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# THE POWER OF MOMENTUM

## AN ANALYSIS OF MOMENTUM EXTREMES WITHIN SPORTS BETTING

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Bachelor Thesis

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**The power of momentum: An analysis of various instances of momentum and behavioral biases within sports betting**


Abstract:

In this paper I examine 20862 betting contracts within the sport of soccer for the last decade within 5 major leagues. I perform tests of pricing anomalies for different instances of momentum by using sports betting as a laboratory environment. I find evidence of overreaction within the general price movements and for standard momentum portfolios. I do not find sufficient evidence to conclude the economic magnitude of momentum extremes which could be explained by the characteristics of the chosen dataset.



Keywords:

Behavioral finance, Financial markets, asset pricing, cognitive bias, misreaction



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# Introduction

During the last couple of decades there has been dramatic progress within the phenomenon of predicting expected returns within financial assets. Numerous findings have been presented aimed at analyzing security characteristics and behavioral factors in order to determine the cause of mispricing and anomalous returns. The discussion of mispricing is related to the phenomenon of market efficiency, where a central point of discussion has been to determine whether behavioral factors are driven by irrationality, thereby causing market inefficiency. Despite progress, the reliability of recent findings has become somewhat debatable as a result of inability to come to a final consensus regarding which behavioral factors that are driving market inefficiencies and the actual magnitude of their effect Jensen (1978).

One of the underlying reasons for why the validity of results has been questioned is related to the recent findings of Fama and French(1991) who proposed the joint hypothesis problem. The hypothesis is built upon the inherent difficulties of testing for market efficiency, as it requires theoretical returns generated by asset pricing models. They proposed the dilemma that each test for market efficiency will subsequently be impossible to perform without theoretically assumed expected returns. In addition, it becomes impossible to determine whether anomalous returns are driven by market inefficiency or estimation errors within the pricing model used to perform the actual test.

In this paper I intend to build upon the previous work of Moskowitz (2020) who proposes that the very platform of financial markets constitute a flawed empirical laboratory to even assess the behavioral factors of investors, as preferences and the degree of rationality is unobservable to a high extent. In line with the core argument of his paper, I will take use of the fact that one is able to circumvent many of the dilemmas related to the joint hypothesis problem by using sports betting contracts as a laboratory setting. These contracts are by their nature idiosyncratic with no relation to risk premia and the contracts are associated with an actual terminal value with little relation to price movements. In contradiction to the continuous financial market, an analysis of sports betting contract also provides the option to detect mispricing as the terminal values directly resolves the uncertainty. Important to note is that changes within risk premia for the overall economy might imply shits in terms of betting activity and price movements, which is also confirmed by Edmans et al (2007) who concludes that systematic forces may affect sport betting markets as well as financial markets. However, sports betting markets provides contracts with terminal values independent of betting activity, which implies little to no sensitivity to systematic risk in regard to actual outcome.

The analysis which I will conduct will be built upon the most prominent behavioral factor proposed within previous research which is momentum. In contradiction to the method proposed by Moskowitz (2020) I choose to ignore the behavioral factors value and size, as momentum has been proven to be the least controversial factor, enabling a more direct comparison of findings between the two markets. By retrieving actual betting lines from one of the largest bookmakers, I am able to perform various analysis on behavioral theories within decision making within a platform uncontaminated by systematic risk.

The methodology follows the intuition of previous literature which tests whether previous performance and price movements has any predictive implication for future return. By observing the price movements within opening to closing odds and its relation to the predictive value of end to outcome returns I am able to propose different hypothesis which separates theories of behavioral decision making.

One apparent uncertainty with the proposed method is the ability to directly apply the findings to the financial market. The arbitrage possibility for investors within financial market is largely affected by systematic risks which implies that anomalous returns and price fluctuations are driven by other factors besides behavioral misreactions(Sullivan & L Feijoo 2016). The results will to some extent be somewhat speculative, but I argue for a suggestive applicability of results due to the highly similar characteristics between the two markets in accordance to Moskowitz (2020). Levitt(2004) propose that both market contains strong elements of profit seeking, arbitrage activity and investor beliefs which is heterogenous. The anomalous returns within both markets are to a high extent explained by the same factors of behavior which strengthens the argument for the use of sports betting as a laboratory environment Feddersen et al (2013)

## Related literature and contribution

The contribution I will make within this study is that I will extend the analysis of Moskowitz (2020) and replicate his method on a different data set where I incorporate extreme shapes of momentum. It has been provenly difficult to determine the actual magnitudes of behavioral factors as a result of the continuous structure of the financial market. Carhart(1997) has concluded that asset pricing models need to incorporate irrational behavioral reactions from momentum to reduce the model's estimation error. As a result, an extensive four factor component formula was constructed where momentum return is defined and calculated in accordance with the established long-short momentum strategy where investors take a long position on high momentum stocks and a short position on low momentum stocks

