effects in sports betting markets may be related to mispricing due to overreaction. This raises two questions. First, what prevents arbitrageurs from eliminating the mispricing? Since betting contracts face no aggregate risk, the main impediment to arbitrage is transactions costs, which are quite high in these markets. Using the actual costs of betting on these contracts, profits to momentum strategies are easily wiped out by transactions costs, thus preventing arbitrage from eliminating the mispricing. However, price movements, even if not profitable, are interesting and useful to test theories for what drives them. In this setting, the market is efficient within transactions costs (Fama (1970)), but the price patterns that emerge within those costs allow for a direct test of theory that distinguishes between rational expectations, overreaction, and underreaction models.

The second that the findings raise is, to what extent do the results generalize to momentum and value return premia in financial markets? Extrapolating to financial markets is speculative. While sports betting markets isolate tests of behavioral theories from risk-based theories, other differences between sports and financial markets may reduce generalability of the results. For example, arbitrage activity is likely different in the two markets, as investors in financial markets face systematic risk and possibly other frictions as well. Preferences of market participants may also be different in the two markets, since bettors often have an “entertainment” motive too. In addition, the magnitudes of value and momentum effects in sports betting markets are smaller than those in financial markets, despite transactions costs being much higher in sports betting markets, which suggests that arbitrage forces could be weaker in financial markets (due to aggregate risk exposure) or that the return premia in financial markets may come from sources besides investor misreaction. A key fact of momentum and value in financial markets is their strong covariance structure (Fama and French (1993), Asness, Moskowitz, and Pedersen (2013)), which is notably absent in sports betting contracts.

However, sports betting markets and financial markets share several features: large transaction volume, widely available information, market making-activity, arbitrage activity (from professional bettors and even some hedge funds), and professional analysts. Moreover, although some bettors may participate for entertainment motives, they also prefer to make rather than lose money,[7] and entertainment motives are also present in the stock market (Dorn and Sengmueller (2009) and Grinblatt and Keloharju (2009)). In addition, the fact that behavioral theories designed to explain financial market anomalies also predict similar patterns in sports betting markets may not simply be coincidence. The experimental psychology evidence motivating the behavioral theories comes from generic risky gambles, and hence should apply to sports betting contracts too. Finding momentum premia implied by these theories suggests that there may be a link between the two markets. In this sense, finding a positive result is easier to interpret, since it suggests that the predictions of behavioral models are confirmed in another market, one in which they are not confounded by risk-based theories. While this out-of-sample evidence does not necessarily imply that these same theories drive similar patterns in financial markets, it is at least suggestive. The alternative is to offer different explanations for the same patterns in different markets, which may be less appealing. A null result, however, would be more difficult to interpret, since a lack of findings in sports betting markets would not necessarily say much about the relevance of these models for patterns that do exist in financial markets.

[7] The majority of sports betting volume consists of investors who use this market professionally and not simply for entertainment, such as professional gamblers and even hedge funds – see Centaur Galileo, a UK-based sports betting hedge fund that was launched in 2010 but subsequently closed in January 2012. Peta (2013) discusses the industry of professional gambling and the use of financial tools from Wall Street in the sports betting market.

Assuming that asset pricing models apply to all markets and securities, and that investor preferences are not wildly different across markets, this setting can be useful to test broader asset pricing themes. In particular, since the results are consistent with models of overreaction for momentum and value, I investigate these models further by examining additional implications of the theory and test them in *both* sports betting and financial markets. An additional implication of overreaction and extrapolation models is that price continuation is stronger when uncertainty about valuations is greater and investors are less confident (Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Rabin (2002), Rabin and Vayanos (2010), Barberis et al. (2015, 2018)). Consistent with this view, I find stronger momentum effects and weaker value effects in sports betting when there is greater uncertainty, such as near the beginning of each season when team quality is less certain, or for bets for which investors have less information or confidence. Applying the same idea to U.S. equities, I also find stronger price momentum and weaker value premia for firms with more uncertainty, proxied by either stale earnings or greater dispersion in analyst forecasts of earnings.

The rest of the paper is organized as follows. Section I motivates sports betting markets as a useful laboratory for asset pricing and develops a theoretical framework to guide the analysis. Section II provides a primer on sports betting and describes the data. Section III conducts cross-sectional asset pricing tests. Section IV provides additional robustness tests, addresses alternative hypotheses, and tests further implications of theory, including a novel test applied to equity markets using insights from the sports betting market. Section V concludes by speculating how the results may connect to financial market anomalies.

I. Motivation and Theory

This section discusses the sports betting market as an asset pricing laboratory and develops a theoretical framework to guide the empirical analysis.

A. Asset Pricing Laboratory

Sports betting markets are large, liquid, and active. Global sports betting produced an aggregate gross gaming yield (notional bets taken minus winnings paid out) of nearly $200 billion in 2017 (Statista.com), and 50% of U.S. adults have made a sports bet (which is higher than stock market participation rates; see Vissing-Jørgensen (2002)). In the U.S., the American Gaming Association estimates that four to five billion U.S. dollars are wagered legally each year at Nevada sportsbooks, the only state in which it was legal (prior to 2018), but the amount bet illegally with local bookies, offshore operators, and other enterprises may be 30 times that figure (see Weinberg, Ari, 2003, The case for legal sports gambling, *Forbes*). With the May 2018

U.S. Supreme Court decision overturning the Professional and Amateur Sports Protection Act of 1992 that prohibited state-sanctioned sports betting, the expectation is that this market will grow considerably.

Sports betting markets share some important features with financial markets, such as investors with heterogeneous beliefs and information that seek to profit from their trades (Levitt (2004)). However, two key features of sports betting markets make it a uniquely useful laboratory to test asset pricing theory. The first is that the *cross-section* of bets is completely idiosyncratic, having no relation to systematic risk. The second is that the contracts have a known (and very short) termination date with a terminal value determined by outcomes that are (to a first order) independent of investor behavior or preferences. The exogenous terminal value allows for identification of mispricing, and the direction of price correction is a distinguishing implication of various behavioral models.

Identifying price correction is difficult in financial markets because there is no terminal value that is exogenous to investor behavior, beliefs, and preferences. For example, fixed income securities, options, and other derivative securities have finite terminal payoff dates, but their terminal values are based on an underlying security whose value depends on investor preferences and beliefs, all raising the specter of the joint hypothesis problem that confounds detection of mispricing. Sports contracts, by contrast, are purely idiosyncratic and have exogenous terminal values that are being based on the outcome of sports contests, which together eliminate these confounding possibilities.

B. A Theoretical Framework

In this section I develop a simple theoretical framework to guide and interpret the empirical analysis.

B.1. General Price Movements

The data sample provides prices on betting contracts at the open and the close of betting, as well as the game outcome that determines the terminal value of the contract. The opening price is set by bookmakers and then betting begins and continues until the game is about to start, when the closing betting price is set. The next section describes how these prices are set, but prices can move from the open to the close for information or noninformation reasons, and may respond to information rationally or irrationally. The time between open to close varies by sport from several hours (NBA) to as much as a week (NFL). Bettors receive the price at the time they make their bet, irrespective of whether the betting price changes later. Each contract contains three prices: open, close, and terminal.

The timeline of prices on each betting contract and the return horizons are as depicted in Figure 1.

********** INSERT FIGURE 1 HERE **********

If prices move on information (e.g., a key player is injured after the open but before the game starts) and the market reacts rationally to the news, then the closing price (which reflects the news) will be a better predictor of the game's outcome than the opening price (which did not contain the news). If priced correctly, there will be no return predictability from the close to the end of the game, since the closing price equals the expectation of the terminal value, $P_1 = E[P_T]$. Movement from the open to the close will therefore not have any predictive value for the return from the close to the end of the game. Since the return from the open to the game's outcome is the sum of the return from the open to the close and the return from the close to the end, it will also equal the return from the open to the close in expectation ($E[R_{open:end}] = E[R_{open:close}] + E[R_{close:end}]$, where $E[R_{close:end}] = 0$ if priced rationally). More formally, running the regression

$$R_{j,close:end} \quad = \quad \alpha + \beta_1 R_{j,open:close} + \epsilon_j, \tag{1}$$

a rational response to information leads to the following prediction.[8]

Prediction 1: If prices move ($P_0 \neq P_1$) on information and markets respond rationally, then $\beta_1 = 0$.

Alternatively, if prices move from the open to the close for purely noninformation reasons, such as investor sentiment or noise, the closing price will be incorrect but will be corrected once the game ends to reveal the true (exogenous) price. In this case, closing prices will be poorer predictors of game outcomes than opening prices, implying predictability in open-to-close returns on final payoffs. Moreover, the open-to-close return should negatively predict the close-to-end return as prices revert to the truth at the terminal date. Absent information content in the price movement, prices will fully revert back to the original price at the open, leading to the following prediction.

Prediction 2: If prices move ($P_0 \neq P_1$) for noninformation reasons, then $\beta_1 = -1$.

Another possibility is that prices move for information reasons but the market reacts irrationally to the news. For example, markets may underreact or overreact to information. Under- and overreaction are two of the leading behavioral mechanisms proposed in the asset pricing literature (Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999)). In this case, closing prices would still be wrong and would therefore imply predictability of the close-to-end return by the

[8] Alternatively, one could run the regression $R_{j,open:end} = \alpha + \beta_0 R_{j,open:close} + \epsilon_j$ and test whether $\beta_0 = 1$. Since $R_{open:end} = R_{open:close} + R_{close:end}$, $\beta_0 = 1 + \beta_1$.

open-to-close return. However, the sign of the return predictability depends on the nature of the misreaction to news on the part of investors. For example, if markets overreact to the news, then the open-to-close return will *negatively* predict the close-to-end return, while if the market underreacts to the news, then the open-to-close return will *positively* predict the close-to-end return. More formally,

PREDICTION 3: If prices move ($P_0 \neq P_1$) for information reasons but markets respond irrationally, then

(a) $\beta_1 > 0$ if underreaction

(b) $\beta_1 < 0$ if overreaction.

All three hypotheses make distinct predictions for the regression coefficients from equation (1), which are testable and identifiable because of the exogenous terminal value of the contracts.

Figure 2 summarizes the implications of Predictions 1 through 3. In the first case, assuming that the price movement contains some information, overreaction implies that the sum of the return from P_1 to P_T will be opposite the sign of the return from P_0 to P_1, while underreaction implies that the two returns will take the same sign. In the second case, if prices move based on no information, then there should be a full price reversal by the game's outcome, where the return from time 0 to 1 will be exactly offset by an opposite-signed return from time 1 to T. Noninformation price moves are a special case of overreaction.

********** INSERT FIGURE 2 HERE **********

These tests can shed light on asset pricing theory more generally and are unique to the sports betting literature. The general idea of using differences in the ability of the opening versus final point spreads to predict game outcomes to differentiate information from sentiment effects is also explored in Gandar et al. (1988), Gandar et al. (1998), and Avery and Chevalier (1999). However, the tests here are novel in several respects. First, the data used in this study, as described in detail in the next section, are the most comprehensive to date – they span three decades and four professional sports, and they contain multiple contracts that bet on different outcomes of the same game. This last feature (different contingent contracts on the same game score) is unique to the literature and helps rule out many alternative explanations. For example, showing the same patterns for bets on who wins and by how much versus total points scored by both teams (where the latter outcome is empirically uncorrelated with the former outcomes) suggests that omitted team-specific or matchup variables are not likely to drive the results. Previous studies only look at one contract per game, and typically in one sport only. Second, I use actual betting prices from online bookmakers (described in the next section) and compute real investment returns from implementable trading strategies that an investor would experience in real time. Most studies, including the few that use opening lines (Gandar et al. (1988), Avery and Chevalier (1999), Levitt (2004)), use data from media sources or composite betting lines, which are not actual transaction prices. Third, the use of real returns is novel, where the dynamics of returns provide a stronger test of asset pricing theories. By examining actual return patterns over different contract horizons, I can uniquely differentiate among behavioral theories, such as over- and underreaction. Redefining betting lines in terms of financial returns not only allows for more powerful tests and identification of mispricing, but also provides quantifiable economic magnitudes to determine the extent of mispricing. For questions of market efficiency, it is critical to look at actual returns. Finally, the goal of this study is quite different: to link cross-sectional characteristics in asset pricing from financial markets to similar patterns in betting markets and compare their real returns (per dollar invested).

B.2. Cross-Sectional Return Characteristics

The primary goal of this paper is to investigate whether cross-sectional characteristics found to predict returns in financial markets – momentum, value, and size – are related to return predictability in sports betting markets. Using the general framework above, I examine whether price movement from the open to the close is related to a particular characteristic by running the regression

$$\tilde{R}_{j,0:1} \quad = \quad \alpha_1 + \beta_1 Char_j + \tilde{\epsilon}_{j,0:1}, \tag{2}$$

where $Char_j$ is the characteristic of contract j.

Following equation (1), close-to-end returns can then be regressed on the same characteristic,

$$\tilde{R}_{j,1:T} \quad = \quad \alpha_T + \beta_T Char_j + \tilde{\epsilon}_{j,1:T}. \tag{3}$$

The cross-sectional characteristic is essentially an instrument for betting line movements, where equation (2) is the first-stage and equation (3) is the second-stage regression, represented in reduced form. The idea is to test various theories of price movement coming only through their relation to these characteristics. Hence, $\beta_1 - \beta_T$ represents the total price movement from open-to-close and from close-to-end based on $Char_j$. The sum $\beta_1 + \beta_T$ is the total price movement from open-to-end based on $Char_j$, which if different from zero indicates mispricing of the opening line based on the characteristic.

The pattern through which the characteristics considered affect returns over the two horizons helps distinguish among various theories, as summarized by the following hypotheses.

HYPOTHESIS 1 (No Relevance): *The characteristic is not related to either information or sentiment* $\Rightarrow \beta_1 = \beta_T = 0$ *(and where* $\beta_1 - \beta_T = 0$ *and* $\beta_1 + \beta_T = 0$*).*

HYPOTHESIS 2 (Information Efficiency): *The characteristic is related to information that is priced efficiently*

$\Rightarrow \beta_1 = \beta_T = 0$ *(where* $\beta_1 - \beta_T = 0$ *and* $\beta_1 + \beta_T = 0$*).*

Hypothesis 3 (Noninformation/Noise): *The characteristic is related to noninformation or pure noise that erroneously moves prices* $\Rightarrow \beta_1 \neq 0$, $\beta_T = -\beta_1$ *(and hence* $|\beta_1 - \beta_T| > 0$ *and* $\beta_1 + \beta_T = 0$*).*

Hypothesis 4 (Information Inefficiency/Sentiment): *The characteristic is related to information, which moves prices (*$\beta_1 \neq 0$*), but the market responds inefficiently. There are two types of misreaction:*

(a) *Underreaction* $\Rightarrow \beta_1 \times \beta_T > 0$ *or* $|\beta_1 - \beta_T| < |\beta_1 + \beta_T|$.

(b) *Overreaction* $\Rightarrow \beta_1 \times \beta_T < 0$ *or* $|\beta_1 - \beta_T| > |\beta_1 + \beta_T|$.

Hypotheses 1 and 2 cannot be distinguished because both imply no relation between returns and the cross-sectional characteristic over any horizon. Under Hypothesis 1, the characteristic has no information content or it is not an attribute that bettors care about, while under Hypothesis 2 the characteristic has relevant information content but is priced efficiently so there is no predictability in returns.

Hypotheses 3 and 4 are behavioral models. As Barberis (2018) summarizes, behavioral models deviate from rational expectations in one of two fundamental ways: differences in beliefs or nonstandard preferences. Under Hypothesis 3, prices move for noninformation reasons, such as preferences for a certain team or match-up. Alternatively, investors may use signals that are pure noise but erroneously believe that they have information content. In either case, if prices move for noninformation reasons, prices become inefficient and returns will be predictable, with movement from the open to the close reversing sign from the close to the end of the game. If noninformative signals are related to characteristics of the contract, then those patterns will show up in equations (2) and (3), where $\beta_T = -\beta_1$.

Hypothesis 4 corresponds to beliefs – the characteristics may have information content, but the market misreacts to that information, leading to mispricing. Behavioral asset pricing models and experimental psychology suggests that individuals underreact to mundane pieces of news and overreact to dramatic news (see Kahneman and Tversky (1979) for a general treatment; for references to financial applications, see Barberis and Thaler (2003) and Barberis (2018)). Prominent behavioral theories for financial market anomalies, such as momentum and value, focus on these aspects of misreaction (Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Daniel, Hirshleifer, and Subrahmanyam (1998)).

Equations (2) and (3) distinguish between under- and overreaction, where the former implies return predictability from open-to-close and close-to-end of the same sign (e.g., markets slowly respond to the same information), while the latter implies return predictability from open-to-close and close-to-end that is of opposite sign (e.g., markets overreact, with the overreaction reversing by the game's outcome). Of course, a combination of effects is also possible. Opening prices may be inefficient and closing prices efficient, or vice versa. By looking at the dynamics of returns from opening prices to closing prices to game outcomes, the tests identify whether prices affected by these characteristics are consistent with different theories.

It is worth reemphasizing that the goal of this paper is not to provide an exhaustive search of all betting characteristics or strategies to assess the overall price efficiency of sports betting markets. Rather, the goal is to examine cross-sectional predictors of returns inspired by the literature in financial markets. Of course, the findings may provide an assessment of market efficiency with respect to these characteristics and hence add to the literature on efficiency in betting markets.[9]

II. Sports Betting Primer and Data

This section provides a brief primer on sports betting markets and describes the data, which are among the most comprehensive betting data. In particular, the data cover multiple contracts on the same game across four professional sports and three decades and they contain transactable quotes.

A. *Sports Betting Primer*

Sports betting contracts are contingent claims on the underlying fundamental of a contest between two teams – the points scored by each team, denoted by P_K, the points scored by team K. I examine three separate betting contracts for each game: the Point Spread, Moneyline, and Over/Under contract. For an arbitrary game between team A and team B, the three contracts are bets on the following three outcome variables y:

$$\text{Point Spread: } y = P_A - P_B \qquad \text{Moneyline: } y = sign(P_A - P_B) \qquad \text{Over/Under: } y = P_A + P_B.$$

A.1. Point Spread Contract

The Point Spread (S) contract bets on the point differential between the two teams ($y = P_A - P_B$). Specifically, it is a bet on whether $y > X$, where X is the "point spread," which is essentially the strike price on the contract. It is usually quoted by $-X$ for the favored team, indicating that if team A is favored, a bet on team A pays off only if it beats team B by at least X points. The quoted spread for betting on team B would be $+X$, meaning that team B must win or lose by less than X points for the bet to pay off.