Fama and French(1991) conducted a study with the aim of analyzing the reliability of this enhanced asset pricing model where they suggested that it poorly predicts portfolios with extreme tilts towards winners or losers. By combining the methodology of Moskowitz (2020) I can evaluate the proposed critique towards the four-factor component model, as I am able to extend their work by circumventing potential joint hypothesis problems. As a result of the exogeneous terminal value within sports betting contracts, I can determine the actual magnitude of irrational misreactions caused by extreme instances of momentum. I believe that my contribution would be of value to the literature since it provides speculative insights regarding how decision making is affected once momentum increases to more extreme instances. I make the choice to solely look on sports betting contract within soccer as it has been proven to contain strong evidence of momentum given the large discrepancies between teams within the major leagues(Wheatcroft 2020).

Research question

*How and to what magnitude are extreme shapes of momentum affecting behavioral biases and investor decision making?*

# Theoretical assumptions and Methodology

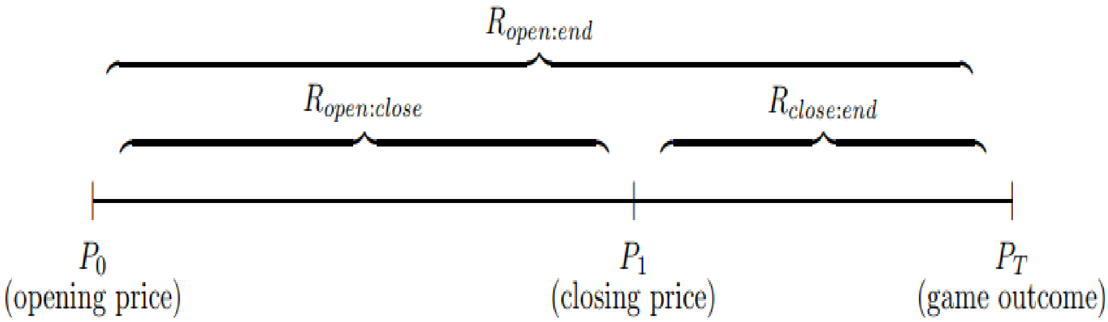
In this section I will provide detailed explanations regarding the theoretical assumptions and methodology which constitutes my analysis.

## Price movements and contract horizons

I have retrieved data containing information regarding opening odds, closing odds and game outcome for actual historical games within the major league in soccer for the last decade. The opening price of any betting contract is initially set by a bookmaker through relatively advanced calculations on their belief of probability of outcome. Once odds are released investors are allowed to take position at any time up until the game starts. Just as within financial markets prices are driven by the purchase activity of the investors, with the difference that investors within sports betting market receive the odds offered at the time of investment regardless of future price movement. In accordance with previous literature, I make the theoretical assumption that one can only take a position either at the opening right after odds are released or at the closing when the game is about to start. This theoretical assumption results in three prices for each contract: Open, Close and terminal

According to the theoretical limitation that investors can only take positions at the opening and closing I implement the assumption regarding contract horizon and return periods according to (Moskowitz 2020)

Figure 1 Contract timeline: the figure illustrates the three different prices within sports betting contract as well as the different returns investors can obtain at respective horizon.




The test I will perform is based on the assumptions regarding the theoretical contract horizons presented above, where I explore whether the price movements within $R_{Open:close} = return\ open: close$ has any predictive value for $R_{close:end} = return\ close: end$. I incorporate tests for irrationality and rationality based on the assumption that if a contract is priced efficiently at T=1 at close:end you can conclude that regardless of movement in price, there will be no return predictability for period T=1 to t=T. As derived from figure 1 above we can express the return from the open:end as:

$$R_{Open:end} = R_{Open:close} + R_{close:end.} \qquad E(R_{close:end}) = 0 \quad \text{if efficient}$$

Aligning with the method presented by (Moskowitz 2020) I implement the first equation for regression:

Equation (1). $$R_{close:end} = \alpha + \beta_1 * R_{open:close.} + \epsilon$$

Through equation 1 I am able to construct 3 separate predictions which explains different outcomes for movement through behavioral effects.

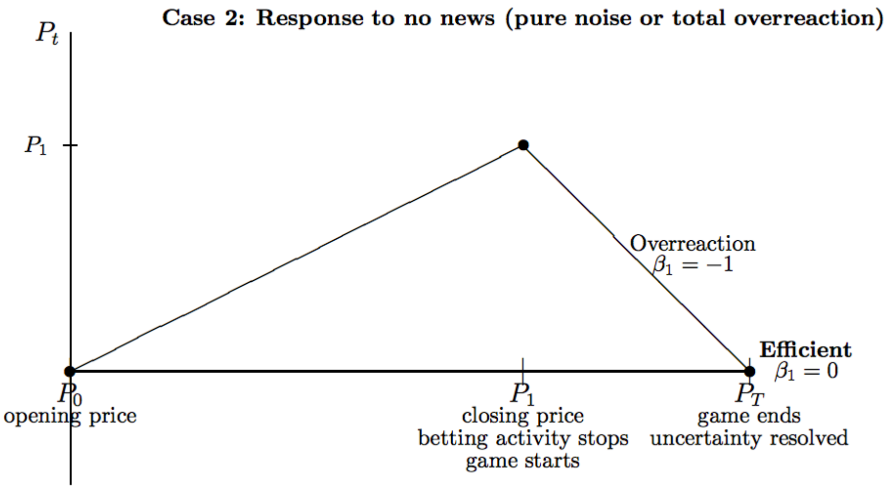
Prediction 1: The market's response is rational, and prices move accordingly: $P_0 \neq P_1$ and $\beta_1 = 0$