The typical bet is \$11 to win \$10, with the \$1 difference between the amount bet and the amount that can be won, known as the "juice," "vigorish," or "vig," is the commission that sportsbooks collect for taking

[9] The evidence on market efficiency in sports betting is mixed. Golec and Tamarkin (1991), Gray and Gray (1997), Gandar et al. (1988), Gandar et al. (1998), Avery and Chevalier (1999), Kuypers (2000), Lee and Smith (2002), Sauer, et al. (1988), Woodland and Woodland (1994), and Zuber, Gandar, and Bowers (1985) examine the efficiency of sports betting markets in a single sport for a single contract (Point Spread contracts).

the bet (a transactions cost). The payoffs for an \$11 bet on team A over team B on a Point Spread contract of $-X$ points are

$$\text{Payoff}_A^S = \begin{cases} 21, & \text{if } y > X \quad (\text{“cover”}) \\ 11, & \text{if } y = X \quad (\text{“push”}) \\ 0, & \text{if } y < X \quad (\text{“fail”}) \end{cases}. \tag{4}$$

The payoffs for a bet on team B on a spread of X are the opposite, $\text{Payoff}_B^S = 0 \cdot \mathbf{I}(y > X) + 11 \cdot \mathbf{I}(y = X) + 21 \cdot \mathbf{I}(y < X)$, where $\mathbf{I}(\cdot)$ is an indicator function. About half of the time point spreads, X, are quoted in half-points, which precludes the possibility of pushes, since teams can only score in full-point increments.

I examine returns with and without the transactions cost or vig. With no transactions cost, the bet is simply \$10 to win \$10 and the net returns to betting on team A and B can be expressed as

$$ret_A^S \;=\; 1 \cdot sign(y - X) = -ret_B^S. \tag{5}$$

Point spreads are set to make betting on either team roughly a 50-50 proposition or to balance the total amount bet on each team, which are not necessarily the same thing, but are often very close (Levitt (2004)).

A.2. Moneyline Contract

The Moneyline (M) contract bets on which team wins ($y = sign(P_A - P_B)$). Instead of providing points to even the odds on both sides of the bet paying off as in the Point Spread contract, the Moneyline instead adjusts the dollars paid out depending on which team is bet. Defining the Moneyline for team A as M_A, if team A is favored, then a bet on A requires betting $\$M_A$ to receive \$100 if $P_A > P_B$, where $M_A > 100$. A Moneyline bet on team B, the underdog in this example, bets \$100 to win M_B, where $100 < M_B < M_A$. The Moneyline on the favorite (underdog) is quoted as $-M_A$ ($+M_B$) to indicate risking M_A (\$100) to win \$100 (M_B). The difference between M_A and M_B represents the commission or vig to the bookmaker, where arbitrage forces ensure that difference does not lead to a riskless betting opportunity. The returns to a Moneyline contract with $y = sign(P_A - P_B)$ are represented by

$$\begin{aligned} ret_A^M &= \frac{100}{M_A} \cdot \mathbf{I}(y > 0) + 0 \cdot \mathbf{I}(y = 0) - 1 \cdot \mathbf{I}(y < 0) \\ ret_B^M &= -1 \cdot \mathbf{I}(y > 0) + 0 \cdot \mathbf{I}(y = 0) + \frac{M_B}{100} \cdot \mathbf{I}(y < 0). \end{aligned} \tag{6}$$

With no transactions cost, $M_A = M_B$. The case of $y = 0$ (ties) occurs rarely and hence can be ignored.[10]

[10] Across the 59,592 games in the data set, only 10 games ended in a tie, and only five of those had opening betting lines, all of which are in the NFL. Ties are not allowed in the NBA or MLB, and are not allowed in the NHL since the 2005 to 2006 season, when the data starts, and when the NHL instituted shoot outs at the end of tie games to eliminate them. None of the results are affected by excluding the five tied games in the NFL.

A.3. Over/Under Contract

Finally, the Over/Under contract, "O/U)" is a contingent claim on the total number of points scored ($y = P_A + P_B$). Sportsbooks set a "total," T, that is the predicted total number of points that the two teams will score. Bets are placed on whether the actual outcome of the game will fall "over" or "under" T. The payoffs are similar to the Point Spread contract in that a bet is for \$11 to win \$10:

$$\begin{aligned} \text{Payoff}^{OU}_{over} &= 21 \cdot \mathbf{I}(y > T) + 11 \cdot \mathbf{I}(y = T) + 0 \cdot \mathbf{I}(y < T) \\ \text{Payoff}^{OU}_{under} &= 0 \cdot \mathbf{I}(y > T) + 11 \cdot \mathbf{I}(y = T) + 21 \cdot \mathbf{I}(y < T). \end{aligned} \tag{7}$$

With no transactions cost, the net returns to betting on the over and under can be expressed as

$$ret^{OU}_{over} = 1 \cdot sign(y - T) = -ret^{OU}_{under}. \tag{8}$$

Over/Under totals are set to make betting on either side roughly a 50-50 proposition or to balance the total amount bet on each side.

A.4. Bookmaking

Bookmakers set an initial "line" or price on each contract at the open, with an objective of maximizing risk-adjusted profits by either equalizing the dollar bets on both sides of the contract or equalizing the probabilities of the two teams winning the bet (so that they receive the vig with little or no risk exposure). If bookmakers are better on average than gamblers at predicting game outcomes or can predict betting volume, they may also choose to take some risk exposure to earn higher profits.[11] In the empirical analysis, I account for whatever bookmakers are doing in setting prices and can test for whether these biases are related to the contract characteristics I focus on.

Once the opening price is set, betting continues until the start of the game, where betting volume flows can change the price as the bookmaker tries to balance the money on both sides of the contract. In addition, if new information arrives (e.g., an injury to a key player), prices can move without volume.

B. Data

Data on sports betting are obtained from Covers.com (via SportsDirectInc.com) and SportsInsights.com. Covers.com provides historical data on sports betting contract prices, point spreads, and outcomes, as well as team and game information. The data come from the largest sportsbooks in Nevada and outside of the

[11] Levitt (2004) finds that NFL bookmakers predominantly do the former, though sometimes also do the latter. In some cases they are good at predicting betting volume and strategically take advantage of investor biases such as overbetting favorites or certain teams. However, bookmakers are careful not to distort prices so much as to make a simple betting strategy, like always betting on the underdog, become profitable.

U.S. and pertain only to Point Spread contracts for four different professional sports: the NFL from 1985 to 2013, NBA from 1999 to 2013, NHL from 1995 to 2013, and MLB from 2004 to 2013. For MLB and NHL, the Moneyline contract is the primary market. The Point Spread contracts or the "run line" in MLB report an identical -1.5 point spread for all favorites and the Point Spread or "puck line" in NHL is usually 0.5 or 1.5. Since these Point Spread contracts are secondary markets in MLB and NHL and they provide little cross-sectional variation, I drop them from the analysis.

SportsInsights.com has a shorter time series of data but contains a larger cross-section of betting contracts. The data begin in 2005 and end in May 2013 for all four sports. In addition to the Point Spread contract, SportsInsights data contain Moneyline and Over/Under contracts. Opening and closing betting lines are provided on all three betting contracts for each game. In addition, information on betting volume (the total number of bets, not dollars) is provided from three sportsbooks per game, which come from Pinnacle, 5Dimes, and BetCRIS, which are three of the largest sportsbooks and collectively considered the "market-setting" sportsbooks that dictate pricing.[12]

For each contract on each game, the data contain team names, start and end time of game, final score, and the opening and closing betting lines. The betting lines come from the Las Vegas legalized sportsbooks and online sportsbooks and are transactable quotes. For the majority of contracts, bookmakers offer nearly identical opening lines in the database. On the rare occasion when opening lines differ (less than 1% of the time), that contract is removed from the sample. Results are robust to using the highest or lowest line, or an average of all lines when there is discrepancy in lines.[13]

The data offer some unique advantages relative to previous studies on sports betting. The data are more comprehensive, covering multiple sports over several decades (most studies cover a single sport over a few years), and uniquely provide multiple contracts on different outcomes of the same game. This last feature helps control for team-specific effects and provides a richer sample to test asset pricing theory. In addition, the data contain actual betting lines/prices to compute actual realized returns to betting strategies. Many studies (Gandar et al. (1988), Avery and Chevalier (1999), Levitt (2004)) use newspaper-sourced, composite, or even survey betting lines that are not real transaction prices. The data also contain opening and closing lines from the same source, which allows me to examine the evolution of prices from a single source. Most studies

[12]Market setting means that other sportsbooks "move on air," meaning that if one of these three big sportsbooks moves their line, other sportsbooks would follow even without taking any significant bets on the game.

[13]While some sportsbooks may offer different lines to different customers, the analysis here only looks at the prevailing line offered to the public at the time and prices at which the average bettor could transact. In addition, although historically lines differed across bookmakers, prices are more integrated across bookmakers in my more recent sample period, due to the internet and electronic trading. Betting lines today can move near simultaneously across bookmakers and without the bookmaker necessarily receiving heavy betting activity.

only examine one price, with the exception of Avery and Chevalier (1999), who analyze opening and closing lines, but obtain their closing lines from a different source than their opening lines, making comparisons problematic. Finally, using real returns over different horizons and constructing trading strategies allows me to quantify the economic magnitude of return dynamics and compare them to similar investment strategies in financial markets.

The data from both sources include all games from the regular season and playoffs/post-season. Both data sets also include a host of team and game information and statistics, which are supplemented with information obtained from ESPN.com, Baseball Reference.com, Basketball Reference.com, Football Reference.com, Hockey Reference.com, as well as the official sites of MLB, NFL, NBA, and NHL.[14] Table I summarizes the data on betting contracts across sports. The data contain 117,442 betting contracts on 59,592 games. Table I also reports the distribution of closing betting prices for each contract in each sport, with the last row in each panel reporting the implied probability of the home team winning for each Moneyline value reported at each distributional percentile.

********** INSERT TABLE I HERE **********

C. *Cross-Section of Betting Returns*

Returns for a betting contract are computed as the percentage change in the initial investment in the contract at the posted betting lines using the realized payouts of the contract. These are the exact real-time returns a bettor would receive from the contract. The open-to-end returns assume betting at the opening line and realizing the payout from the game outcome, and the close-to-end returns assume betting at the closing line and receiving the payoff from the outcome of the game. Open-to-close returns are then the difference between these two returns (open-to-end minus close-to-end returns), which is equivalent to betting at the open and unwinding (taking the opposite bet) at the close. All betting lines are treated from the perspective of the home team (results are the same if treated from the perspective of the favored team). Returns are computed with and without the vig, where the latter removes the commission to the bookmaker, to examine returns net and gross of transactions costs.[15]

[14]For each data set, I first check duplicate games for accurate scores and remove lines that represent just first-half, just second-half, or other duplicate entries that show the same teams playing on the same date (except for a few "double headers" in MLB – two games played on the same day – which were hand-checked). I also remove pre-season games, all-star games, rookie-sophomore games, and any other exhibition-type game that does not count toward the regular season record or playoffs. I merge the two data sets and check the accuracy of overlapping games. When a discrepancy arises in final score (less than 0.1% of the time), I verify the actual score from a third source (official league website) and use the information from the data set that matched the third source.

[15]One could also look at the actual point differential versus the expected point differential or a "return" based in points rather than dollars. However, while points are highly correlated with dollar returns in basketball, in football where scores predominantly occur in increments of 3 and 7, returns and points can be quite different because scores of 5 and 11 are quite rare but scores of 6

Table IAI in the Internet Appendix reports the distribution of returns across contracts for each sport. Moneyline returns have much fatter tails than Point Spread or Over/Under contract returns, due to their embedded leverage.[16] The correlation in close-to-end returns between the Point Spread and Moneyline contracts is 0.73 on average, which makes sense since these contracts bet on correlated outcomes (who wins and by how much). The Over/Under contracts are uncorrelated with the Point Spread and Moneyline contracts for all return horizons across all sports, offering an uncorrelated bet on the *same* game, which provides independent return variation for the same contest. The asset pricing tests (detailed in the next section) focus on the cross-section of betting returns across contracts, games, and sports, which are unaffected by any risk premia in the economy.[17]

III. Asset Pricing Tests

In this section I begin by looking at general price movements in betting contracts. I then examine the relation between these price dynamics and various cross-sectional characteristics.

A. Testing General Price Movements

Panel A of Table II reports results from estimating equation (1) to test Predictions 1 through 3. The first row reports results across all sports and all three betting contract types. The results show a consistent and highly significant negative coefficient for β_1, indicating that the close-to-end return is strongly negatively related to the open-to-close price movement for all three contract types. The results reject Prediction 1, the rational informationally efficient hypothesis. The regression coefficients are all also statistically different from -1, which rejects Prediction 2, which holds that the price movements are pure noise. The results are most consistent with Prediction 3, specifically 3b, the overreaction hypothesis. The magnitude of the coefficient is about -0.50, which suggests that half of the total price movement from open-to-close is reversed at game

and 10 are quite frequent. Also, since winning the bet by one point versus 10 points confers the same payoff, dollar returns and point returns can be different. Dollar returns take all of this into account because they incorporate these probabilities. Finally, dollar returns are the right measure from an arbitrage perspective, whereas points cannot be arbitraged away. However, for robustness, I replicate the main results using point returns.

[16] The Internet Appendix is available in the online version of the article on The Journal of Finance website.

[17] Even at the aggregate level, sports betting returns are uncorrelated with financial market returns. Figure IA1 in the Internet Appendix plots the cumulative returns to aggregate sports betting for all Point Spread and Moneyline contracts, as well as Over/Under contracts, across all sports. Three separate return series are plotted for: betting on the home team in the Point Spread and Moneyline, betting on the favorite in the Spread and Moneyline, and betting on the over for the Over/Under contract. These series are then plotted with the cumulative returns on the U.S. stock market (Center for Research in Security Prices (CRSP) value-weighted index) over the same sample period (1998 to 2013). Across all sports and games, sports betting returns in aggregate are virtually uncorrelated with stock market returns. The correlations of betting on the home team, favorite, and over with the stock market index are 0.06, -0.01, and 0.03, respectively. The lack of correlation, even at the aggregate level, is testament to these contracts being purely idiosyncratic bets. Their idiosyncratic nature and being in zero net supply are also consistent with these contracts not carrying any risk premium, as evidenced on the graph.

outcome.

Panel B of Table II repeats the regressions excluding the betting lines with no price movement. The results are nearly identical, indicating that the -0.50 coefficient is not driven by the contracts with no price movement. Rather, contracts whose prices move from open-to-close observe about half of that price movement reversed by the game outcome. This result indicates that the conditional expectation of close-to-end returns, conditional on no price movement from open-to-close, is zero, $E[\frac{P_T}{P_1}|\frac{P_1}{P_0}=0]=0$. The next four rows report results separately for the NBA, NFL, MLB, and NHL, which exhibit similar, although more noisy, effects.

********** INSERT TABLE II HERE **********

A.1. Bookmaking Effects?

While the results in Table II are consistent with overreaction in betting markets, I test alternative hypotheses for the negative relation between open-to-close and close-to-end returns related to bookmaking activity. For instance, if bettors are better informed than bookmakers (though Levitt (2004) finds the opposite), then like the market makers in Stoll (1978), they may set closing prices that do not reflect the average betting price to shield their exposure to adverse selection. In this case, they may move prices more aggressively with volume, which could induce a negative correlation between the opening return and the closing return.

To test this hypothesis, Panel C of Table II reestimates equation (1) for the highest and lowest betting volume contracts across all sports. Contracts are sorted within each sport into the top and bottom third of betting volume (number of contracts), and β_1 is estimated separately for the high- and low-volume bets. If bookmaking activity is driving the negative relation, then there should be an even more negative effect for the most heavily bet games, since this is where bookmakers face the greatest risk. As Panel C shows, however, the coefficients are if anything less negative for the high-volume contracts, although the differences are statistically indistinguishable from zero. This result is inconsistent with bookmaking activity driving the negative relation between open-to-close and close-to-end returns.

Panel D of Table II repeats the analysis after separating contracts into "big interest" games – shown on national prime-time television, involving two of the top-five teams in terms of market size or performance at that point in the season, and playoff games – and all other games. The results are no different across the two sets of games, further suggesting that bookmakers are not driving the empirical relation between open-to-close and close-to-end returns.

As another test of bookmaking effects, I obtain betting prices from Betfair, a U.K.-based gambling company that operates one of the largest online betting exchanges. Betfair operates as an exchange, where bettors trade with each other, rather than a bookmaker. The results over a different sample period and for a different sport (European professional football or soccer) are very similar. The next section and the Internet Appendix detail these results.[18]

In sum, the results in Table II are most consistent with overreaction. However, the focus of this paper is not whether sports betting markets in general are prone to investor sentiment or bias, but whether cross-sectional return predictors found in financial markets also impact sports betting returns. When prices move from open-to-close, is such movement due to investors chasing returns by following momentum, value, or size-related signals? And, do such price movements reverse upon the game's outcome?

B. *Cross-Sectional Trading Strategies*

I investigate whether momentum, value, and size characteristics, commonly used to describe the cross-section of returns in financial markets, are related to the cross-section of sports betting contract returns.

To test for premia associated with these characteristics, I construct trading strategies that are implementable in real time using sports betting contracts. The strategies are formed by ranking all betting contracts at a point in time within contract type (Point Spread, Moneyline, Over/Under) and sport based on a characteristic (momentum, value, size as defined below). Since every game is a contest between two teams, the characteristic for a betting contract is the *difference* between the team characteristics for Point Spread and Moneyline contracts. Hence, a contract with high-momentum bets in favor of the team on a recent winning streak facing a team on a recent losing streak and a low-momentum contract would be the opposite. A neutral-momentum contract is one where the two teams have the same recent past performance. For Over/Under contracts, which bet on the total number of points scored, the *sum* of the two teams' characteristics is used.

I sort all contracts on a given day into quintiles based on the characteristic and go long the highest ($Q5$) and short the lowest ($Q1$) quintile. The quintile portfolios invest $1 in each betting contract on a given day, so that days with more games invest more dollars. Since contracts are treated from the perspective of the favored team, $Q5$ contains bets on favorites with the highest characteristic relative to their opponent. For Over/Under contracts, the bet is from the perspective of the over.[19]

[18] I thank Angie Andrikogiannopoulou, a discussant of this paper, for initially suggesting and running these results, which I have replicated thanks to her graciously providing the code and data.

[19] By relaxing the implicit short-sale constraint, I can also take short positions to bet on the home and away contracts (or the over and under) in each game. In reality only the bookmaker can take these positions, but for the purposes here of calculating the gross return predictability from these characteristics absent real-world trading costs and frictions, I allow shorting. Below when I examine the net trading returns to real-world strategies, I re-impose the shorting constraint to match investment returns that would be achieved in real time.

I compute four returns for the "long-short" strategy that is long $Q5$ contracts and short $Q1$ contracts: the open-to-close return, the close-to-end return, the open-to-end return (which is the sum of the first two returns), and a trading strategy return that is long the characteristic from the open-to-close and then short the characteristic by taking the opposite position from close-to-end (which is the difference between the two returns). The four returns for the quintile spread strategy across all N contracts at time t with weight w_i on contract i formed from characteristic $char_{i,t-1}$ of that contract are

$$w_i = \frac{\mathbf{1}(char_{i,t-1} \in Q5)}{\sum_{i=1}^{N} \mathbf{1}(char_{i,t-1} \in Q5)} - \frac{\mathbf{1}(char_{i,t-1} \in Q1)}{\sum_{i=1}^{N} \mathbf{1}(char_{i,t-1} \in Q1)} \tag{9}$$

$$\text{Open-to-close: } \tilde{R}_{o:c,t} = \sum_{i=1}^{N} w_i \tilde{r}^i_{o:c,t} \qquad \text{Close-to-end: } \tilde{R}_{c:e,t} = \sum_{i=1}^{N} w_i \tilde{r}^i_{c:e,t}$$

$$\text{Open-to-end: } \tilde{R}_{o:e,t} = \tilde{R}_{o:c,t} + \tilde{R}_{c:e,t} \qquad \text{Trading strategy: } \tilde{R}_{TS,t} = \tilde{R}_{o:c,t} - \tilde{R}_{c:e,t}. \tag{10}$$

The last two returns represent trading strategies that provide tests of under- versus overreaction in markets related to the characteristic. If markets underreact, then the open-to-end return will be the biggest return, where the optimal strategy is to hold the contract until the end. If, however, markets overreact, then the trading strategy that goes long from open-to-close and short from close-to-end will produce the biggest return as it takes advantage of the initial price movement and subsequent reversal. These implications follow from the theoretical implications of Section I. I use the returns without the vig or transaction cost of betting. Below I examine returns that take actual transactions costs into account.