In addition to prediction 1 there is a possibility that the prices could move related to reasons unrelated to any information. In that case we will observe incorrect prices at closing which will be corrected once the exogenous price is presented. Given the noninformation price movement we cannot use closing price as a good estimator for game outcome. Once investors act on no information it follows intuitive sense that close:end returns are negatively predicted by open:close returns resulting in prediction 2

Prediction 2: price movements based on noninformation. $P_0 \neq P_1$, $\beta_1 = -1$

Lastly, there is the scenario of mispricing as a result of cognitive biases or an irrational response to news or information. Previous literature make two distinctions between irrationality in the shape of underreaction and overreaction(Said Musnadi et al 2018) Unlike prediction 2 where prices are incorrectly set at the closing but are corrected on the game's outcome, irrational investor response suggests that open:close returns will have predictive power for the close:end return as shown in the figure below.

Figure 2: graphical illustration of prediction 2




I implement the mathematical intuition used by (Moskowitz 2020) to define measurements for under-or-overreaction. A market overreaction would imply that investors has driven the prices in the direction of past performance. The open:close return would therefore negatively predict close:end returns. Underreaction suggests the opposite, where close:end returns are positively predicted since the market responds slowly to the news.

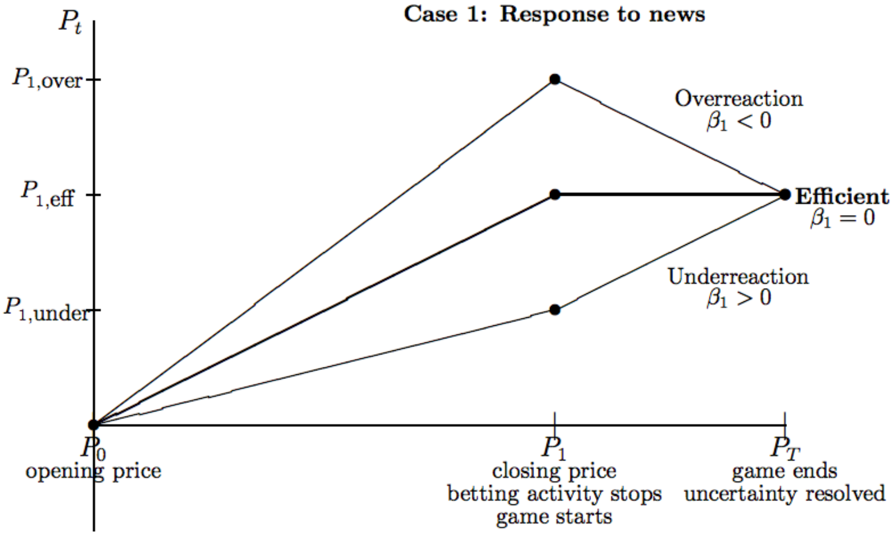
Prediction 3: prices move on market information but decision making is driven by irrationality. $P_0 \neq P_1$,

a) $\beta_1 => 0$ indicated underreaction
b) $\beta_1 =< 0$ indicates overreaction

As is observed, the predictions above is derived from equation 1. By implementing these theories of behavioral biases, I am able to extend the analysis to more extreme shapes of momentum. By performing various tests on sports betting contracts within soccer I am able to determine if there are any differences in terms of decision-making once momentum is increased to more extreme instances by analyzing the trend.

Danie and Moskowitz performed a study with the aim of analyzing differences in behavioral biases when reaching more extreme shapes of momentum and was able to conclude evidence of overreaction and an increase in prices for normal instances of momentum. Once momentum is increased sufficiently however, investor's express a skepticism towards purchasing as a result of fear of potential crashes in combination with a subjective belief that the assets are overpriced as they are also affected by overreaction(Daniel, Moskowitz 2016). My approach enables me to conclude whether trends within more extreme momentum confirms or contradicts similar findings.

Figure 3: Graphical illustration of prediction 1 and




As is shown in the figure above, the differences between overreaction and underreaction is the change in directions for the graphs once reaching the close:end period. Since overreaction proposes a negative return predictability for open:end from open:close the signs of $\beta_1$ and $\beta_T$ will be the opposite, whilst they are the same for underreaction.