B.1. Momentum

I define cross-sectional characteristics in sports betting markets analogous to those in financial markets. Momentum is the least controversial characteristic to match to financial markets, since it is based on past performance, which is well defined in sports. I use a number of past performance measures based on wins, point differentials, and past returns to betting on the same team and contract type. The last measure provides momentum at the betting contract level. Theory provides little guidance on what horizon is appropriate for momentum.[20] I therefore construct a number of past return measures over various horizons, much like Jegadeesh and Titman (1993) do in their original study of momentum in equity markets. Given the short maturity of the contracts, the horizon relevant for momentum is likely different (shorter) than in equities.

[20] The theoretical literature is largely silent on the horizon for momentum. Empirically, momentum is found for individual stocks based on past returns of six to 12 months (Jegadeesh and Titman (1993) and Asness (1994)). For industry portfolios, momentum is found at one to 12 months, with the one-month past return being the strongest predictor (Moskowitz and Grinblatt (1999)). Time-series momentum in futures contracts is found at one to 12-month horizons too (Moskowitz, Ooi, and Pedersen (2012)). For all momentum strategies, subsequent reversals occur two to three years after portfolio formation.

To illustrate the measures, consider NBA Point Spread contracts. I examine past performance (wins, point differentials, betting returns) over the last one to eight games (eight games is roughly 10% of the 82-game NBA regular season).[21] Positive (negative) past betting returns imply that a particular team has consistently covered (failed) its point spread over the last N games. At each horizon, the momentum measures are highly correlated (see Table IAII in the Internet Appendix).[22] I also create a momentum index of measures by taking an equal-weighted average of the measures after rescaling each to mean zero and unit variance.

I use the same momentum measures for the NBA Moneyline contracts since they are bets on who wins. However, for Over/Under contracts, not all momentum measures make as much sense since the contract is a bet on total points scored and not who wins. For example, momentum measures based on past wins should be weaker predictors for Over/Under contracts than past point differentials. Nevertheless, to maintain consistency and guard against data-mining biases, I use the same momentum measures, where for Over/Under contracts it is the sum of the two teams' measures.

Table III reports the average returns, t-statistics, and Sharpe ratios of momentum strategies in NBA betting contracts, using a composite momentum index measure over the previous four games. For ease of interpretation, I report annualized returns (scaling by the number of games per season and reporting in annual terms). Panel A reports results combining all betting contracts in the NBA. The open-to-close betting return of the $Q5 - Q1$ betting strategy generates an annual return of 4.73% per year, with a Sharpe ratio of 0.73 that is statistically different from zero (t-statistic = 5.32). This result indicates a statistically significant positive relation between momentum (past performance) and movement in betting prices from the open-to-close. This finding could be consistent with bettors chasing past performance that drives betting prices in the same direction as bookmakers balance their books, or perhaps with information about the game outcome contained in past performance not being incorporated into the opening price.

To distinguish these theories, the second column of Panel A reports momentum strategy returns from the close to end. The average returns are significantly negative (-8.34, with a t-statistic = -2.52), indicating a reversal of the momentum effect by the game's outcome. This result rejects a rational expectations model or an underreaction model of momentum in favor of a model of overreaction whereby investors push prices too far from the open based on past performance and then reverse course by the game's outcome. The next

[21] All lagged measures within a season pertain only to games within that season. Games from the previous season are not used to construct past game performance measures since there is a significant time lag between seasons.

[22] Analogous to the financial market literature, the team-level momentum measures (win percentage and net point differentials) can be thought of as "fundamental momentum" like earnings or cash flows for stocks, while the past return to betting contracts on the team can be thought of as "price" momentum. The average correlation between fundamental and price momentum is 0.65, which is quite similar to Chan, Jegadeesh, and Lakonishok (1996) and Novy-Marx (2015), who find that price and earnings momentum are about 0.60 correlated among U.S. equities.

column adds the two returns, which gives the open-to-end return, and shows that the momentum strategy's average return from open-to-end is statistically no different from zero (-3.61% with a t-statistic = -1.10), implying that the positive return to momentum from open-to-close is fully offset by the negative return from close-to-end, consistent with the price movement containing no additional information. Finally, the last column reports the momentum returns to a trading strategy that seeks to take advantage of the full price reaction by going long (short) momentum at the open (close), to capture both the positive and the reversal effects of momentum. The average return is 13.07% per year (t-statistic of 3.66) with a Sharpe ratio of 0.47.

The results are consistent with bettors overreacting to recent past performance, in line with the literature on the hot-hand fallacy in sports (Gilovich, Vallone, and Tversky (1985), Moskowitz and Wertheim (2011)). The total momentum return from open-to-end being zero indicates that the opening price is set efficiently by bookmakers on average with respect to past performance. Bettors appear to chase recent performance that pushes the closing price in the direction of momentum, which gets reversed by the game outcome.

Panels B, C, and D report momentum performance for Point Spread, Moneyline, and Over/Under contracts separately. Although there is less power and precision in these smaller samples, the results are remarkably consistent in terms of sign and magnitude across all contract types (although the Moneyline results are insignificant).[23] Of particular note, the results for Over/Under contracts, whose returns are uncorrelated with those on the Point Spread and Moneyline contracts, provide an independent test of momentum on the *same game* that is unlikely to be confounded by other betting or team effects. The Over/Under momentum strategy generates trading profits of 17.12% per year (t-statistic = 2.86).

For robustness, Panels E and F report results for other portfolio formations. Panel E reports results for strategies that go long and short contracts in proportion to the rank of their momentum characteristic (rank-weighting), and Panel F reports results from a long-short strategy that weights contracts in proportion to their momentum characteristic (signal-weighting). Specifically, the two alternative waiting schemes are

$$\begin{aligned}
\text{Rank-weighted: } w_i &= \phi_R(rank(Char_{i,t-1}) - \frac{1}{N}\sum_{i=1}^{N} rank(Char_{i,t-1})) \\
\text{Signal-weighted: } w_i &= \phi_S(Char_{i,t-1} - \frac{1}{N}\sum_{i=1}^{N} Char_{i,t-1}),
\end{aligned}$$

where the total bets summed across all games are rescaled to add up to one dollar long and one dollar short at each point in time using the scalars ϕ_R, ϕ_S. These strategies take an average position of $1 in each contract in proportion to the contract's rank or demeaned signal, respectively. The overreaction trading strategies

[23] The insignificant Moneyline results in the NBA may be due to the Moneyline being a secondary betting market in the NBA (although it is the primary market in MLB and the NHL) and to the much higher volatility of Moneyline contracts.

for the rank and signal-weighted portfolios produce 12.70% and 9.36% per annum (with t-statistics of 2.31 and 1.75), respectively. Given the similarity in results, I stick with the $Q5-Q1$ strategy for the remaining analysis.

********** INSERT TABLE III HERE **********

The same momentum measures for the NBA are then applied out of sample to other sports. Table IV reports results for the momentum strategies in other sports. Panel A reports results that combine all sports, where each contract type within each sport is ranked on momentum and the $Q5-Q1$ strategy in each sport and contract type is equal-weighted across all contracts and sports. The combination of all contract types across all four sports leagues provides additional statistical power to detect price movements. As Panel A shows, there is statistically reliable positive momentum from open-to-close in all sports betting contracts of 2.97% per year on average (t-statistic of 7.75), with a Sharpe ratio of 1.33. The close-to-end returns for momentum are negative -3.37% (t-statistic of -1.63), which offsets the open-to-close positive return. Consequently, the open-to-end momentum return (sum of the two) is a negligible -0.40% return per year (with a t-statistic of -0.04), which is a fairly precise estimate of zero, as predicted if the opening prices are set efficiently. The results indicate that it is the closing prices that are being distorted by momentum – prices are moving in the direction of past performance, but on average are corrected by the game's outcome. Such patterns can be exploited by an overreaction trading strategy, which the last column shows generates an average return of 6.34% (t-statistic of 2.96).

Panels B, C, and D of Table IV report results across all sports for Point Spread, Moneyline, and Over/Under contracts and Panels E, F, and G report results for the NFL, MLB, and NHL, respectively. For each contract type and for each sport, the results continue to show positive momentum from open-to-close followed by a reversal from close-to-end, consistent with overreaction in markets due to chasing past performance (i.e., momentum). The trading strategy that exploits this overreaction is consistently positive and generally significant for each contract type and for each sport (although it is insignificant in MLB). The total return from open-to-end of game is consistently indistinguishable from zero. Finding the same patterns in three different betting contracts across four distinct sports using the same momentum measures provides compelling out-of-sample evidence.

********** INSERT TABLE IV HERE **********

Figure 3 summarizes the results visually across all four sports by plotting the opening and closing returns to momentum for every contract type. A consistent pattern emerges. In every sport and contract type, the momentum returns exhibit a tent-like shape over the betting horizons – significantly positive from open-to-close and significantly negative from close-to-end, with the initial price movement fully reversed by the game's outcome. These patterns match the predictions of the overreaction model in Figure 2.

********** INSERT FIGURE 3 HERE **********

To assess the robustness of momentum measures across different horizons, Figure 4 plots the coefficients from return predictability regressions of measures of momentum (using past returns) for various lags, ranging from the most recent game to all games over the last three seasons. Specifically, the returns from open-to-close and from close-to-end of each contract in each sport are regressed on lagged momentum measures from the last N games. The regression coefficients (with standard errors clustered at the daily level) are plotted for all sports combined. As the figure shows, there is significant momentum from open-to-close for all shorter-term horizons, from one- to eight-game lags. There is also evidence of reversals from close-to-end that are stronger when open-to-close momentum is stronger. The results are robust to various past return lags, although the effects are stronger the more recent the performance. Lagging a full season of past games or two or three years, the open-to-close momentum returns diminish and the close-to-end returns rise substantially. This latter effect may be picking up value bets, which I investigate next.

********** INSERT FIGURE 4 HERE **********

B.2. Value

Value is a more difficult characteristic to match to sports betting markets. A general measure of value applied to all asset classes follows Asness, Moskowitz, and Pedersen (2013), who define value as long "cheap" assets and short "expensive" assets. They apply this concept to multiple asset classes using different measures of this theme. In equities, value is often measured using the ratio of book value of equity to market value of equity or some other ratio of "fundamental" value to market value of the firm. However, another commonly used measure of value is the negative of the long-term past return on the asset, following DeBondt and Thaler (1985), Fama and French (1996), and Asness, Moskowitz, and Pedersen (2013), who show that it is highly correlated with other value metrics, including book-to-market equity ratios.[24] A value trade is about convergence and measures of cheapness are designed to identify assets that currently deviate from, and will revert back to, their fundamental or long-term values.

Using this concept, I apply the following value measures to sports betting contracts:

1. Long-term past performance: measured over the previous one, two, and three seasons.
2. Contract fundamental-to-market ratio: the ratio of the fundamental value of the contract relative to its price. Sports analytics derive a number of measures of team quality or strength for use in predicting

[24] Asness, Moskowitz, and Pedersen (2013) show that long-short equity strategies sorted on the negative of past five-year returns have a correlation of 0.86 with strategies formed on book-to-market equity in both U.S. stocks and globally.

wins. The most popular is known as the Pythagorean win expectation formula. Internet Appendix Section I provides details and intuition for this formula, which generates an expected win percentage for each team based on team fundamentals (points scored).[25] The difference between the expected win percentage for each team from this model is a measure of the expected value of the betting contract, denoted by $E(P)$. Dividing this value by the market betting contract price, $E(P)/P$, produces a value measure. This measure captures the difference between a model-predicted win percentage from fundamentals and betting markets. On average these are expected to converge.

3. Team talent-to-market ratio: difference in player payroll divided by the current price on the betting contract. Although labor markets for athletic talent are not perfectly efficient, they do correlate well with marginal productivity (Murphy (2007)). Thus, two teams with vastly different payrolls should face different probabilities of winning the game. Since payroll is a slow-moving measure of team quality, and the betting price provides the market's current assessment of how likely a team will win, a game that pits two teams with big differences in payroll but little difference in point spread from betting lines (or opposite signed differences in the point spread) will look "cheap."

4. Value index: weighted average of the value measures, rescaled to mean zero and unit variance, with equal weights on the negative of the long-term past performance measures and the talent-to-market ratio.

The long-term past return measures are highly correlated with each other (Table IAII in the Internet Appendix), with lagged one-year performance having a correlation of 0.72 with two-year lagged performance and 0.60 with three-year lagged performance. The positive correlations indicate that although teams can change year-to-year in terms of personnel and front office, those changes are on average slow moving (or the changes each year are typically not that dramatic) and hence there is persistence in team performance from year to year. The contract fundamental-to-market ratio has a negative correlation with long-term past performance (-0.18 with one- and two-year past performance and -0.08 with three-year past performance). This negative correlation is consistent with the equity literature where book-to-market equity and other fundamental-to-market ratios are negatively correlated with long-term past returns. The team talent-to-market ratio, however, is uncorrelated with the other value measures. The composite index of value measures (with long-term past performance negated) has a correlation of -0.13 with the momentum composite index, which is consistent with the negative correlation between value and momentum in financial markets (Asness, Moskowitz, and Pedersen (2013)).

Table V reports average returns, t-statistics, and Sharpe ratios of value strategies in sports betting contracts. For each contract type within each sport, I rank games based on the value composite index and form the $Q5-Q1$ trading strategy. Since value is designed to capture a measure of cheapness, I sign each individual

[25]This formula is essentially a logit model for the probability of winning or the expected win percentage on the logarithm of historical points scored by the team and points scored against the team. As shown in Internent Appendix Section I, the regression coefficient is around two for MLB, the NHL, and the NFL, and around 14 for the NBA. Bolton and Chapman (1986) use a related multinomial logit model to characterize horse racing odds that is used in practice.

value measure so that it predicts returns positively. Panel A reports results aggregated across all contracts and sports. The open-to-close return to betting on value generates a 0.29% return per year (t-statistic = 0.53) and a Sharpe ratio of 0.14. The close-to-end return to value is 2.13. None of these average returns is significant. The open-to-end return that combines the two price movements is negligibly different from zero, indicating that value is priced correctly by bookmakers at the open. Finally, the trading strategy that goes long value at the open and short at the close produces a return of −1.84% (t-statistic of −0.59) with a Sharpe ratio of −0.18. Panels B, C, and D report results separately for Spread, Moneyline, and Over/Under contracts, which yield similarly insignificant patterns. The results for value are weak to nonexistent for these trading strategies, although in additional tests below I find some effects for value that are consistent with an overreaction framework. Moreover, I show that value signals enhance momentum trading strategies, consistent with similar findings in the financial markets literature (Asness (1997), Asness, Moskowitz, and Pedersen (2013)).

********** INSERT TABLE V HERE **********

B.3. Size

I capture size using the annual franchise value, ticket revenue, or total revenue of the team (which is a function of the popularity of the team and the size of its local market). Size is slow moving and does not change much over time (e.g., the New York teams are always "large"). The size measures are all highly correlated with each other (between 0.88 to 0.97; see Internet Appendix Table IAII).

Table VI reports average returns, t-statistics, and Sharpe ratios for size strategies in sports betting contracts. For each contract type within each sport, I rank games based on a size composite index, which is an equal-weighted average of the size measures, and form the $Q5-Q1$ trading strategy. I go long small-market games and short large-market games, to match the small-minus-big premium in financial markets. Panel A reports results aggregated across all contracts in all sports, and Panels B, C, and D report results separately across contract type. There is no evidence of return predictability for size over any horizon in any of the panels. All results are statistically and economically insignificant and the coefficients are not of consistent sign. The evidence suggests that size is efficiently priced in both opening and closing lines (or is irrelevant to sports markets). These results may also be consistent with financial markets, as recent literature raises questions as to whether there is a size effect in equity returns (Alquist, Israel, and Moskowitz (2018), Asness et al. (2018)).

********** INSERT TABLE VI HERE **********

B.4. Multifactor Returns

Table VII reports average returns, t-statistics, and Sharpe ratios of multifactor strategies. For each contract type within each sport, I rank games based on the sum of momentum, value, and size composite index measures and form the $Q5 - Q1$ trading strategy based on the combined information across the three characteristics. Table IAII shows that the correlations between momentum, value, and size composites are low, with value and momentum having a correlation of -0.13, size and momentum a correlation of 0.05, and size and value a correlation of -0.09.

Panel A of Table VII reports results aggregated across all contracts and all sports. The open-to-close return to betting on the multifactor signal generates a 2.48% return per year (t-statistic $= 4.68$) and a Sharpe ratio of 1.83. The close-to-end return is -1.70 (t-statistic $= -0.87$), indicating that the open-to-close price movement reverses almost fully, where the open-to-end return is 0.78 (t-statistic $= 0.02$). Finally, the trading strategy that goes long the multifactor combination at the open and short at the close produces a return of 4.18% (t-statistic of 1.67) and a Sharpe ratio of 0.66. Panels B, C, and D report results separately for Point Spread, Moneyline, and Over/Under contracts, which yield similar patterns. The results indicate that value (and to some extent size) enhances the returns associated with momentum trading strategies, consistent with the financial markets literature (Fama and French (2012), Asness, Moskowitz, and Pedersen (2013)).

********** INSERT TABLE VII HERE **********

C. Comparison to Financial Markets

I compare the economic significance of the return predictability in sports betting markets to those in financial markets from the same characteristics, including accounting for real-world transactions costs.

C.1. A "Survey" of Expert Opinions

With the aim of matching the asset pricing characteristics in financial markets that deliver return predictability to similar measures in sports betting markets, I employ a variety of measures for robustness and also take averages across measures to help reduce noise (Israel and Moskowitz (2013)). The robustness of the results across measures and out-of-sample evidence across sports and contracts helps mitigate data-mining concerns. However, a concern remains as to how well the measures match those in financial markets. While seeking broad consensus on the measures among scholars is likely unattainable, I asked two of the leading scholars from both sides of the efficient markets debate – Eugene Fama, pioneer and proponent of efficient markets and winner of the 2013 Nobel Prize in Economic Sciences, and Richard Thaler, pioneer of behavioral finance and its explanation of market inefficiencies and winner of the 2017 Nobel Prize in Economic Sciences – to weigh in on the plausibility of these measures *before* they (or I) saw the results.[26] The following are quotes from each when asked whether they thought these measures are reasonable ex ante proxies for the asset pricing characteristics analogous to those in financial markets:

> Fama: *"Most of these make sense to me. . . . I like past team record longer-term for value, shorter-term for momentum. But the rest seemed ok."*
> Thaler: *"Momentum is easier. For value, since that's my* [referring to long-term past performance] *measure with DeBondt, I guess I have to like that one. I also like the difference in power rankings or quality divided by contract price as a measure of value."* [referring to $E(P)/P$]

C.2. Economic Significance

Table VIII compares the economic significance of return predictability in sports betting and financial markets by reporting trading strategy profits to momentum, value, and size-based strategies in both markets. The sports betting $Q5 - Q1$ strategies are applied across all sports and all contract types.

For financial markets, long-short portfolios are formed based on momentum, value, and size in U.S. equity as well as global equity markets. Specifically, I use the Fama and French long-short factors for size (SMB), value (HML), and momentum (UMD) from Ken French's website for U.S. stocks, and the international factors constructed in the same way from the U.K., Europe (excluding the U.K.), and Japan from Asness, Moskowitz, and Pedersen (2013). Since the sports betting contacts face no aggregate risk but equity markets do, I adjust the equity strategies for their market exposure (by running a regression on the CRSP value-weighted index return in excess of the Treasury bill rate for the U.S. portfolios or the MSCI World index in excess of the T-bill rate for the international factors). The market-adjusted alphas of each strategy are reported. The sports betting contract returns pertain to the period September 1985 to March 2013 and the financial market returns cover the period January 1972 to December 2013.[27]

Panel A of Table VIII reports the results for momentum strategies. The gross average returns to momentum in sports betting are 2.97%, 3.37%, and 6.34% per year (returns are annualized for both sports betting and financial markets for ease of comparison) for the open-to-close, close-to-end, and trading strategy returns, respectively. The momentum strategy in U.S. equities delivers an alpha of 10.45% per year (over the market) and in international equities it is 8.10% per year. However, since the strategies in different markets may face different volatilities, a better comparison might be their Sharpe ratios or return (alpha in the case

[26] That way nobody could complain ex post about the measures if the results failed to confirm their priors!

[27] Although the sample periods differ slightly, with equity markets offering another 13 years of data, the sports betting market and financial market are uncorrelated, and since the goal here is to simply calculate an unconditional mean return, I use the longest available equity sample period to obtain a more precise estimate.

of equity strategies) per unit of (residual) volatility. In sports betting markets, the momentum Sharpe ratio is 0.60, compared to 0.67 in U.S. equities and 0.80 in international equities. The economic magnitude of the momentum effect in sports betting is a bit weaker than in financial markets, but of similar magnitude.

Panel B reports results for value strategies. The trading strategy for value that is long open-to-close and short close-to-end is -1.84% per year (Sharpe of -0.18). Comparing these returns to those in financial markets, value earns an alpha above the market of 3.76% in the U.S. and 6.10% internationally, which are considerably larger than in sports betting markets. The Sharpe ratios for value in equity markets (0.33 in the U.S. and 0.54 internationally) are also larger. This result could stem from differences between the two markets, such as limits to arbitrage, which I explore below.

Panel C reports results for size-based strategies, which yield no significance in either sports betting or financial markets. Despite a long history of documented size premia in U.S. equity markets (Banz (1981), Fama and French (1992)), there is little evidence of such a premium in recent data or internationally, a result confirmed by other work (Alquist, Israel, and Moskowitz (2018), Asness et al. (2018), Blitz and Hanauer (2020)). Hence, the lack of a size premium also seems to match the evidence in financial markets.

Finally, Panel D reports results for multifactor portfolios that combine momentum, value, and size signals. The diversification benefits of combining factors in financial markets is well documented (Asness, Moskowitz, and Pedersen (2013), Asness, et al. (2015)). As Table VIII shows, the multifactor strategies in sports betting markets produce profits that are a fraction of those in financial markets – the trading strategy returns that take advantage of the open-to-close price movement as well as the close-to-end price convergence generate a Sharpe ratio of 0.66 compared to multifactor information ratios of 0.81 and 1.38 in U.S. and international equities, respectively. The multifactor premia in sports betting markets are about one-half the size of those in global equity markets. The diversification benefits of multiple factors are much larger in financial markets than they are in sports betting markets. The efficient frontier of financial assets with respect to these characteristics appears to have a much higher return-to-risk ratio than that in sports betting markets.

********** INSERT TABLE VIII HERE **********

C.3. Net of Transactions Costs Returns

Although sports betting markets deliver qualitatively similar momentum, value, and size effects as those in financial markets, their magnitudes are smaller. Differences between the two markets in terms of investor preferences, limits to arbitrage, risk, and transactions costs may help explain this gap. I explore transactions costs here.

The third row of each panel of Table VIII reports the average returns of the sports betting strategies net of transactions costs that take into account the commission or "vigorish" that contracts incur. Transactions costs are quite punitive and render all sports betting strategies unprofitable; in fact, they lose substantial amounts of money once these costs are taken into account. Consider, for example, the best open-to-close betting strategy, the multifactor strategy, whcih generates a Sharpe ratio of 1.83. Net of transactions costs this strategy delivers a return of −32.12% per year! The close-to-end strategies do a bit better, but still lose money consistently. For example, the close-to-end momentum strategy averages an annualized return of −11.98 per year. The reason the open-to-close returns are more costly is because to achieve these returns, one must buy at the open and close out the position (by taking the opposite side of the contract) at the close, which pays the commission twice. The evidence in Table VIII shows clearly that transactions costs in sports betting markets easily wipe out any profits to trading on momentum, value, size or any combination of these characteristics.[28] These results indicate why these premia continue to exist in sports betting markets, since the predictability of returns is not easily arbitraged away due to high trading costs.

Do the same premia survive transactions costs in financial markets? Frazzini, Israel, and Moskowitz (2018) use live trading data from a large investment manager who trades in these strategies to estimate the net-of-trading-cost returns (market impact plus commissions) to momentum, value, and size portfolios and find that the premia do survive transactions costs at reasonably large fund sizes. Using their estimates and the price impact model, in Table VIII I report the net-of-trading-cost returns over my sample period assuming a portfolio that traded 1% of daily trading volume in each stock. At that portfolio size, both momentum and value strategies are still significantly positive. Hence, value and momentum premia net of trading costs (at a reasonable size) survive in equity markets but fail to survive transactions costs in sports betting markets.

C.4. Covariance Structure

Another key difference between financial markets and sports betting markets is that financial markets face aggregate risk that is not perfectly diversifiable. One of the key features of characteristic portfolios that predict returns in financial markets is that they exhibit a significant covariance structure. Firms with similar characteristics, such as value and momentum, face significant comovement (e.g., Fama and French (1993, 1996), Asness, Moskowitz, and Pedersen (2013), Lewellen, Nagel, and Shanken (2010), and Daniel and Titman (2012)). This covariance structure may be evidence of underlying common risk sources driving

[28]Moreover, I just account for the vigorish here and ignore price impact or "moving the line" from betting large quantities, which would raise trading costs even further for large dollar bets.

returns or simply covariation due to common investor behavior (e.g., Barberis and Shleifer (2003), Vayanos and Wooley (2013)). In either case, the common variation implies that trading strategies based on these characteristics face risk, which may limit arbitrage activity in financial markets. Given the idiosyncratic nature of sports betting, the covariance structure of betting strategies is absent, unless due to correlated investor behavior.

Table IAIII in the Internet Appendix reports regression results of portfolios of contracts formed on momentum and value and regressed on a momentum and value "factor," similar in spirit to what is done in the financial markets literature. There is no covariance structure across the quintiles, which is in sharp contrast to the strong structure found in financial markets for these strategies.

The predictability of returns due to momentum and size is similar in sports betting markets to that in financial markets, although weaker for value, providing rather unique out-of-sample evidence for these premia. The evidence in sports betting markets is most consistent with behavioral asset pricing models (namely, overreaction models) since aggregate risk is absent in these markets. However, comparing the characteristic premia in sports betting markets to those in financial markets, there are also some differences – the premia are a fraction of those in financial markets, they do not survive transactions costs, and they do not exhibit any common variation among contracts with similar characteristics. In sports betting markets, these premia survive because they are small and too costly for investors to arbitrage away given the high transactions costs in these markets. In financial markets, these premia may survive because they expose investors to common risk, which either represents compensation for that risk in a rational expectations equilibrium or limits the positions that arbitrageurs are willing to take to exploit these premia fully (Shleifer and Vishny (1997)).

IV. Robustness and Additional Implications

I conduct several robustness tests that examine other outcome variables besides betting returns and control for alternative phenomena in sports betting markets. I also examine additional implications of the overreaction theory and test them in sports betting *and* financial markets.

A. *Hypothetical "Point Returns"*

Since the payoffs to the betting contracts are discrete, betting outcomes may truncate useful information. For example, facing a point spread of -3.5, a four-point win pays the same as a 20-point win, which potentially throws out useful information. To extract more information from outcomes, I also compute hypothetical returns from points scored rather than simply the discrete dollar outcomes of the contracts. These are, of course, not real returns and hence cannot be arbitraged away, and hence examining these hypothetical returns is not useful for assessing market efficiency. However, they do convey additional information that can be used to further test theory.

This inquiry is analogous to looking at analyst forecasts versus actual earnings or survey responses versus actual outcomes in financial markets. These, too, are not tradeable returns but can be useful in assessing additional implications of theory. In sports betting markets, the underlying fundamental that all contracts are written on are the points scored by both teams. All contracts are contingent claims on points scored, and points scored are observable quantities for which there are ample data to observe their underlying distribution. I examine the expected point differential taken from betting markets and compare it to the average actual point differential to test for any bias in betting expectations that might be consistent with overreaction. By looking at point difference realizations instead of investment returns, there is potential to gain more information about investor beliefs. Actual versus expected point difference outcomes provide more cross-sectional variation in bettor beliefs across contracts than the dollar payoffs. Contract payoffs depend only on the sign of the actual minus expected point difference, but there is information in the magnitude of the difference.

I compute hypothetical "point" returns by replacing the dollar payoffs to the contracts with the actual points scored for Point Spread and Over/Under contracts.[29] The correlation between the actual returns and the hypothetical point returns is 0.79 for close-to-end returns (Table IAIV in the Internet Appendix), indicating that the returns are highly correlated but also indicating that the point outcomes contain additional information. For the open-to-close returns, the correlation between actual returns and point returns is only 0.28. If bettors follow signals such as momentum in forming their beliefs, then the results using hypothetical point returns are predicted to be stronger than those that use actual betting returns, because the point returns contain more information about beliefs and cannot be arbitraged away.

To test this theoretical implication, I estimate regression equations (2) and (3) from Section I using "point returns." The regression analysis also allows for the use of other controls, such as team and game fixed effects to control for other potentially confounding factors. The regressions include sport, team matchup, and year fixed effects with standard errors used to compute t-statistics clustered at the daily level. Table IX reports

[29]For Moneyline contracts the concept of point returns does not apply since those contracts are simply bets on who wins or loses, where the payoffs have already been adjusted to reflect the likelihood of who wins. While it is possible to convert the Moneyline into a point spread using standard conversions at sportsbooks or empirically matching spreads to moneylines and then computing point returns from these implied spreads, this would be the same as looking at the Spread contracts directly.

results for the "point returns" that are stronger for both momentum and value. Momentum positively impacts the implied open-to-close point expectations by 0.086 with a t-statistic of 12.06. Those expectations are reversed from the close-to-end, with a -0.107 point expectation (t-statistic $= -2.63$). These patterns are consistent with, but are stronger and more precise than, those estimated using actual betting returns. The results indicate that additional information from the cross-section further supports the idea that momentum matters in these markets, where the pattern of beliefs is consistent with overreaction models.

The results for value are much stronger than the actual betting returns. Value has an open-to-close impact on point expectations of 0.049 with a t-statistic of 6.49. Alas, size still has no predictability.

The sum and difference between β_1 and β_T are less intuitive here since these are not actual returns (hence, there is no expectation that $\beta_1 + \beta_T$ should be zero, for instance), but nevertheless the results show that the sum of the point returns from open-to-close and close-to-game outcome are consistently no different from zero across all characteristics.

********** INSERT TABLE IX HERE **********

B. Alternative Hypotheses

I investigate alternative hypotheses for the findings and conclude that other influences are unlikely to affect the results. The literature on sports betting documents other biases that may influence the efficiency of closing prices, such as favorite-longshot and home-team bias (Woodland and Woodland (1994), Gray and Gray (1997)), as well as familiarity, sentiment, and prestige effects (Avery and Chevalier (1999), (Durham, Hertzel, and Martin (2005)). Could these other biases be confounding the results?

First, for any of these other effects to confound the results, they would have to be related to the momentum, value, and size characteristics, which seems unlikely. For example, every team plays an equal number of home games, so, especially for slow-moving measures like value, high- and low-value teams play an equal number of home versus away games. More directly, I regress the momentum, value, and size measures on a home/away team dummy variable and variables designed to capture favorite/longshot odds such as implied probabilities of a team winning being greater than 60% and find no significant relations. These characteristics are uncorrelated with home versus visitor status or with extreme favorite-longshot odds.

Second, focusing on the Over/Under contracts, which exhibit the same return patterns, provides another test that is immune to other documented effects on betting. Since the Over/Under contract corresponds to total points scored and not who wins or by how much, these contract payoffs are not affected by home or favorite-longshot biases.[30] The returns from Over/Under contracts are uncorrelated with the returns on Point Spread and Moneyline contracts. Hence, these contracts provide an independent test that abstracts from other betting biases.

Third, a more direct way to control for a multitude of potential betting biases is to include fixed effects in the regressions for team matchups (and sport and year too). Team matchup effects account for unobservables about the particular game in question, which controls for a host of potential effects. Because there are three betting contracts on each game – Point Spread, Moneyline, and Over/Under – including matchup fixed effects exploits the variation across these three contracts on the *same* contest. Hence, home-team bias, favorite-longshot bias, or any team or matchup-related effect should difference out. This test therefore provides a strong control for other potentially confounding betting influences.

Finally, another possible confounding factor is bookmakers' behavior. For bookmakers to matter, the momentum and value characteristics have to be correlated with their behavior. While unlikely, perhaps bookmakers respond differently to teams with momentum and adjust their betting lines accordingly. To test directly whether bookmaker activity contributes to the results, I obtain data from Betfair, an online exchange that has no bookmaker, and rerun the momentum tests. Data are obtained from 2006 to 2013 for European professional football (soccer).[31] In addition to removing the potential influence of bookmakers, these data provide an independent sample from a different sport – soccer – in a different geography over a different sample period, producing another out-of-sample test. Table IAV in the Internet Appendix reports the results and show strong momentum effects from open-to-close that reverse from the close-to-end of game. These results are similar in terms of both sign and magnitude to the previous findings, providing strong out-of-sample support that also shows that bookmaker activity is not affecting the results.

C. Additional Implications: A Further Test of Overreaction

In addition to ruling out alternative hypotheses, another way to strengthen the interpretation of the findings is to test additional implications of the theory. With the results supporting an overreaction story for momentum and value in betting markets, I test an additional implication of overreaction models.

Daniel, Hirshleifer, and Subrahmanyam (1998) provide a model of overreaction whereby greater uncer-

[30] Games involving large spreads (e.g., favorite versus longshot) do no predict total points and the Over/Under total is no different on average for these games.

[31] I only examine the "match winner" contracts, which are bets on who wins with given odds covering the following professional leagues that show sufficient liquidity/betting volume: Jupiler (Belgium), Eredvisie (Netherlands), English League Championship, English Premier League, French Ligue 1 and 2, German Bundesliga 1 and 2, Greek Super League, Italian Serie A and B, Portuguese Super Liga, Scottish Premier League, Spanish Primera and Segunda divisions, and the Turkish Super League. Since the momentum measures are readily available in Betfair, I focus on momentum. I thank Angie Andrikogiannopoulou for initially suggesting this test and providing the data and code.

tainty implies less precise information for investors to update and allows overreaction to continue unchecked. In this setting, an investor overreacts to recent performance, causing more momentum. Value, in contrast, measures price to an anchor of fundamental value, which investors anchor to more when there is *less* uncertainty, that halts the overreaction. Another possible connection between uncertainty and overreaction comes from Rabin (2002) and Rabin and Vayanos (2010) (based on intuition from Kahneman and Tversky (1972, 1974)). If investors view small samples as representative of the true population, this "representativeness" bias can lead to two possible judgment errors. First, in cases in which the true probabilities are known, individuals fall prey to the gambler's fallacy, erroneously predicting negative autocorrelation in future outcomes in order to match population moments in their small sample. For example, following a fair coin that is flipped heads, an individual with this bias will more likely predict subsequent flips to land tails. Chen, Moskowitz, and Shue (2016) provide field evidence of the gambler's fallacy influencing real-world decisions. The prediction of too many reversals can be viewed as a form of underreaction, in this case underreacting to the probability of heads being flipped again. Conversely, if the true probabilities are unknown, then individuals tend to succumb to the hot-hand fallacy, erroneously predicting continuation (momentum) in a sequence of outcomes as they try to infer the true probabilities. The prediction of too many streaks can be viewed as an overreaction to recent outcomes. If greater uncertainty implies less knowledge of the true underlying process, then it should lead to stronger overreaction, and hence more momentum, and weaker convergence or value.

Empirically, I examine the effects of momentum and value as uncertainty varies, to provide a further test of overreaction.[32] The predictions of overreaction imply that when uncertainty is higher, momentum should be stronger and value weaker. To implement these tests empirically, two measures of uncertainty are used. The first examines games early in the season, when there is more uncertainty about team quality, due to lack of actual past game information as well as potential team changes between seasons. Panel A of Table X reestimates equations (2) and (3) for momentum and value for games "early" in each sport's season (first 25% of games) versus "late" in the season (the remaining 75% of games). I interact the momentum and value characteristics with the uncertainty measure – a dummy for early games – and report the open-to-close return effect, close-to-end return effect, and the difference between them. Results aggregate across all contract types and all sports.

The results are consistent with the predictions of overreaction models: momentum returns from open-to-close are stronger early in the season when uncertainty is highest. Bettors seem to chase past performance more strongly when there is more uncertainty, pushing opening prices further in the direction of past per-

[32]Size, being unrelated to returns and exhibiting no relation to overreaction, is dropped from the analysis here.

formance. Absent solid information about team quality early in the season, bettors place more weight on recent performance. There is also a stronger reversal from close-to-end predicted by the initial price movement, consistent with overreaction. The differences between early versus late in the season are statistically significant (t-statistic of 2.97 for the difference).

For value, the opposite pattern emerges. Value returns appear weaker early in the season and are stronger later in the season. Value effects are stronger when there is less uncertainty. Later in the season, when team quality is more precise, bettors expect recent performance to revert back to team quality, which acts like an anchor, much like Rabin's (2002) agent when the underlying process is known, or, as in Daniel, Hirshleifer, and Subrahmanyam (1998), where a signal of fundamental value mitigates overreaction. The differences between more- versus less-uncertainty games are statistically significant for value as well (t-statistic of -4.03 for the difference).