In contrast to (Moskowitz 2020) I collect data for only one type of contract, namely standard odds contracts, which implies a potential flaw within my proposed method. My data set is very comprehensive in terms of lookback horizon and sample size. I retrieve data dating back one decade from several major and minor leagues in order to avoid any league-related bias. Similar studies have been conducted earlier under similar data sample containing only one contract and one sport, where potential flaws were raised related to the problems of omitted variables. I will elaborate further on this subject more thoroughly in a later section.

Overall, I believe that my data sample is in many ways sufficient to provide reliable results given the large sample size and comprehensive lookback horizon.  In stark contrast to multiple studies I use actual betting lines from the same bookmaker throughout my data which is considered relatively extensive compared to the quality of previous datasets Gandar et al (1988) and Avery and Chevalier (1999). By computing actual returns from historic betting contracts and observe various contract horizons I am able to determine the economic magnitude of behavioral effects through the same approach as Moskowitz(2020). I am able to make my own contribution by observing the trend in terms of economic magnitude once momentum is increased where results of different momentum limits are directly comparable as a result of the exogenous terminal value within the contracts unlike financial markets.

The purpose of this study is ultimately to conclude the magnitude of behavioral biases and its effects on price movements and anomalous returns within financial markets by using sports betting as a laboratory environment. I refer to recent findings  and argue that the strong similartities within the two financial market in addition to the comprehensive comparison performed by (Moskowitz 2020) provides sufficient evidence to conclude that behavioral factors are driving decision making within sports betting markets, eliminating the need to further test my result in a financial market setting.

## Return characteristics of contracts

The fundamental assumption of this paper is that behavioral characteristics such as momentum will generate implications for return predictability where the former is excluded from equation 1. Following the same theoretical assumptions presented above I derive the following regression equation in line with previous literature.

Equation (2) $$R_{j,0:1} = \alpha_1 + \beta_1 Char_j + \epsilon_{j,0:1}$$

The equation examines whether price movements from open:close is related to different characteristics such as momentum.

The same intuition can be applied to regress the relationship between characteristics and movement in closing:end returns.

Equation (3) $$R_{j,1:T} = \alpha_T + \beta_T Char_j + \epsilon_{j,1:T}$$

By deriving the relationship of returns according to the two steps in equation (1) and (2) I can test for specific price movements solely as a result of characteristics of momentum. Just as (Moskowitz 2020) I present 4 alternative hypothesis similar to the predictions 1 to 3 presented above with the modification that characteristics of a betting contract is assumed to affect return predictability where Equation 2 $\beta_1 - \beta_T$ reflects the total price movement from open:close and consequently $\beta_1 + \beta_T$ equals the total price movement from open:end.

Hypothesis 1: *No relevance, the characteristic of the contract is not related to any information.* $\beta_1 = \beta_T = 0$

Hypothesis 2: *Information efficiency, prices are set efficiently, and the characteristic is related to information.* $\beta_1 = \beta_T = 0$

Hypothesis 3: *Noninformation/noise, Prices are driven up as a result of market responding to noninformaton,* $\beta_1 \neq 0$, $\beta_T = -\beta_1$

Hypothesis 4: *information inefficiency, prices move* $\beta_1 \neq 0$ *as the characteristic is related to information. The market response is however inefficient implying two types of misreactions:*

a) *Underreaction:* $\beta_1 \times \beta_T > 0$
b) $\beta_1 \times \beta_T < 0$

Hypotheses 1 and 2 imply identical results in terms of relationship between betas which makes them indistinguishable, both imply no relationship between returns and characteristic. The former suggests a scenario in which characteristics does not contain relevant information or attributes which affect investors while the latter does contain relevant information which however is efficiently incorporated in the set price.

Hypotheses 3 and 4 constitute the behavioral models which are aimed at explaining the irrational misreactions of investors. Barberis(2018) proposes that there are two fundamental ways in which a behavioral model could deviate from rational expectations: differences in beliefs or nonstandard preferences. Hypothesis 3 illustrates the problem of omitted variables and team specific match-biases where investors are prone to cause price movements as a result of different preferences in the shape of favorite team etc which is concludes in their paper Newall, Cortis (2021). As my dataset only contains one type of contract it is important to note that my results could potentially be affected by noninformation price movements which is confirmed by Avery and is in line with previous literature(Avery 1999).

Hypothesis 4 suggests that the beliefs are affecting the price movements where characteristics are related information content but not fully reflected in the actual price since the market misreacts. Given that my extension is built upon analyzing eventual patterns for behavioral effects once momentum increases, I wish to test the results presented by Lukis and Zhang(2022) among others who proposes that greater momentum causes results in larger instances of overreaction as investor believe that recent performance is not sufficiently captured within the proposed price.