Panel B reports results for uncertainty based on the percentage of betting volume the contract is involved in parlays. A parlay is a portfolio of bets spanning multiple games. Parlay bets pay off only if all bets involved in the parlay win. Hence, contracts more heavily involved in parlays should involve those that bettors are most certain or confident about – not necessarily those that bettors actually have better information about, but those that they *think* they have better information about.[33]

Dividing the sample into the top and bottom third of contracts based on the percentage of each contract's volume involved in parlays (within each sport), I interact the value and momentum characteristics in the regressions with a dummy for high- or low-percentage parlay volume. Panel B of Table X reports the results. Consistent with the predictions of overreaction models, contracts used in parlays less frequently, and therefore perceived through revealed preferences as having higher uncertainty by bettors, have stronger momentum effects and weaker value effects. These results are consistent across the three contract types and provide another unique test of overreaction and its interaction with uncertainty. Moreover, contracts with stronger initial price movement from open-to-close also have stronger subsequent correction from close-to-end, indicative of mispricing and consistent with overreaction.

********** INSERT TABLE X HERE **********

[33]In fact, most sportsbooks and professional bettors describe parlays as "sucker" bets because the odds offered on them are far below what they should be for independent gambles (i.e., a three-game parlay on independent contests should pay off 8-to-1 but is often quoted at 6-to-1). However, the point here is *not* that parlay bets are better informed, but rather that conditional on a bettor picking three games for a parlay, they should select the three games they are most confident in. Whether they should consider a parlay bet at all is a separate question that is beyond the scope of this paper.

D. From Sports to Financial Markets

If the return patterns in sports betting markets are consistent with investor overreaction, does this help shed light on the same patterns found in financial markets?

Given the differences between sports betting and financial markets, one should be cautious in drawing any general conclusions, but my results can be interpreted both positively and negatively with some speculation. On the positive side, the evidence in sports betting markets suggests that momentum and value patterns are being generated by investor overreaction, consistent with models designed to explain the same phenomena in stock markets. On the negative side, the momentum and value effects in sports betting markets are a fraction of those in financial markets, which suggests that either other (e.g., risk-based) sources may contribute to these premia in financial markets or the idiosyncratic nature and institutional differences of sports betting markets leads to smaller effects. Furthermore, given the large trading costs faced in sports markets relative to financial markets, the influence of behavioral biases may be even smaller in financial markets if arbitrage activity is less limited there. However, arbitrageurs in financial markets face common risk associated with value and momentum strategies that is not diversifiable and hence limits the size of positions they are willing to take.

Another way to connect the results to financial markets is to use an insight from sports betting markets to test a prediction in financial markets with regard to momentum and value. Using the insights of overreaction and uncertainty from the previous subsection, I apply the same idea to U.S. equity returns. This analysis yields new results for stocks and also refines the interpretation of similar results in the equities literature. The analysis highlights how the sports betting market can be a useful laboratory to gain insights into traditional capital markets.

Table XI reports results for tests of momentum and value returns in U.S. equities inspired by the tests in Table X. Specifically, the table reports returns from momentum and value strategies in U.S. equity markets interacted with the uncertainty of firm earnings. The data are U.S. stocks from CRSP from July 1963 to December 2013. Panel A reports results using the recency of earnings announcements as a proxy for uncertainty. Firms with very recently announced earnings should have less uncertainty relative to firms whose most recent earnings number is from some time ago. If earnings provide an important signal of firm value that investors anchor to, then more recent earnings should be more informative.[34] This measure of uncertainty is novel to the literature.

[34] Earnings announcement dates are also set and announced in advance (usually several weeks before the earnings announcement) and are stable and predictable (Frazzini and Lamont (2007)), making them less susceptible to other market influences.

At portfolio formation date t, I first look only at firms with recent earnings announcements, defined as those firms with earnings announced within the last two weeks. I also separately form a universe of firms *at the same time* t who have "stale" earnings numbers, defined as those firms whose last earnings announcement was at least 11 weeks ago.[35] Within each group, stocks are then sorted by momentum (past 12-month average return, skipping the most recent month) or value (book-to-market ratio, BE/ME), where I then compute long-short momentum and value strategies following the construction of Fama and French's UMD momentum and HML value factors. Panel A reports the returns to momentum and value for high- and low-uncertainty firms, and tests for the difference between them. Raw average returns and four-factor alphas (relative to the Fama-French factors RMRF, SMB, HML, and UMD formed from the whole universe of firms) are reported.

As the first two columns of Panel A show, price momentum is stronger among the stale earnings (e.g., higher-uncertainty) firms, exhibiting an annual return of 11.81% compared to only 1.98% among recent earnings announcement (lower-uncertainty) firms. The difference of 9.83% between the two momentum strategies across stale and recent announcers is statistically significant (t-statistic = 1.97). At first, this result may seem surprising given evidence of earnings momentum or post-earnings announcement drift (Bernard and Thomas (1989), Chan, Jegadeesh, and Lakonishok (1996), Novy-Marx (2015)), but a key difference here is that firms are sorted simply by whether they had an earnings announcement within the last two weeks or at least 11 weeks ago, and *not* by the content, sign, magnitude, or surprise of the earnings announcement, which is what the earnings momentum literature focuses on. Alphas with respect to the Fama-French four factors show an 11.44% difference (t-statistic = 2.18) for momentum among stale versus recent earnings announcers. The results are consistent with momentum being stronger under more uncertainty, supporting the implications of overreaction models and the sports betting results. This result is consistent with Zhang (2006), who also shows that momentum is stronger when there is more uncertainty, using idiosyncratic risk as a measure of uncertainty. My measure of stale earnings as a proxy for uncertainty is novel and, in contrast to Zhang (2006), I interpret these results in the context of an overreaction framework.

The next two columns of Panel A report results for value portfolios, which are opposite those of momentum.

[35]Since earnings occur quarterly for most firms about every 12 weeks and to cover enough firms, a two-week window at the beginning and end of the earnings cycle is chosen. Results are robust to other window lengths and generally get weaker as the window expands (see additional results in Internet Appendix Figure IA2). Momentum premium differences decline as the definition of recent versus stale becomes more coarse. In addition, the figure plots the difference in returns of momentum portfolios two to three years after portfolio formation to test whether the subsequent reversals that often accompany momentum strategies are also stronger for the stale announcers. The long-term reversals of momentum strategies have often been characterized as a measure of price correction following momentum price movements (Jegadeesh and Titman (1993, 2001), Hong and Stein (1999)), much like the terminal value of sports betting contracts provides a measure of mispricing. Consistent with this notion, when initial momentum is stronger, subsequent long-term reversals are stronger.

Value returns are strongest among the recent earnings announcers and weakest among the stale earnings announcers, with the difference being -10.39% alpha per year (t-statistic $= -2.11$). These results are consistent with those from sports betting contracts, where value is stronger with less uncertainty.

Panel B reports results using the dispersion in analyst forecasts of one-year earnings per share as another measure of earnings uncertainty. Diether, Malloy, and Scherbina (2002) show that dispersion in analyst forecasts is related to the cross-section of returns and Johnson (2004) offers an explanation for that link and how it might relate to the value premium. Doukas, Kim, and Pantzalis (2004) examine whether dispersion in analyst forecasts captures the value premium. However, these papers do not look at the interaction between analyst dispersion and value and momentum, nor relate these facts to overreaction theories.

Following Diether, Malloy, and Scherbina (2002), dispersion in analyst forecasts is measured as the cross-sectional standard deviation across analysts of their fiscal year earnings-per-share forecast, scaled by the mean forecast for a given stock (requiring at least five analysts). Firms are sorted independently into three groups based on analyst dispersion, and UMD and HML are constructed within the highest and lowest third of dispersion groups. Analyst data cover July 1990 to December 2013. High dispersion in analyst forecasts indicates more uncertainty of firm earnings. As the table shows, momentum is stronger among high-analyst dispersion stocks, exhibiting a 4.89% higher return (t-statistic $= 2.35$), and 4.59% higher alpha (t-statistic $= 2.55$), than low-analyst dispersion stocks. Conversely, value premia are weaker among high-analyst dispersion stocks, exhibiting -5.49% per year lower returns (t-statistic $= -2.79$) and -6.24% lower alpha (t-statistic $= -3.34$) than among low-dispersion stocks. The results are consistent with uncertainty exacerbating momentum returns and reducing value returns, consistent with the implications of overreaction and matching the patterns found in sports betting markets. While a connection between the two markets is speculative, the results highlight the potential to learn about asset pricing more generally from insights in betting markets.

********** INSERT TABLE XI HERE **********

V. Conclusion

Using a novel laboratory of sports betting contracts, I test cross-sectional asset pricing theories for financial market anomalies. Two key aspects of sports betting allow me to develop for distinguishing tests of behavioral asset pricing theories that are not confounded by rational risk-based theories: 1) the idiosyncratic nature of contracts implies that the cross-section of returns cannot be driven by aggregate risks, and 2) the revelation of an exogenous terminal value at the game's outcome that is independent of investor behavior implies that mispricing can be detected. Examining characteristics analogous to those in financial markets, I find significant momentum premia in sports betting contracts, with the return dynamics most consistent with models of overreaction. The results therefore provide an out-of-sample test of behavioral asset pricing theory. Trading costs in sports betting wipe out any profits to trading on these patterns, preventing arbitrage from eliminating the mispricing that allows these patterns to persist in the data. While linking these results to similar patterns in financial markets may be speculative, future research may well explore sports betting markets as a useful asset pricing laboratory that can shed light on broader phenomena in capital markets.

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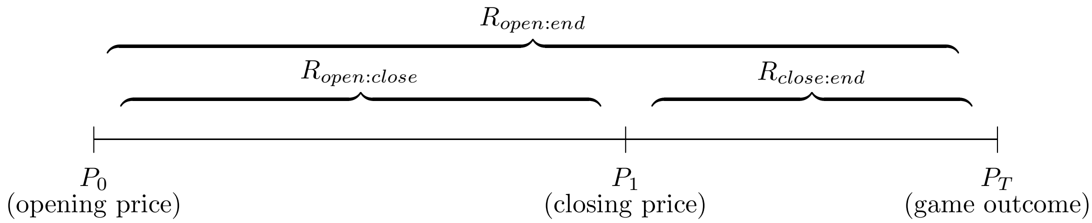


Figure 1. Timeline and return horizons. The figure depicts the timeline and return horizons of the sports betting contracts, showing the three betting prices for each contract in the sample.

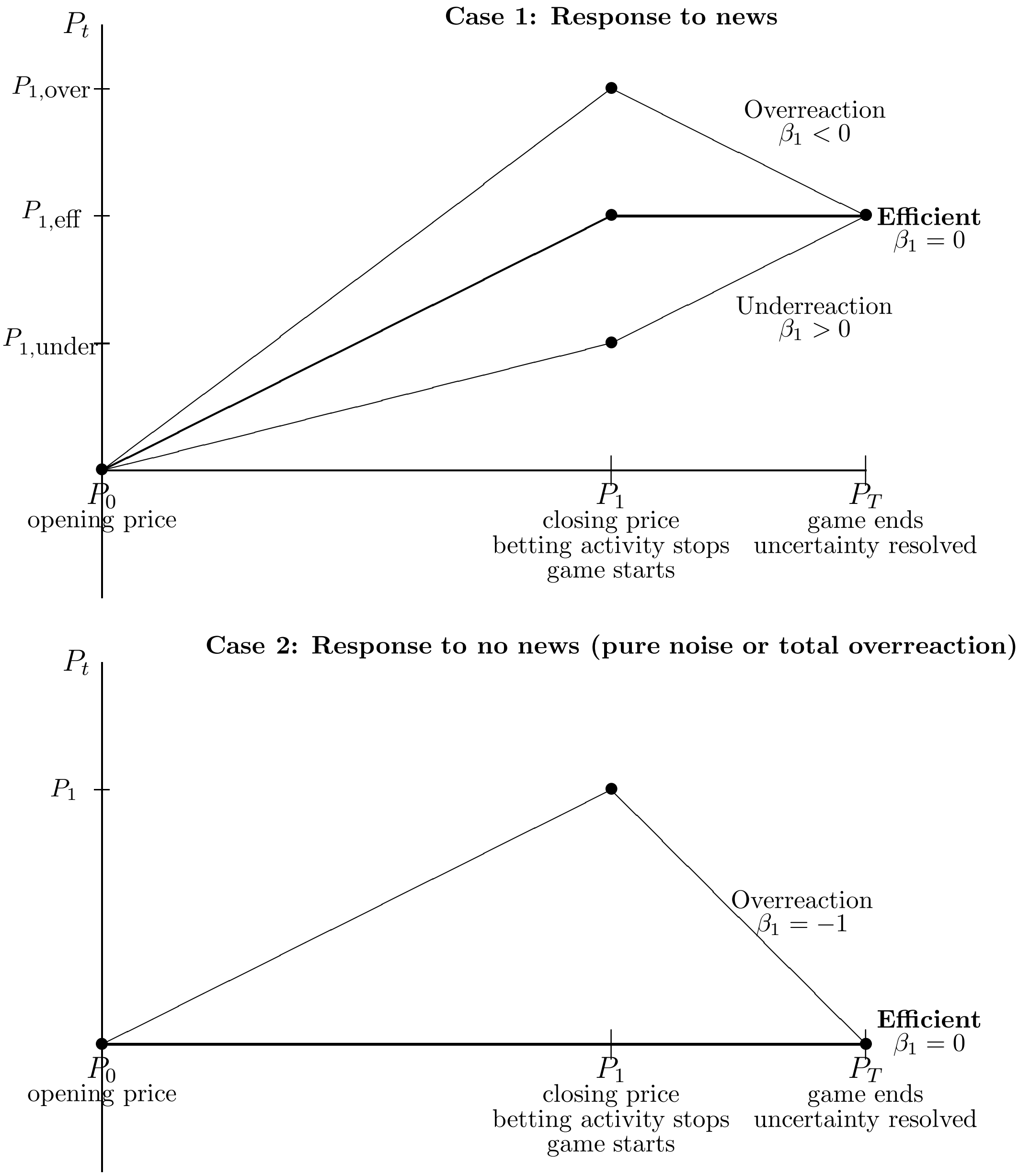
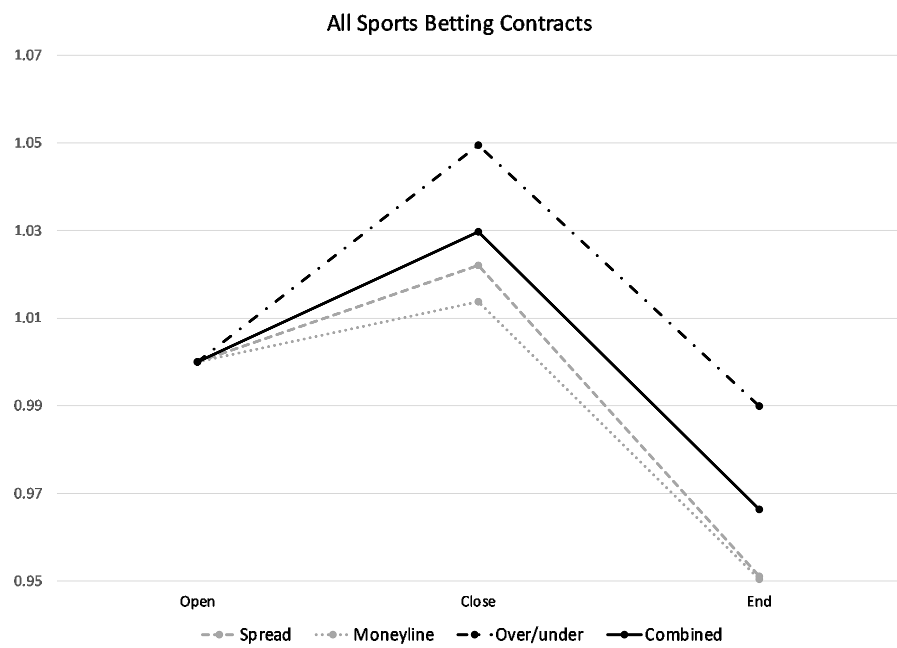


Figure 2. Theoretical implications of price movements. The figures illustrate the theoretical implications of betting contract price movements from various theories in Section I. The predictions pertain to regression equation (1), which regresses the close-to-end return on the open-to-close return of a generic betting contract, where β_1 is the regression coefficient. In the first case, the price movement contains some information, where the market can respond efficiently or inefficiently to the news, with the latter resulting in over- or underreaction. The second case illustrates the implications for noninformative price moves due to pure sentiment or noise.



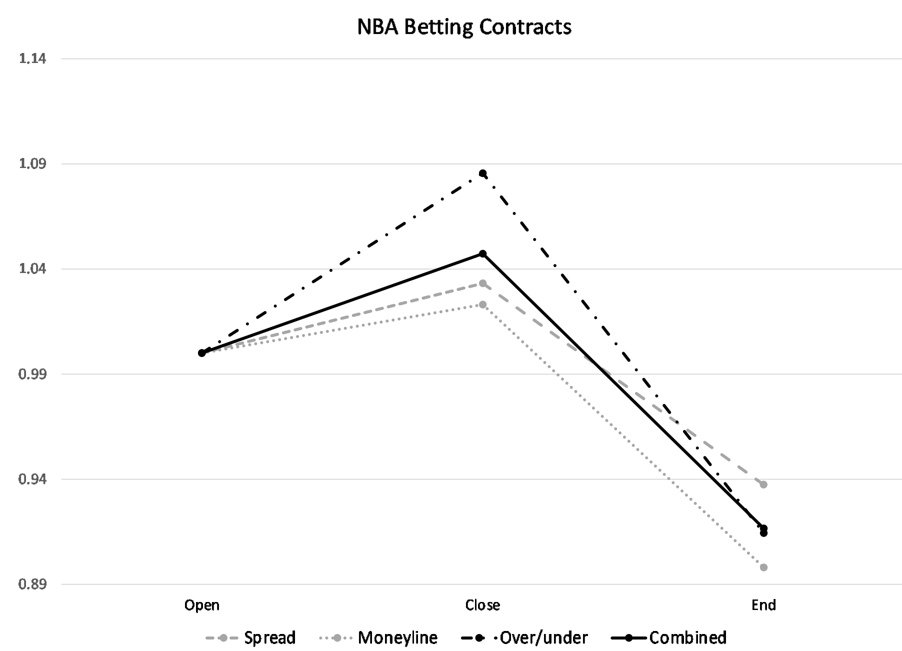
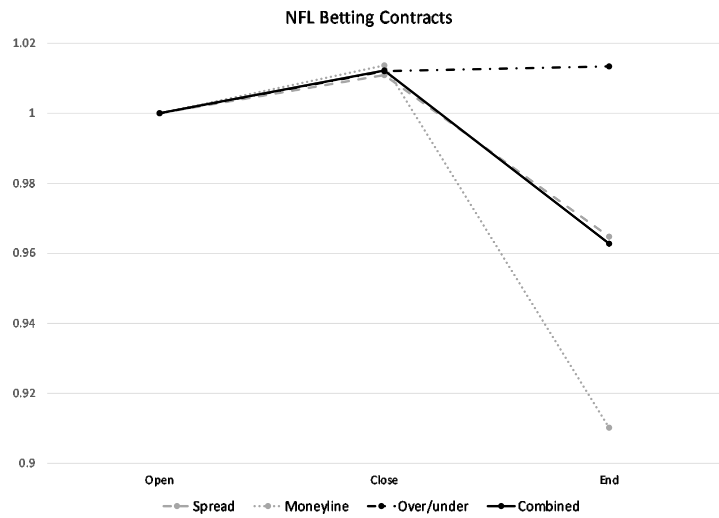
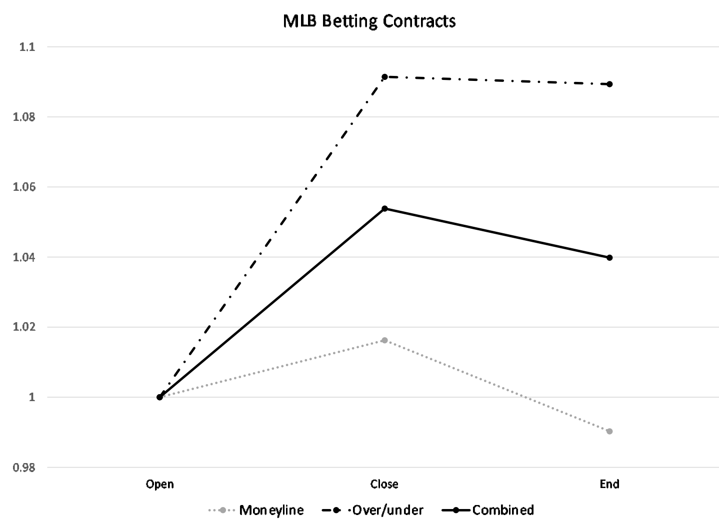


Figure 3. Momentum return patterns. Plotted are the average returns of the momentum strategies in sports betting contracts over the life of the contract – the return from open-to-close and from close-to-end – for Point Spread, Moneyline, and Over/Under contracts in each sport, as well as the combination of all contracts within a sport and across all sports. The returns are calculated by ranking contracts within a contract type and sport based on their momentum characteristic (using the momentum index) and going long the highest quintile of momentum contracts and short the lowest, and calculating their returns from the openinig of betting to closing line (open-to-close return) as well as from the closing line to the game outcome (close-to-end return). Average returns are reported for the NBA, NFL, MLB, NHL, and all sports combined.





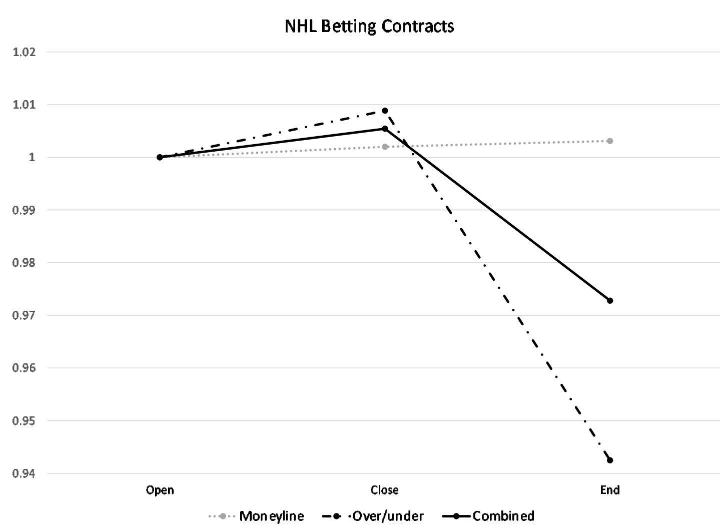


Figure 3 (continued)

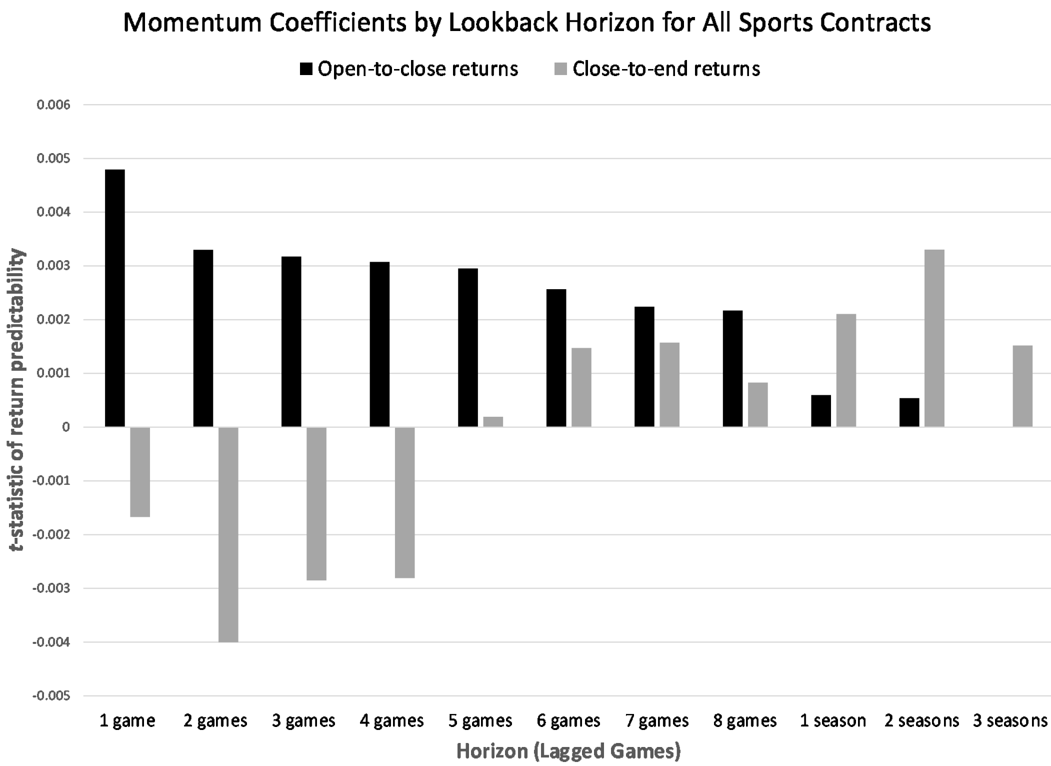


Figure 4. return predictability over various horizons. Plotted are the coefficients from return predictability regressions of past returns across various lags ranging from the most recent game to all games over the last three seasons. Specifically, the return from open-to-close and from close-to-end of each betting contract (across Point Spread, Moneyline, and Over/Under) in each sport are regressed on lagged measures of returns to betting on that team from the last N games (results are similar if using lagged win percentage or point differential relative to opponent) and the regression coefficients are plotted for open-to-close and close-to-end returns separately for lags of $N = 1, 2, \cdots 8$ games and one to three past seasons. The plot is for all sports (NBA, NFL, MLB, NHL) combined.

Table I
Summary Statistics of Sports Betting Contracts Across Sports

The table reports summary statistics for the sports betting contracts for each sport. Panel A reports statistics for the NBA, Panel B for the NFL, Panel C for MLB, and Panel D for the NHL. The number of seasons, total number of games, and total number of betting contracts are reported. Each game can have up to three betting contracts that depend on the game's outcome: 1) the Point Spread contract, which is a bet on whether a team wins by at least a certain amount of points, known as the "spread," 2) the Moneyline contract, which is a bet on which team wins for different dollar amounts, specified as betting $|x|$ dollars to win \$100 if $x < 0$ or betting \$100 to win \$$x$ if $x > 0$, and 3) the Over/Under contract, which is a bet on whether the total score (sum of both teams' points) is over or under the specified number. Reported are summary statistics on the mean, standard deviation, 1st, 10th, 25th, 50th, 75th, 90th, and 99th percentiles of the closing betting lines for each contract in each sport from the perspective of a bet on the home team. MLB and the NHL do not have Point Spread contracts as every contract is quoted at ± 1.5, simply indicating which team is expected to win, with no cross-sectional variation in these contracts. The final row of each panel reports the betting-implied probability of the home team winning the game based on the implied probabilities from the Moneyline contracts at each reported distributional percentile.

	mean	stdev	$1^{st\%}$	$10^{th\%}$	$25^{th\%}$	$50^{th\%}$	$75^{th\%}$	$90^{th\%}$	$99^{th\%}$
Panel A: NBA, 1999 - 2013 18,681 games; 38,939 betting contracts									
Point Spread	-3.4	6.0	-15.0	-10.5	-7.5	-4.5	1.5	5.0	10.0
Moneyline	-220.0	438.8	-2200.0	-565.0	-315.0	-172.0	107.0	177.0	330.0
Over/Under	196.1	11.4	172.0	182.5	188.0	195.0	203.5	211.0	226.0
P(win)			*0.99*	*0.89*	*0.76*	*0.64*	*0.48*	*0.34*	*0.13*
Panel B: NFL, 1985 - 2013 7,035 games; 10,775 betting contracts									
Point Spread	-2.6	6.0	-15.5	-10.0	-7.0	-3.0	2.5	5.5	11.5
Moneyline	-160.6	208.0	-700.0	-370.0	-270.0	-174.0	-112.0	144.0	264.0
Over/Under	42.3	4.8	32.5	36.5	38.5	42.5	45.5	48.0	54.5
P(win)			*0.96*	*0.84*	*0.75*	*0.59*	*0.46*	*0.31*	*0.12*
Panel C: MLB, 2005 - 2013 23,986 games; 47,964 betting contracts									
Point Spread	-1.5	0	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5
Moneyline	-69.7	128.9	-265.0	-187.0	-154.0	-124.0	104.0	130.0	173.0
Over/Under	8.7	1.1	6.5	7.5	8.0	9.0	9.5	10.0	11.5
P(win)			*0.73*	*0.65*	*0.61*	*0.55*	*0.51*	*0.44*	*0.37*
Panel D: NHL, 2005 - 2013 9,890 games; 19,764 betting contracts									
Point Spread	-1.5	0	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5
Moneyline	-93.6	120.7	-280.0	-201.0	-165.0	-133.0	-105.0	120.0	158.4
Over/Under	5.6	0.4	5.0	5.0	5.5	5.5	6.0	6.0	6.5
P(win)			*0.74*	*0.67*	*0.62*	*0.57*	*0.51*	*0.46*	*0.39*

Table II
Information versus Sentiment in Betting Price Movements

The table reports estimates of regression equation (1), $R_{close:end} = \alpha + \beta_1 R_{open:close} + \epsilon$. Panel A reports results for all four sports combined, as well as each sport separately. Panel B reports estimates of the regression for the subsample of betting contracts where the price moved from open to close (e.g., excluding betting lines with no open-to-close price movement). Panel C reports results across all sports for the most- and least-heavily bet games using betting volume (number of contracts), where the sample is split into the top third and bottom third of betting volume games within each sport and the coefficients among the highest- and lowest-volume games are estimated. Panel D reports results for "big interest" games, defined as games shown nationally on prime-time television, big market teams (two top-five market teams), playoff games, or games involving two of the (top-five) best-performing teams at that point in the season. For Point Spread and Over/Under contracts, only one contract per game is used in the regression, namely betting on the home team and the Over, respectively, since the payoff to betting on the visitor or the Under is symmetric (with opposite sign). For the Moneyline contracts, both the home and away contracts are included since payoffs are not symmetric, with standard errors used to compute t-statistics clustered at the game level.

	Point Spread	Moneyline	O/U	Point Spread	Moneyline	O/U
	Panel A: Full sample			Panel B: Price moves only		
	All Sports			All Sports		
β_1	-0.51	-0.68	-0.51	-0.50	-0.68	-0.51
	(-29.32)	(-4.17)	(-28.55)	(-29.61)	(-4.16)	(-28.61)
	NBA			NBA		
β_1	-0.51	-1.28	-0.51	-0.51	-1.28	-0.51
	(-20.36)	(-4.97)	(-20.21)	(-20.44)	(-4.97)	(-20.26)
	NFL			NFL		
β_1	-0.47	-0.09	-0.50	-0.47	0.09	-0.50
	(-8.66)	(-0.21)	(-9.08)	(-8.68)	(0.22)	(-9.11)
	MLB			MLB		
β_1		-0.11	-0.52		0.15	-0.70
		(-1.34)	(-16.14)		(1.20)	(-6.06)
	NHL			NHL		
β_1		-0.15	-0.70		-0.11	-0.52
		(-1.20)	(-5.77)		(-1.34)	(-17.17)
	Panel C: By Betting Volume			Panel D: Big Interest Games		
	High betting volume			Big interest games		
β_1	-0.52	-0.61	-0.53	-0.50	-0.70	-0.51
	(-10.81)	(-1.35)	(-13.60)	(-22.45)	(-3.07)	(-21.90)
	Low betting volume			All other games		
β_1	-0.51	-1.32	-0.50	-0.51	-0.65	-0.52
	(-14.90)	(-4.61)	(-12.46)	(-18.86)	(-2.98)	(-18.33)
	Difference			Difference		
	-0.01	0.71	-0.03	0.01	-0.05	0.01
	(-0.15)	(1.26)	(-0.49)	(0.29)	(-0.17)	(0.20)

Table III
Momentum Strategies in the Cross-Section of NBA Betting Contracts

The table reports average returns, t-statistics, and Sharpe ratios of momentum strategies in NBA betting contracts. For each contract type (Point Spread, Moneyline, and Over/Under), I rank games based on the momentum index measure and form a strategy that is long the top quintile of contracts based on momentum and short the bottom quintile within each contract type. Returns are computed from the opening line to the closing betting line (open-to-close returns) and from the closing line to the game outcome (close-to-end returns) from realized returns of the contract if betting at the open and unwinding the contract (by taking the other side) at the close and by betting at the close and receiving the payoff from the game's outcome, respectively. These returns represent the gross realized average returns a bettor following this strategy would achieve in real time (before transactions costs). I also report the return from open-to-end which is the sum of the two returns, and is equivalent to betting at the open and holding until the game's outcome, as well as the difference between open-to-close and close-to-end returns, which is a trading strategy that goes long momentum at the open and short momentum at the close ("trading strategy returns"). Panel A reports results for all contracts combined, Panel B for Point Spread contracts, Panel C for Moneyline contracts, and Panel D for Over/Under contracts. For robustness, Panels E and F report results for other portfolio formations across all contracts. Panel E reports results for strategies that go long-short contracts in proportion to the rank of their momentum characteristic (rank-weighting) and Panel F reports results for a long-short strategy that weights contracts in proportion to their momentum characteristic (signal-weighting). Rank and signal-weights are formed within each contract type and then averaged across all contracts. The contracts cover 18,132 games from 1998 to 2013 in the NBA. Returns are reported in percent and both returns and Sharpe ratios are annualized, with t-statistics computed using the time series of the daily portfolio returns.

	(1) Open-to-close	(2) Close-to-end	(1)+(2) Open-to-end	(1) − (2) Trading strategy
Panel A: All contracts				
Mean	4.73	-8.34	-3.61	13.07
t-stat	(5.32)	(-2.52)	(-1.10)	(3.66)
Sharpe	0.73	-0.32	-0.14	0.47
Panel B: Point Spread contracts				
Mean	3.32	-6.26	-2.94	9.58
t-stat	(2.63)	(-1.48)	(-0.69)	(2.07)
Sharpe	0.51	-0.29	-0.13	0.40
Panel C: Moneyline contracts				
Mean	2.31	-10.20	-7.89	12.51
t-stat	(1.69)	(-1.14)	(-0.90)	(1.34)
Sharpe	0.53	-0.36	-0.28	0.42
Panel D: Over/under contracts				
Mean	8.56	-8.56	0.00	17.12
t-stat	(4.36)	(-1.62)	(0.00)	(2.86)
Sharpe	1.05	-0.39	0.00	0.69
Panel E: All contracts, Rank-weighted				
Mean	6.06	-6.64	-0.58	12.70
t-stat	(4.58)	(-1.29)	(-0.11)	(2.31)
Sharpe	0.62	-0.16	-0.01	0.29
Panel F: All contracts, Signal-weighted				
Mean	5.86	-3.50	2.35	9.36
t-stat	(4.55)	(-0.70)	(0.48)	(1.75)
Sharpe	0.60	-0.08	0.06	0.22

Table IV
Momentum Strategies Across All Sports Betting Contracts

The table reports average returns, t-statistics, and Sharpe ratios of momentum strategies in all sports betting contracts across the NBA, NFL, MLB, and NHL. For each contract type within each sport, I rank games based on momentum and form a strategy long the top quintile of contracts and short the bottom quintile as described in Table III. Open-to-close returns, close-to-end returns, open-to-end returns, and trading strategy returns that go long momentum from the open to the close and short momentum from the close to the game's outcome are all reported as described in Table III. Panel A reports results aggregated across all contracts in all sports, Panels B, C, and D report results across all sports for Point Spread, Moneyline, and Over/Under contracts, separately, and Panels E, F, and G report results for the NFL, MLB, and NHL, respectively. Returns are reported in percent and both returns and Sharpe ratios are annualized, with t-statistics computed using the time series of the daily portfolio returns.

	(1) Open-to-close	(2) Close-to-end	(1)+(2) Open-to-end	(1) − (2) Trading strategy
PANEL A: ALL SPORTS, ALL CONTRACTS				
Mean	2.97	-3.37	-0.40	6.34
t-stat	(7.75)	(-1.63)	(-0.19)	(2.96)
Sharpe	1.33	-0.33	-0.04	0.60
PANEL B: ALL SPORTS, POINT SPREAD CONTRACTS				
Mean	2.20	-4.89	-2.69	7.10
t-stat	(2.63)	(-1.73)	(-0.95)	(2.31)
Sharpe	0.61	-0.41	-0.22	0.54
PANEL C: ALL SPORTS, MONEYLINE CONTRACTS				
Mean	1.38	-4.96	-3.58	6.34
t-stat	(3.44)	(-1.24)	(-0.90)	(1.56)
Sharpe	1.01	-0.40	-0.29	0.50
PANEL D: ALL SPORTS, OVER/UNDER CONTRACTS				
Mean	4.95	-1.01	3.94	5.96
t-stat	(6.81)	(-0.32)	(1.27)	(1.82)
Sharpe	1.80	-0.09	0.36	0.51
PANEL E: NFL, ALL CONTRACTS				
Mean	1.22	-3.72	-2.50	4.94
t-stat	(2.88)	(-2.25)	(-1.51)	(2.82)
Sharpe	0.451	-0.32	-0.21	0.41
PANEL F: MLB, ALL CONTRACTS				
Mean	5.38	3.98	9.37	1.40
t-stat	(6.57)	(0.74)	(1.76)	(0.26)
Sharpe	1.59	0.18	0.43	0.06
PANEL G: NHL, ALL CONTRACTS				
Mean	0.54	-2.72	-2.18	3.26
t-stat	(1.58)	(-0.63)	(-0.50)	(0.75)
Sharpe	0.44	-0.17	-0.13	0.20

Table V
Value Strategies Across All Sports Betting Contracts

The table reports average returns, t-statistics, and Sharpe ratios of value strategies in all sports betting contracts across the NBA, NFL, MLB, and NHL. For each contract type within each sport, I rank games based on value (an index of negated long-term past performance over the past one and two seasons, the negative of cumulative returns from betting on the team over the past one and two seasons, the fundamental-to-price ratio of player payroll expenses to the closing point spread of the betting contract, and the ratio of the expected point spread/contract price from leading sports analytical models to the actual betting line/contract price) and form a strategy long the cheapest quintile of contracts and short the most expensive quintile. Open-to-close returns, close-to-end returns, open-to-end returns, and trading strategy returns that go long value from the open to the close and short value from the close to the game's outcome are reported. Panel A reports results aggregated across all contracts in all sports, while Panels B, C, and D reports results across all sports for Point Spread, Moneyline, and Over/Under contracts. Returns are reported in percent and both returns and Sharpe ratios are annualized, with t-statistics computed using the time series of the daily portfolio returns.