Consistent with the predictions presented for equation 1, the factor which distinguishes overreaction and underreaction within hypothesis 4 is the sign of return predictability from open:end from open:close. Overreaction drives prices in the direction of past performance which is corrected by the game's outcome and is associated with an opposite sign, while an underreacting market are slow to react to additional information implying the same sign for return predictability and price movements.

## Derivation of betting contract returns, odds and bookmaking

I examine one type of contract within the sport of soccer which is the standard odds contracts. If one considers the scenario in which team 1 plays a game vs team 2, an odds contract allows the investor to take a position on who wins. If $Team\ 1_{point\ scored} > Team\ 2_{point\ scored}$ the return would be positive for a long position at team 1 and a short position on team 2. Odds are expressed as the total amount investors receives for a 1-dollar bet. Offered odds of 1,5 would result in a return of 0,5 dollar return for every dollar invested in the case of a win. A positive return is only obtained in the event that the investor's chosen team wins, whilst both draw and loss results in a return of -1 per dollar invested.

The contract horizon is identical for every sport where various bookmakers determine the initial price of each contract with the purpose of maximizing profit. Price movements are purely dependent on the betting volume on respective sides(team 1 and 2) which occurs immediately after odds are released. Odds are continuously balanced throughout the contract horizon in accordance to changes in amount placed on each team within the market. The efficiency of bookmaker prices is tested within hypothesis 2 where $\beta_1 = \beta_T = 0$ where recent performance is efficiently incorporated in the price if held true.

## Contract returns and constraints

As illustrated in figure 1, My method follows the intuition of (Moskowitz 2020) who makes the theoretical assumption that betting is only possible at two distinct points in time, at the opening and at the closing and seeing it through till the outcome of the game. According to figure 1, $R_{open:end}$ makes up the entire contract horizon from odds release to game outcome and terminal value. Mathematically the interval of $R_{open:close}$ can then be derived as $R_{open:end} - R_{open:close}$ which is equivalent to a strategy where an investor takes a long position at the opening and a short position right before the game starts at the closing. The open:close return could be viewed as the residual between these two actual contract returns and to be representative of the total price movement during the betting horizon of the contract. Multiple studies within the area implements the theoretical approach that investors have an option to take a short position of any contract, which in practice would be impossible given that only bookmakers are granted that possibility. However, loosening the short-position constraint allow for the construction of hypothetical momentum portfolio strategies which are implemented in the financial markets regularly built on taking a long position on the “winners” and a short position on the “losers”( Jegadeesh and Titman. 2001)).

In line with the approach of (Moskowitz 2020) I perform my analysis from the perspective of always betting on the favored team, since results are proven to be identical regardless if you take the perspective of the favorites or the home team. This constraint is implemented to ensure that various portfolio strategies does not allow for multiple bets on the same game.

## Data description and valuation

The data sample is retrieved from football-data.co.uk who provides historical betting lines for multiple major and minor leagues within soccer. The database contains information regarding actual betting lines as well as information regarding game outcome and point differential. I observe contracts within Premier League, Bundesliga, La Liga, Serie A and Ligue 1 for every game within each season starting at 2012/2013 to the most recent season 2022. As described above, my method contradicts with that of (Moskowitz 2020) in terms of number of contracts used per game, where I only look at odds contract whereas he uses more extensive data set including over/under, money line and point spread contracts. Betting lines from other contracts besides odds are only available for the last year which would imply a hefty reduction in sample size especially for analysis on more extreme shapes of momentum. Future researchers would generate more reliable results by implementing the method on a more extensive data set where multiple contracts are incorporated to avoid favorite team-biases.

Unlike previous studies who uses opening and closing betting lines from different bookmakers my data set includes contract prices from Pinnacle Sports for each contract which enables more reliable test for behavioral asset pricing models. A direct comparison between the opening and closing is enabled where real returns for contracts and portfolios can be constructed. The data which I retrieve does not contain the actual opening odds rather pre-closing as they are collected with a slight delay from Pinnacle, Friday afternoon for weekend games and Tuesday mornings for mid-week games. This could suggest that some observation generate weaker economic magnitude as prices changes drastically relatively instantaneous after the price of the contract has been release. Much of the total price movement could potentially already have occurred according to the theory of immediate arbitrage exploitation and market reaction (Fama 1991). However, I mainly seek to analyze the direction of mispricing caused by irrational behavior and determine the general trend once momentum increases. I therefore argue that the results might bear lower absolute economic magnitude, but it is reasonable to assume that the results will follow the same economic interpretation in terms of return predictability.

The data set contains a total of 20862 contracts with date of match played, actual point differentials as well as information on home/away team given that my method will be analyzed from the perspective of betting on the favorites in line with (Moskowitz 2020).

# Results

In this section I present the results found

## General contract descriptives

table 1 provides descriptive general statistics of the collected betting contracts. Every game is associated with three possible outcomes(home win, draw or away win). The table shows the average closing line from the perspective of betting on the favorites represented by the mean. The standard deviation, standard error and confidence levels are also computed.