	(1) Open-to-close	(2) Close-to-end	(1)+(2) Open-to-end	(1) − (2) Trading strategy
Panel A: All Sports, all contracts				
Mean	0.29	2.13	2.42	-1.84
t-stat	(0.53)	(0.71)	(0.81)	(-0.59)
Sharpe	0.14	0.21	0.24	-0.18
Panel B: All Sports, Point Spread contracts				
Mean	0.09	1.55	1.64	-1.46
t-stat	(0.09)	(0.47)	(0.50)	(-0.41)
Sharpe	0.02	0.13	0.14	-0.11
Panel C: All Sports, Moneyline contracts				
Mean	0.26	1.83	2.08	-1.57
t-stat	(0.42)	(0.28)	(0.32)	(-0.24)
Sharpe	0.20	0.15	0.17	-0.13
Panel D: All Sports, Over/Under contracts				
Mean	0.42	2.72	3.14	-2.30
t-stat	(0.39)	(0.56)	(0.65)	(-0.45)
Sharpe	0.16	0.25	0.28	-0.20

Table VI
Size Strategies Across All Sports Betting Contracts

The table reports average returns, t-statistics, and Sharpe ratios of size-based strategies in all sports betting contracts across the NBA, NFL, MLB, and NHL. For each contract type within each sport, I rank games based on size (an average of franchise book value, ticket revenue, and total revenue of the team) and form a strategy long the quintile of contracts with the smallest size exposure and short the quintile of contracts with the largest size exposure. Open-to-close returns, close-to-end returns, open-to-end returns, and trading strategy returns that go long from the open to the close and short from the close to the game's outcome are reported. Panel A reports results aggregated across all contracts in all sports, while Panels B, C, and D reports results across all sports for Point Spread, Moneyline, and Over/Under contracts, respectively. Returns are reported in percent and both returns and Sharpe ratios are annualized, with t-statistics computed using the time series of the daily portfolio returns.

	(1) Open-to-close	(2) Close-to-end	(1)+(2) Open-to-end	(1) − (2) Trading strategy
Panel A: All Sports, all contracts				
Mean	0.51	-2.62	-2.11	3.13
t-stat	(0.97)	(-0.89)	(-0.72)	(1.03)
Sharpe	0.25	-0.26	-0.21	0.30
Panel B: All Sports, Point Spread contracts				
Mean	-0.06	-0.76	-0.81	0.70
t-stat	(-0.06)	(-0.23)	(-0.25)	(0.20)
Sharpe	-0.02	-0.06	-0.07	0.05
Panel C: All Sports, Moneyline contracts				
Mean	0.53	-9.30	-8.77	9.83
t-stat	(0.75)	(-1.42)	(-1.34)	(1.48)
Sharpe	0.37	-0.75	-0.71	0.78
Panel D: All Sports, Over/Under contracts				
Mean	0.78	3.13	3.91	-2.35
t-stat	(0.78)	(0.69)	(0.86)	(-0.49)
Sharpe	0.30	0.28	0.35	-0.20

Table VII
Multifactor Strategies Across All Sports Betting Contracts

The table reports average returns, t-statistics, and Sharpe ratios of strategies based on a combination of momentum, value, and size in all sports betting contracts across the NBA, NFL, MLB, and NHL. For each contract type within each sport, I rank games based on an average of their momentum, value, and size characteristics (as defined in Tables IV, V, and VI) and form a strategy long the quintile of contracts with the highest expected return and short the quintile of contracts with the lowest. Open-to-close returns, close-to-end returns, open-to-end returns, and trading strategy returns that go long the open-to-close and short the close-to-end return are reported. Panel A reports results aggregated across all contracts in all sports, while Panels B, C, and D reports results across all sports for Point Spread, Moneyline, and Over/Under contracts, respectively. Returns are reported in percent and both returns and Sharpe ratios are annualized, with t-statistics computed using the time series of the daily portfolio returns.

	(1) Open-to-close	(2) Close-to-end	(1)+(2) Open-to-end	(1) − (2) Trading strategy
Panel A: All Sports, all contracts				
Mean	2.48	-1.70	0.78	4.18
t-stat	(4.68)	(-0.87)	(0.02)	(1.67)
Sharpe	1.83	-0.28	0.13	0.66
Panel B: All Sports, Point Spread contracts				
Mean	2.08	-7.63	-5.56	9.71
t-stat	(1.41)	(-0.77)	(-0.35)	(1.09)
Sharpe	0.86	-0.97	-0.71	1.13
Panel C: All Sports, Moneyline contracts				
Mean	0.72	-4.15	-3.43	4.86
t-stat	(2.37)	(-1.38)	(-1.14)	(1.60)
Sharpe	1.03	-0.54	-0.45	0.63
Panel D: All Sports, Over/Under contracts				
Mean	2.05	1.61	3.66	0.44
t-stat	(3.99)	(0.71)	(1.62)	(0.18)
Sharpe	1.22	0.22	0.50	0.06

Table VIII
Net of Transactions Cost Returns in Sports Betting and Financial Markets

The table reports trading strategy profits, net of transactions costs, from using momentum, value, and size in sports betting markets and compares them to the same characteristic-based strategies applied in financial markets. The sports betting contracts are applied across the NBA, NFL, MLB, and NHL and aggregated across all contract types (Point Spread, Moneyline, and Over/Under). For each contract type within each sport, I rank games based on an average of their momentum, value, and size characteristics (as defined in Tables IV, V, and VI) and form a strategy long the quintile of contracts with the highest expected return and short the quintile of contracts with the lowest expected return. Open-to-close returns, close-to-end returns, and trading strategy returns that go long the open-to-close and short the close-to-end return are reported. The gross average returns and Sharpe ratios of the strategies are reported, as well as average returns net of transactions costs that take into account the broker's commission or "vigorish" that every contract bet incurs in sports betting markets. All returns and Sharpe ratios are reported as annualized numbers. For financial markets, long-short portfolios are formed based on momentum, value, and size in U.S. equity as well as global equity markets. Specifically, the Fama and French long-short factors for size (SMB), value (HML), and momentum (UMD) from Ken French's website for U.S. stocks and international factors constructed similarly from international equity returns following Frazzini, Israel, and Moskowitz (2018) are used. The annualized market-adjusted gross return or CAPM alpha of each strategy is reported (to remove the systematic equity market component of returns) along with an estimate of the net of trading cost (market impact plus commissions) alpha using the model from Frazzini, Israel, and Moskowitz (2018). Returns and Sharpe ratios are annualized. Panel A reports results for momentum strategies, Panel B for value strategies, Panel C for size strategies, and Panel D for all three characteristic-sorted strategies ("Multifactor"). The sports betting contract returns pertain to the period September 1985 to March 2013 and the financial market returns to the period January 1972 to December 2013.

	Sports betting contracts			Financial markets	
	Open-to-close	Close-to-end	Trading strategy	U.S. equities†	Global equities†
Panel A: Momentum strategies					
Gross return	2.97	3.37	6.34	10.45	8.10
Sharpe	1.33	0.33	0.60	0.67	0.80
Net of tcost return	-27.15	-11.98	-15.18	6.95	4.60
Panel B: Value strategies					
Gross return	0.29	2.13	-1.84	3.76	6.10
Sharpe	0.14	0.21	-0.18	0.33	0.54
Net of tcost return	-29.16	-18.34	-10.82	2.26	4.60
Panel C: Size strategies					
Gross return	0.51	-2.62	3.13	1.17	-0.76
Sharpe	0.25	-0.26	0.30	0.11	-0.09
Net of tcost return	-30.87	-13.86	-17.01	-0.33	-2.60
Panel D: Multifactor strategies					
Gross return	2.48	-1.70	4.18	5.22	7.50
Sharpe	1.83	-0.28	0.66	0.81	1.38
Net of tcost return	-32.12	-16.23	-15.89	3.22	5.50

†Alphas with respect to the equity market portfolio.

Table IX
"Point Return" Analysis of Sports Betting Contracts

The table reports regression results of open-to-close point returns and close-to-end point returns on momentum, value, and size measures (as defined in Tables IV, V, and VI) across the Point Spread, Moneyline, and Over/Under contracts, aggregated across all sports (NBA, NFL, MLB, and NHL). Point returns are imputed returns based on points scored, which capture more information about the distribution of the underlying fundamentals but are not real returns. The specific regression equations are

$$\tilde{R}_{i,0:1} = \alpha_1 + \beta_1 Char_i + \tilde{\epsilon}_{i,0:1} \qquad \tilde{R}_{i,1:T} = \alpha_T + \beta_T Char_i + \tilde{\epsilon}_{i,1:T}$$

for $Char \in \{\text{Mom, Val, Size}\}$. Also reported are tests for the difference between the coefficients $\beta_1 - \beta_T$, which measures the cumulative absolute magnitude of the return movement from open to close and from close to the game's outcome due to each characteristic. In addition, I report tests on the sum of the two coefficients $\beta_1 + \beta_T$ to capture the total net return from open-to-end of game that accounts for any offsetting return movement from open to close and from close to the game's outcome. Regressions include sport, team, contract, and year fixed effects with standard errors used to compute t-statistics clustered at the daily level.

Dependent variable = Point returns				
	β_1	β_T	$\beta_1 + \beta_T$	$\beta_1 - \beta_T$
Momentum	0.086	-0.107	-0.018	0.190
	(12.06)	(-2.63)	(-0.45)	(4.52)
Value	0.049	0.030	0.079	0.019
	(6.49)	(0.46)	(1.21)	(0.30)
Size	0.005	0.013	0.019	-0.008
	(0.78)	(0.20)	(0.30)	(-0.13)
Multifactor	0.079	-0.077	0.004	0.155
	(14.95)	(-1.87)	(0.09)	(3.70)

Table X
Momentum, Value, and Uncertainty: Evidence from Sports Betting Markets

The table reports returns from momentum and value strategies in sports betting markets interacted with measures of uncertainty. Two measures of game uncertainty are used. Panel A measures uncertainty using early games (more uncertainty) versus late games in the season (less uncertainty), measured as the first 25% of games and last 75% of games each season, respectively. Team quality is more uncertain early in the season. Panel B proxies for uncertainty using the percentage of betting volume involved in parlays. Parlay bets are those that involve multiple bets across multiple games simultaneously, where every bet in the parlay has to win to receive any positive pay off. Games more likely to be involved in parlay bets should be those for which bettors *believe* they have the most certainty. Using the regressions from Table IX I interact the momentum and value characteristics with the uncertainty measures – dummies for early and late games in the season (Panel A) and dummies for the top and bottom third of games based on the percentage of betting volume involved in parlays (Panel B) – and report the open-to-close return effect, close-to-end return effect, and the difference between them (trading strategy of going long open-to-close and short close-to-end) for the interactions between momentum, value, and the uncertainty measures. Results are reported aggregating across all contract types (Point Spread, Moneyline, and Over/Under) and across all sports (NBA, NFL, MLB, and NHL) over the period 1998 to 2013. The difference in return effects between the high- and low-uncertainty games is also reported. Regressions include sport, game matchup, and year fixed effects with standard errors used to compute t-statistics (in parentheses) clustered at the daily level.

	Momentum			Value		
	(1)	(2)	(1)−(2)	(1)	(2)	(1)−(2)
	Open-to-close	Close-to-end	Trading strategy	Open-to-close	Close-to-end	Trading strategy
Panel A: Uncertainty Measured by Games Played Early versus Late in Season						
Less uncertainty	0.01	-0.13	0.14	0.15	-0.63	0.78
games late in season	(0.37)	(-1.34)	(1.40)	(3.19)	(-3.76)	(5.61)
More uncertainty	0.13	-0.27	0.40	0.01	-0.11	0.12
games early in season	(3.53)	(-3.55)	(5.95)	(0.15)	(-0.38)	(0.49)
More − less	0.12	-0.13	0.25	-0.15	0.51	-0.66
	(3.28)	(-1.12)	(2.97)	(-2.88)	(2.39)	(-4.03)
Panel B: Uncertainty Measured by Contracts with High versus Low % Parlay Activity						
Less uncertainty	0.02	-0.04	0.06	0.01	-0.05	0.06
high %parlay volume	(-2.25)	(-1.52)	(3.00)	(-1.69)	(-2.98)	(4.00)
More uncertainty	0.12	-0.12	0.24	-0.01	-0.02	0.02
low % parlay volume	(3.37)	(-2.23)	(5.28)	(-0.59)	(-1.90)	(2.10)
More − less	0.10	-0.08	0.18	-0.01	0.03	-0.04
	(3.15)	(-1.64)	(4.51)	(-1.63)	(1.64)	(-2.53)

Table XI
Momentum, Value, and Uncertainty: Evidence from Financial Markets

The table reports returns from momentum and value strategies in U.S. equity markets interacted with the uncertainty of firm earnings. The data are U.S. stocks from CRSP from July 1963 to December 2013. Panel A reports results using the recency of earnings announcements as a proxy for uncertainty. Firms with higher earnings uncertainty are those whose most recent earnings number is stale (at least 11 weeks old), while firms with less earnings uncertainty are those with recent earnings numbers (within the past two weeks). At the portfolio formation date, time t, I first look only at firms with recent earnings announcements, defined as those firms with earnings announced within the last two weeks. I also separately form a universe of firms at the same time who have "stale" earnings numbers, defined as those firms whose last earnings announcement was at least 11 weeks ago. Within each universe, I then compute momentum and value returns following the construction of Fama and French's UMD momentum factor and HML value factor. UMD (HML) is constructed by sorting stocks into three momentum (value) groups based on the top 30%, middle 40%, and bottom 30% of past 2 to 12 month returns (book-to-market ratios) and into large and small cap groups based on the NYSE size median. The intersection of the groups produces six portfolios – large high, middle, and low and small high, middle, and low. UMD (HML) is then the average of the two top 30% past two to 12-month return (book-to-market) portfolios minus the average of the two bottom 30%. This procedure creates UMD and HML returns for firms with recent earnings numbers and firms with stale earnings numbers at time t, where the latter should have more uncertain earnings. Panel B reports results using the dispersion in analyst forecasts of one-year earnings per share as a measure of earnings uncertainty. Following Diether, Malloy, and Scherbina (2002), dispersion in analyst forecasts is measured as the cross-sectional standard deviation across analysts of their fiscal year earnings-per-share forecast, scaled by the mean forecast for a given stock (requiring at least five analysts). Firms are sorted independently into three groups based on analyst dispersion, and UMD and HML are constructed within the highest and lowest third of dispersion groups. Analyst data cover July 1990 to December 2013. High dispersion in analyst forecasts indicates more uncertainty about firm earnings. Both panels report the returns to momentum and value for high- and low-uncertainty firms using each uncertainty measure, along with tests for the difference between more- and less-uncertainty firms. Both raw average return differences and four-factor alphas from a regression of the returns on the Fama-French factors RMRF, SMB, HML, and UMD are reported.

	Momentum (UMD)		Value (HML)	
	Raw	4-factor α	Raw	4-factor *alpha*
Panel A: Uncertainty Measured by Recent versus Stale Earnings News				
Less uncertainty	1.98	-5.39	12.12	8.80
earnings < 2 weeks old	(0.41)	(-1.39)	(2.79)	(2.52)
More uncertainty	11.81	6.05	2.96	-1.58
earnings > 11 weeks old	(2.44)	(1.44)	(0.72)	(-0.44)
More − less	9.83	11.44	-9.15	-10.39
	(1.97)	(2.18)	(-1.91)	(-2.11)
Panel B: Uncertainty Measured by Dispersion in Analyst Earnings Forecast				
Less uncertainty	1.62	3.24	4.65	5.19
low dispersion	(0.78)	(1.80)	(2.36)	(2.78)
More uncertainty	6.51	7.83	-0.84	-1.05
high dispersion	(2.46)	(3.02)	(-0.07)	(-0.01)
More − less	4.89	4.59	-5.49	-6.24
	(2.35)	(2.55)	(-2.79)	(-3.34)

Internet Appendix for "Asset Pricing and Sports Betting"

Tobias J. Moskowitz*

The Internet Appendix contains the following supplementary materials.

1. A description of how I estimate the expected contract price from fundamentals for use in one of the value measures used in the paper for sports betting contracts.
2. Figure IA1 – Cumulative Returns to Sports Betting and the Stock Market.
3. Figure IA2 – Price Momentum and Reversals in Financial Markets by Recency of Earnings Announcement.
4. Table IAI – Return Distributions of Sports Betting Contracts.
5. Table IAII – Momentum, Value, and Size Characteristic Correlations.
6. Table IAIII – (Lack of) Covariance Among Betting Strategies.
7. Table IAIV – Correlation of Point Returns.
8. Table IAV – Results from Betfair on European Soccer Betting Returns.

*Moskowitz, Tobias J., Internet Appendix for "Asset Pricing and Sports Betting," *Journal of Finance* DOI STRING. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the author of the article.

A Estimating Expected Contract Price from Fundamentals

One of the measures of value derives a fundamental value of the game itself and divides it by the market price of the contract. The sports analytics community has derived a number of measures of team quality or strength for use in predicting various game outcomes. One of the most popular is known as the Pythagorean win expectation formula, which the sports analytics community has shown is a good predictor of win percentage across many sports. The formula and the parameter estimates across sports are

$$E(\text{win\%}) = \frac{P_F^\gamma}{P_F^\gamma + P_A^\gamma},$$

where P_F is the average number of points scored for the team, P_A is the average number of points scored against the team, and γ is the Pythagorean coefficient with $\gamma = 1.83$ for MLB, 13.91 for the NBA, 2.37 for the NFL, and 2.11 for the NHL. These parameters come from the literature and were estimated on historical data prior to and independent of my sample.[1]

Using this formula, I estimate what the expected contract price would be based solely on this formula and the team's fundamentals (e.g., points scored and points allowed) by converting the Pythagorean formula's win percentage estimate into a Spread or Moneyline value. The formula provides an expected win percentage based on the points scored by a team and points scored against a team. I use the most recent scores of each team in their last 40 games (16 for the NFL) including the previous season to estimate win expectation. Taking the difference between the win expectations of both teams provides a measure of relative team strength in units of win probability. Multiplying this probability difference times the Over/Under total (which is the market's expectation of the total number of points that will be scored by both teams) converts the probability difference into an expected point difference, which I then divide by the actual betting contract expected point difference or Spread. That is, I take the estimated betting contract price, $E(P)$, from the Pythagorean formula and divide it by the actual market price of the betting contract, P. Intuitively, $E(P)/P$ is a measure of the expected point Spread derived from past scoring information through the Pythagorean model relative to the market's expectation from betting markets. A high value for this ratio implies that the Spread contract for a game looks "cheap" or is a value bet while a low ratio looks "expensive" relative to fundamentals.