**table 1: descriptive statistic for contract returns.**

| Soccer betting contracts from Premier league, La liga, Serie A, Bundesliga, Ligue 1: Seasons from 2012-2022 | | | | |
|---|---|---|---|---|
| Mean | Stdev | Standard error | count | Confidence level |
| 1,93 | 0,46 | 0,003 | 20861 | 0,0063 |

## Price movements

Table 2 provides tests of predictions 1 through 3 by running the regression stated in equation 1 $R_{close:end} = \alpha + \beta_1 * R_{open:close.} + \epsilon$. Panel A runs the regression on a full sample where I almost identical results to (Moskowitz 2020) in terms of beta value. The result indicates a very statistically significant negative $\beta_1$ which suggests that increase in price movements from open:close are associated with negative return predictability for close:end. I am able to reject prediction 2 as the regression coefficient is statistically different from 0. The results confirm prediction 3b which implies that investors act in accordance to overreaction where roughly half of total price movement is reversed once reaching the terminal value and game outcome.

In the data section I discussed the potential risks involved with not using actual opening lines but argued that the direction of price movement would be the same despite economic magnitude being a bit lower. For robustness of my paper, I therefore perform the same analysis again where non-changing betting lines are excluded from the sample. The results are almost identical so I can conclude that negative $\beta_1$ in panel A does not occur due to an overrepresentation of contracts with no price movements. The result indicates that investor have a tendency to overreact.

**Table 2: testing for general price movements.**

| Panel A: full sample size of odds contracts | |
|---|---|
| Regression variables | regression output |
| $\beta_1$ | -0,494 |
| T-statistic | (-33,1) |

| Panel B: odds contract without price movements excluded | |
|---|---|
| Regression coefficients | regression output |
| $\beta_1$ | -0,496 |
| T-statistic | (-32,3) |

Presented within figure 1(see appendix) is a graphical illustration over the average returns for open:close and close:end strategies. The results confirms the findings in table 2 where a large portion of the price movement is reversed at the game's outcome. Important to note is that these results argue for the reliability of my data set as I conclude that prices may move by very little on average, but the economic interpretation and proportion of reversal are unaffected.

## Trading strategies and momentum

The fundamental assumption within this paper lies within the hypothesis that characteristics such as momentum are related to contract returns. In this section I will introduce the concepts of momentum for the first time, and in detail explain how I assess relationship between contract characteristics and returns. By incorporating the fundamentals presented by many previous studies and the adaption to sports betting market in accordance to (Moskowitz 2020) I am able to compute actual trading strategies.

The method of portfolio structuring is built on ranking each contract based on the characteristics of momentum. In line with how these theories are implemented within financial markets I create momentum indexes for each team on each contract based on both number of past wins as well as cumulative point differentials. Determining the appropriate lookback horizon is relatively difficult as there are few papers built on this methodology and approach. Jeegadesh and Titman(1991) conclude that momentum can be found within the 6-12 month range which most likely is a much longer lookback horizon than needed once analyzing sports betting contracts given their short maturity dates(Moskowitz 2020). Among the few existing papers, a variety of lookback horizons are presented most commonly ranging from 4-8. I set the limit to 8 since I am interested in capturing the more extreme instances of momentum.

Indexes are created by observing the cumulative wins and point differentials for the last 8 games. Point differentials are included as there is a risk of misrepresenting investor subjective beliefs if solely looking at past wins. Name presents that the subjective valuation of sports teams rises if they reach momentum through scoring more goals(Benz 2019). Each measure is incorporated by taking an equally weighted average.

As is standard for typical momentum strategies, the fundamental is built around buying positive momentum stocks(winners) and shorting low momentum stocks(losers). Momentum portfolios are constructed by dividing the sample size of momentum index In desired upper and lower limits, where you take a long position in contracts within the upper limits and a short position within lower limit contracts. In contrast with previous literature I construct upper and lower limits on a weekly basis instead of daily, as games by nature does not occur on the same day as frequently between major leagues.

In accordance to Moskowitz(2020) I construct three different strategies which stems from the theoretical framework presented earlier. The idea is to construct portfolios with different characteristics where different values for regression coefficient reveals the degree of irrationality within the market.

$Portfolio_{open:end}$. Represented by a long and short position at the opening horizon.