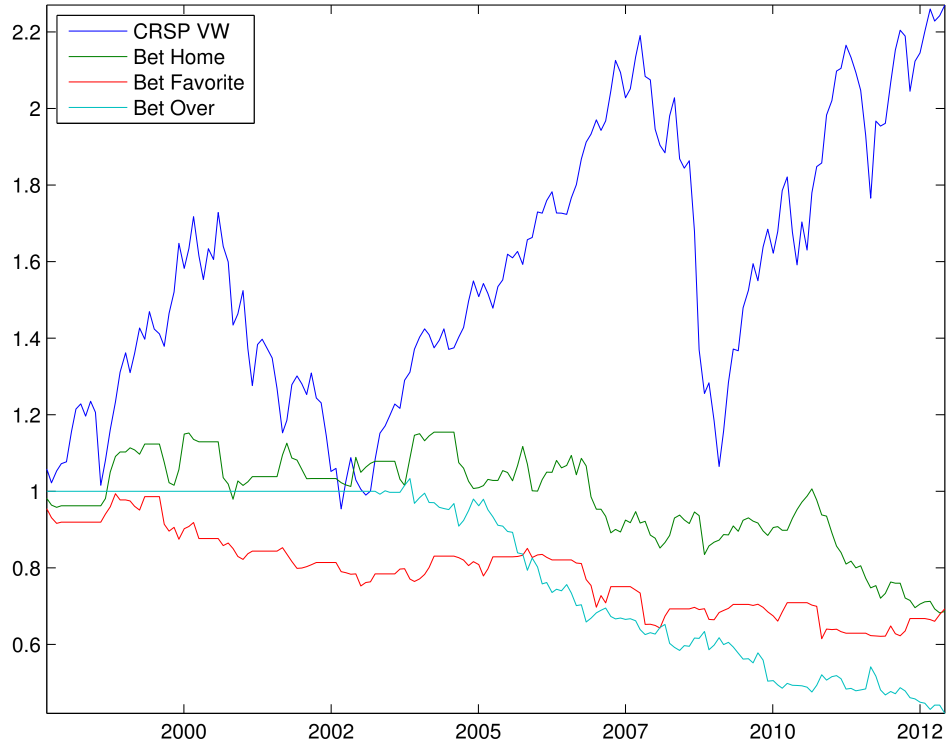
For the Moneyline contracts I follow a similar approach and match the Pythagorean-implied Spread to the corresponding Moneyline based on the distributional mapping of actual Spreads to Moneylines in the data.[2] By mapping the predicted Spread from the Pythagorean formula to the Moneyline using the joint distribution of actual Spreads and Moneyline values, I preserve the feature that the Moneyline values are internally consistent with the predicted Spreads, which is appealing since both the Spread and Moneyline contracts are bets on who wins. Alternatively, I could do the opposite and take the expected win probability from the Pythagorean as above and use that to imply a Moneyline, where a rough translation between win probability and Moneyline is as follows: if π = estimated win probability, then if $\pi > 0.5, ML = -(\pi/(1-\pi)) * 100$, while if $\pi < 0.5, ML = (1-\pi)/(\pi) * 100$. Then, taking the Moneyline estimated from the Pythagorean

[1] The formula was first used by Bill James to estimate how many games a baseball team "should" have won based on the number of runs they scored and allowed. The name comes from the formula's resemblance to the Pythagorean theorem when the exponent equals two. Empirically, this formula correlates well with how teams actually perform. Miller (2007) shows that if runs for each team follow a Weibull distribution and the runs scored and allowed per game are statistically independent, then the formula gives the probability of winning. The formula makes two assumptions: that teams win in proportion to their "quality," and that their quality is measured by the ratio of their points scored to their points allowed. The different values for the exponent across sports reflects the distribution of point differentials across games within each sport (e.g., many baseball games end with one team scoring two, three, or four times more than its opponent, but almost no basketball games end with such a ratio) and how that relates to the probability of winning. For derivations and estimations of the model in each sport, see Morey (1994), Miller (2007), Dayaratna and Miller (2013), and Gardner et al. (2011).

[2] For example, if the Pythagorean-implied spread is -3.5, I take the Moneyline value associated with a -3.5 point spread from the empirical distribution of actual betting contracts. When there are multiple Moneyline values for a given Spread, I take the average of those Moneylines.

win probability, I could match the Moneyline to a Spread using the empirical distribution of Moneylines and Spreads to make the estimates internally consistent. Both methods of computing expected Spreads and Moneylines yield nearly identical results.

For Over/Uunder contracts, which are bets on total points scored by both teams combined, I run a rolling regression model of Over/Under totals on points scored by the home team, points scored against the home team, points scored by visiting team, and points scored against visiting team over the last 40 games (16 games in the NFL) for each team. Using the regression coefficients for both teams, I then apply them to the average points scored for and against each team over the last 40 games (16 games in the NFL) and take an average of the predicted point totals for the two teams, which represents a predicted Over/Under point total from the number of points scored for and against each team over the last 40 games. This predicted point total is then divided by the actual Over/Under total from the betting market to obtain a value measure. Alternatively, I could have taken a moving average O/U total from betting markets over the past 40 games involving either team and taken the average across the two teams for my fundamental Over/Under total. I get very similar results using this measure instead.



Correlation matrix of returns			
	Home	Favorite	Over
Stock Market	0.06	-0.01	0.03
Home		0.10	-0.01
Favorite			-0.01

Figure IA1. Cumulative returns to sports betting and the stock market. The figure plots the cumulative returns to betting on the home team, the favorite team, and the over across all sports—NBA, NFL, MLB, and NHL—and using all betting contracts—Point Spread, Moneyline, and Over/Under. The cumulative returns to these bets versus the stock market (CRSP value-weighted index) are plotted weekly over time. Specifically, every week three portfolios of bets are formed by 1) betting on the home team using the Point Spread and Moneyline contracts, 2) betting on the favorite team using the Point Spread and Moneyline contracts, and 3) betting on the over using the Over/Under contract. The portfolios are equal-weighted bets of one dollar in each game within each sport and then equal-weighted across sports, covering the NBA, NFL, MLB, and NHL. Since none of the sports have seasons that last a full year, and the different sports occur at different times of year, the majority of the time only two or three sports are covered. The weekly returns are aggregated monthly and their cumulative returns are plotted over time along with the cumulative return to the CRSP value-weighted U.S. stock index. All sports betting returns pertain to open-to-end returns. For ease of comparison, all series are scaled to the same ex post volatility that matches the sample volatility estimate of the stock market. Also reported is a correlation matrix of the return series. The sample period is November 1998 to March 2013.

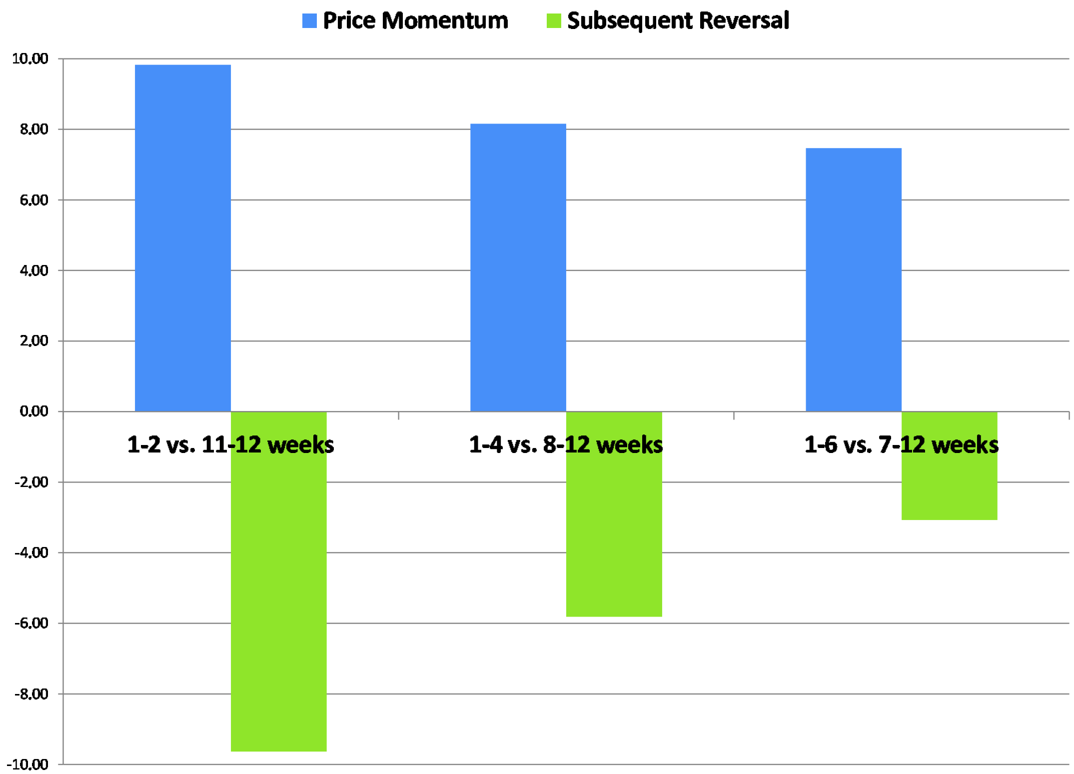


Figure IA2. Price momentum and reversals in financial markets by recency of earnings announcement. Depicted are the difference in momentum premia between stale versus recent earnings announcers for various windows of time used to define "stale" and "recent:" >11 versus <2 weeks since announcement, >8 versus <4 weeks since announcement, and >7 versus <6 weeks since announcement. In addition, the figure plots the difference in returns of these momentum portfolios in years two to three *after* portfolio formation, which represent the subsequent reversals that often accompany momentum one-year momentum returns.

Table IAI
Net Return Distributions of Sports Betting Contracts

The table reports the distribution of gross returns to all sports betting contracts across the NBA, NFL, MLB, and NHL and all contracts on each game: Point Spread, Moneyline, and Over/Under. Summary statistics on the net returns (mean, standard deviation, skewness, and kurtosis) of each contract type in each sport are reported, as well as a correlation matrix of returns between open-to-close and close-to-end returns across all three contract types averaged across all sports.

	Spread		Over/under		Moneyline	
	Open-to-close	Close-to-end	Open-to-close	Close-to-end	Open-to-close	Close-to-end
			NBA contracts			
Mean	-9.3%	-5.2%	-9.0%	-5.1%	-5.3%	-6.4%
Stdev	27.4%	94.6%	33.9%	94.8%	102.9%	121.4%
Skew	-0.17	0.01	0.10	0.01	3.96	2.37
Kurtosis	33.03	-1.98	24.26	-1.99	27.71	15.14
			NFL contracts			
Mean	-8.4%	-5.0%	-9.1%	-3.5%	-3.6%	-25.4%
Stdev	26.7%	94.2%	33.3%	94.5%	83.8%	102.6%
Skew	0.57	0.01	0.23	-0.02	2.03	1.18
Kurtosis	29.75	-1.97	23.03	-1.98	5.86	0.87
			MLB contracts			
Mean			-9.4%	-5.6%	-2.6%	-1.8%
Stdev			19.4%	93.2%	36.1%	101.2%
Skew			-0.43	0.02	0.98	0.21
Kurtosis			33.26	-1.95	1.17	-1.63
			NHL contracts			
Mean			-8.3%	-8.2%	-3.2%	-2.7%
Stdev			7.8%	92.1%	42.5%	102.6%
Skew			5.22	0.07	1.17	0.30
Kurtosis			137.82	-1.92	1.90	-1.48

Return Correlation Matrix Across All Sports

	$r^{S}_{open:close}$	$r^{S}_{close:end}$	$r^{ML}_{open:close}$	$r^{ML}_{close:end}$	$r^{O/U}_{open:close}$	$r^{O/U}_{close:end}$
$r^{S}_{open:close}$	1.00	-0.14	0.00	0.02	0.00	-0.01
$r^{S}_{close:end}$		1.00	-0.27	0.73	-0.01	0.01
$r^{ML}_{open:close}$			1.00	-0.34	0.00	-0.02
$r^{ML}_{close:end}$				1.00	-0.01	0.01
$r^{O/U}_{open:close}$					1.00	-0.13
$r^{O/U}_{close:end}$						1.00

Table IAII
Momentum, Value, and Size Characteristic Correlations

The table reports correlations among various momentum, value, and size measures. Panel A reports correlations among various momentum measures as defined in Section III, win percentage, point differential in excess of the spread, and past betting returns. Panel B reports correlations between various value measures based on long-term past returns, payroll-to-betting spread, and the ratio of the expected contract spread from an analytical model to the actual contract spread. Panel C reports correlations between various size measures, including Forbes' estimates of franchise value, ticket revenue, and total revenue. Panel D reports the correlations between the equal-weighted indices for momentum, value, and size.

Panel A: Momentum measures

	Win%	Point diff	Past returns	Win%	Point diff	Past returns
	Lag = 1 game			Lag = 2 games		
Win%	1.00	0.81	0.62	1.00	0.83	0.60
Point diff		1.00	0.68		1.00	0.65
Past returns			1.00			1.00
	Lag = 4 games			Lag = 8 games		
Win%	1.00	0.85	0.57	1.00	0.88	0.52
Point diff		1.00	0.61		1.00	0.56
Past returns			1.00			1.00

Panel B: Value measures

	Long-term past returns			Payroll/	
	1 season	2 seasons	3 seasons	Spread	$E(P)/P$
1 season	1.00	0.72	0.60	0.02	-0.08
2 seasons		1.00	0.83	0.00	-0.08
3 seasons			1.00	-0.01	-0.08
Payroll/Spread				1.00	0.06
$E(P)/P$					1.00

Panel C: Size measures

	Franchise value	$Tix	Revenue
Franchise value	1.00	0.88	0.97
$Tix		1.00	0.89
Revenue			1.00

Panel D: Momentum, Value, and Size Correlations

	MOM_{index}	VAL_{index}	SIZE_{index}
MOM_{index}	1.00	-0.13	0.05
VAL_{index}		1.00	-0.09
SIZE_{index}			1.00

Table IAIII
(Lack of) Covariance Among Betting Strategies

Reported are regression results of quintile portfolios of games formed on momentum (and value) and regressed on a momentum (value) "factor." The test portfolios are formed by sorting all games in a given month (with at least 40 games) by their momentum (value) characteristic, which is the weighted-average index momentum (value) variable, into five quintiles and then taking the equal-weighted average return of all games within each group. This provides a monthly return to quintile-sorted portfolios based on momentum (value), whose returns are then regressed on the monthly returns of the momentum (value) factor, which is the high- minus low-quintile spread returns, Q5 − Q1. The test assets/portfolios are formed from one set of games and the factors are formed from a completely different set of games. To compute the test portfolios and the factors independently each month, the number of games are split randomly into two groups, with one used to form the test assets and the other used to form the factors. Reported are the coefficient estimates (β) on the factor, its t-statistic in parentheses, and the R^2 from each regression. The intercept is not reported for brevity.

	Low Q1	Q2	Q3	Q4	*High* Q5	*Low* Q1	Q2	Q3	Q4	*High* Q5
	Momentum					Value				
	Point Spread contract returns									
β	0.016	0.056	0.146	0.008	-0.053	-0.177	-0.123	-0.008	0.031	-0.169
	(0.16)	(0.54)	(1.26)	(0.07)	(-0.62)	(-0.86)	(-0.86)	(-0.08)	(0.30)	(-0.83)
R^2	0.00	0.00	0.02	0.00	0.01	0.03	0.04	0.00	0.01	0.03
	Moneyline contract returns									
β	-0.098	-0.131	-0.092	0.086	-0.379	-0.120	-0.059	0.086	0.235	-0.310
	(-0.80)	(-1.02)	(-0.53)	(0.18)	(-2.15)	(-0.30)	(-0.25)	(0.15)	(0.58)	(-1.44)
R^2	0.02	0.03	0.01	0.01	0.13	0.02	0.01	0.00	0.05	0.26
	Over/Under contract returns									
β	0.102	-0.004	0.067	-0.043	0.076	-0.157	-0.432	-0.366	0.191	-0.125
	(1.35)	(-0.04)	(0.66)	(-0.48)	(0.50)	(-1.25)	(-2.55)	(-1.75)	(0.97)	(-0.52)
R^2	0.04	0.00	0.01	0.01	0.01	0.10	0.32	0.18	0.07	0.02

Table IAIV
Correlation of Point Returns

Panel A reports return correlations between dollar-denominated returns and point-denominated returns for the Point Spread contract (S) and the Over/Under contract (O/U) for three sets of returns for each contract: the return from the opening line to the outcome (open:end), the return from the closing line to the outcome (close:end), and the return from the opening line to the closing line (open:close). Panel B reports the correlations among the point-denominated returns across the different contracts and different return horizons.

Panel A: Correlation Between Dollar and Point Returns		
	Spread contract	Over/Under contract
Correlation($R^{\$}_{open:end}, R^{pts.}_{open:end}$) =	0.79	0.75
Correlation($R^{\$}_{close:end}, R^{pts.}_{close:end}$) =	0.79	0.75
Correlation($R^{\$}_{open:close}, R^{pts.}_{open:close}$) =	0.25	0.33

Panel B: Point Return Correlations						
	$R^{S}_{open:end}$	$R^{S}_{close:end}$	$R^{S}_{open:close}$	$R^{O/U}_{open:end}$	$R^{O/U}_{close:end}$	$R^{O/U}_{open:close}$
$R^{S}_{open:end}$	1.00	0.99	0.10	-0.01	-0.01	0.01
$R^{S}_{close:end}$		1.00	-0.01	-0.01	-0.01	0.01
$R^{S}_{open:close}$			1.00	0.00	0.00	0.03
$R^{O/U}_{open:end}$				1.00	0.99	0.13
$R^{O/U}_{close:end}$					1.00	0.01
$R^{O/U}_{open:close}$						1.00

Table IAV
Results from Betfair on European Soccer Betting Returns

The table reports regression results of open-to-close returns and close-to-end returns from equations (2) and (3) on various fundamental-based and price-based momentum measures for "match winner" contracts from Betfair, on online exchange, rather than a sportsbook. The matches cover the following professional leagues that show sufficient liquidity/betting volume: Jupiler (Belgium), Eredvisie (Netherlands), English League Championship, English Premier League, French Ligue 1 and 2, German Bundesliga 1 and 2, Greek Super League, Italian Serie A and B, Portugese Super Liga, Scottish Premier League, Spanish Primera and Segunda divisions, and the Turkish Super League, covering 12,979 games from 2006 to 2011. The momentum measures are past wins, cumulative past goal differentials, and cumulative past returns of betting on the team over the past N games. Also reported is a momentum index measure that is an equal-weighted average of the momentum measures (each first rescaled to mean zero and unit variance).

	Past wins		Past goals		Past returns		
Past games	1	5	3	6	3	6	MOM_{index}
			Open-to-close betting returns				
$\beta_{1,Mom}$	0.014	0.004	0.003	0.002	0.004	0.001	0.011
	(8.00)	(5.33)	(11.52)	(9.76)	(3.56)	(0.53)	(7.20)
			Close-to-end betting returns				
$\beta_{T,Mom}$	0.004	-0.013	-0.005	-0.005	-0.012	-0.039	-0.025
	(0.20)	(-1.54)	(-1.59)	(-2.19)	(-1.11)	(-2.41)	(-1.65)

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