$Portfolio_{close:end}$ Represented by a long and a short position at the closing horizon

$Portfolio_{open:close}$ A residual off $Portfolio_{open:end} - Portfolio_{close:end}$

Portfolio returns are computed by taking positions according to the following weights:

Equation (4). $$w_i = \frac{1(char_{i,t-1} \in XN)}{\sum_{i=1}^{N} 1(char_{i,t-1} \in XN)} - \frac{1(char_{i,t-1} \in X1)}{\sum_{i=1}^{N} 1(char_{i,t-1} \in X1)}$$

Where N represents the upper limit chosen to construct the portfolio. If portfolios are constructed by only incorporating top 5% of the data set, N has a value of 20 since data is divided into parts of 20. Returns are computed through $w_i \times Return$ for each type of portfolio

## Regression of portfolio returns under normal instances of momentum

The following table and analysis constitute a mere replication on the exact method proposed by (Moskowitz 2020). The limit for portfolio construction is set to quintiles(upper and lower 20%). The portfolio returns are regressed on:

equation 2($R_{j,0:1} = \alpha_1 + \beta_1 Char_j + \epsilon_{j,0:1}$) for the open:close

equation 3($R_{j,1:T} = \alpha_T + \beta_T Char_j + \epsilon_{j,1:T}$) for the close:end.

The open:end return values are derived through the sum of open:close and close:end as illustrated in figure 1 and provides tests for whether prices are efficiently incorporating the previous values of momentum.

**Table 3: regression on q5:q1 portfolios**

| Portfolio regressions(Q5:Q1-strategy) | | | |
|---|---|---|---|
| | Open-to-close(1) | Close:end(2) | Open:end(1+2) |
| $\beta$ | 0,0271 | -0,381 | 0,11 |
| T-statistic | 1,95 | -3,52 | 0,20 |

An economic interpretation of the above results suggests that an increase in momentum positively predicts the price movements. The open:close portfolio show a regression coefficient of 0,027 which is remarkably close to being statistically significant with a t-statistic of 1,95. An increase in betting prices from open:close also suggests that investors misreact to information by driving the prices in the direction of past performance which is also confirmed by the statistically significant negative regression coefficient for the close:end portfolio of -0,381(t-statistic of -3,52). As the open:end portfolio results in a regression coefficient which is statistically insignificant and no different from 0 I find evidence that prices are not moving on noninformation reasons as the positive relation between momentum and price movements from open to close is reversed for the close:end.

## Regression on portfolio returns under extreme instances of momentum

As I am able to easily manipulate the specified limit for momentum of the portfolio, I can make my own contribution by extending the previous analysis to more extreme instances of momentum. By increasing(decreasing) the upper(lower) limit from quintiles I am able to analyze the change in behavioral effects for different instances of momentum and determine whether the results are consistent and generates some sort of a pattern.

The analysis I perform in this section does not make any alterations in regard to the method used to generate table 3 except that the momentum limits is changed. As the limit is manually altered to reflect more extreme instances, the sample size reduces as fewer contracts contain sufficient momentum indexes which potentially affects the t-statistics generated. I am interested in analyzing the general trends and patterns however which implies that the results presented below still provides interesting economic interpretations.

**Table 4: regression on q10:q1 portfolios**

| Panel A: Portfolio regression(Q10:Q1-strategy) N=376 | | | |
|---|---|---|---|
| | Open-to-close(1) | Close:end(2) | Open:end(1+2) |
| $\beta$ | 0,0274 | -0,28 | 0,04 |
| T-statistic | 0,96 | -2,35 | 0,47 |

The table above presents regression coefficients and T-statistics for portfolio returns when the limit is set to top/bottom 10% of observations. By analyzing the output for the returns in isolation I conclude identical results as in table 3. Open:close returns are positively predicted by increases in momentum which once again shows that investors drives the prices in line with past performance. The regression coefficient is not statistically significant but provide indications that the price movement is still positively predicted by an increase in momentum to a higher degree than for the Q5:Q1 portfolio. Overreaction is suggested to drive decision making for these portfolios returns as well as we observe the statistically significant beta value with the t-statistic of -2,35. If making a direct comparison between table 3 and 4 I can conclude that the magnitude of overreaction has decreased

**Table 5: regression on q20:q1 portfolios.**

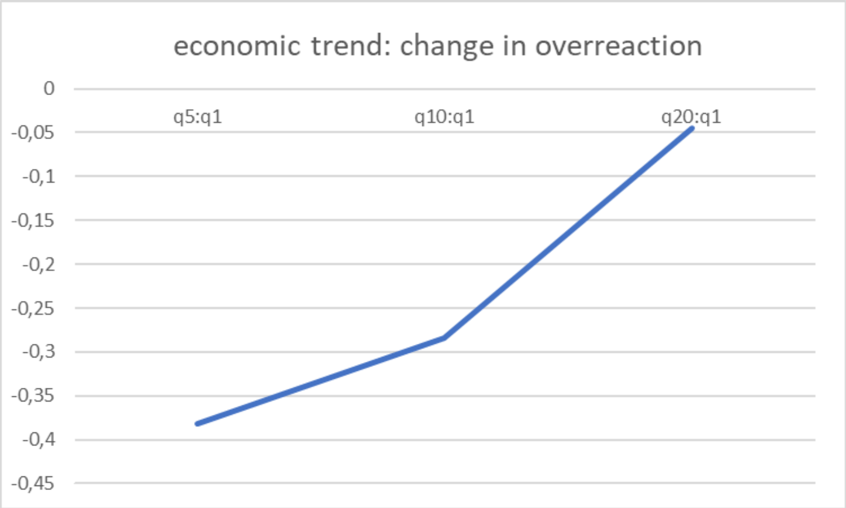
| Panel B:Portfolio regression(Q20:Q1-strategy) N=349 | | | |
|---|---|---|---|
| | Open-to-close(1) | Close:end(2) | Open:end(1+2) |
| $\beta$ | -0,01 | -0,05 | 0,00 |
| T-statistic | -1,10 | -0,36 | -0,01 |

I define the most extreme instance of momentum as the q20:q1 portfolio as it only contains the top 5% observations. None of the values within the regression shows a statistically significant correlation. An interpretation of the economic results would suggest that for most extreme instances of momentum portfolios, prices are negatively predicted by an increase in momentum. The evidence is consistent with the prediction of underreaction but cannot be determined since beta value for close:end is not statistically different from 0.

## Economic interpretation of behavioral trend

The regressions run on the various portfolio returns result in a mixture of statistically significant and insignificant result. Before discussing the validity and generability of my findings I will provide the economic interpretation of the patterns shown in the analysis.

**Figure 4: Behavioral trend within overreaction**




The result indicates that investors do have a tendency to overreact to momentum. For the portfolio representing the normal momentum instances(q5:q1) the result is statistically significant where prices move in the direction of past performance and the effect is reversed by the game's outcome. When increasing the limit of momentum by analyzing the q10:q1 portfolio the same pattern emerge. Investors overreact as momentum effects are reversed by the game's outcome with statistical significance but to a much lesser extent in absolute measures compared to the q5:q1 analysis. Despite the regression output being very week in terms of statistical significance, the q20:q1 portfolio provides the same economic interpretation. Namely that more extreme instances of momentum relate to a diminishing effect of overreaction.

These findings proposes a trend which aligns with previous work who states that once momentum is increased sufficiently, investors expresses a subjective belief that the asset is overpriced or that the risk of future stock crashes is more adjacent once momentum is extreme(Lukis. Zhang 2022). My findings indicates that more extreme instances of momentum results in a negative trend in terms of overreaction effects. In line with the literature, this phenomenon can be explained by the fact that investor perceive the contracts as more risky given the risk of future crashes, which explains the movement in close:end betas.

## Discussion

In this section I discuss the need for additional robustness tests and potential flaws within the chosen method or data sample. I also provide insights regarding the result validity.

### Statistical significance

Just as (Moskowitz 2020) argues, results are only applicable to the financial market if they are of statistical significance. Namely, it bears little explanatory power that my results indicated no statistical relationship. My results implicates that the relationship between momentum and return predictability is nonexistent for more extreme instances which strongly misaligns with the previous papers from the financial markets. It would therefore be flawed to suggest that my findings would invalidate the existence of this relationship within financial markets. A non-statistically significant result within a laboratory platform does not provide many insights regarding behavior within financial markets.

### Sample size and lookback horizon for portfolio construction:

One of the potential explanations of the statistical insignificance is the relatively small sample size used as input for each regression in table 4 to 5. As we move toward more extreme instances of momentum, the sample size gets reduced since fewer observations are included which is confirmed in the top panel of table 4 and 5 where the number of observations is reduced by 27 observations. A lower sample size is proven to have a negative effect on statistical significance of t-tests. As we move towards more extremely tilted portfolios, results are of lesser statistical significance.

The validity of the suggested approach to derive the momentum portfolios could also constitute potential explanation for the non-significant results. My approach contrasts to that of (Moskowitz 2020) by observing upper and lower momentum limits on a weekly basis instead of daily, as my dataset by nature contained too few observations per day to construct more extreme momentum portfolios. This trade-off intuitively generates a much lower sub sample where each observation now contains contracts from a 7-day period. Further research would obtain more reliable results by expanding the analysis to multiple sports as it increases the number of observations per day on average.

Different levels of lookback horizons for momentum will affect the acquired results when constructing portfolios as a longer horizon indicates more extreme shapes of momentum. I implement the regularly used approach where a lookback horizon is set constant throughout the analysis and momentum indexes are constructed for each point in time accordingly. The set limit of 8 matches used in the analysis bears relatively low motivation in previous literature as the available guidance is somewhat limited. Much more extensive research would increase the robustness of results where the lookback horizon limit is not held constant. More reliable composite momentum index could be constructed if the lookback horizon is altered within a given range which is confirmed by Jeegadesh and Titman(1993). It is plausible to assume that the results would become more reliable as it enables the analysis to determine for which lookback horizon momentum appear to be strongest.

### Omitted variables

favorite team preferences have been proven throughout the literature as one potential explanation to price movements due to noninformation reasons discussed in prediction 2. (Moskowitz 2020) performs a regression analysis on contract returns and dummy variables with a home/away structure in order to determine the effects on team-specific biases. The results are implying that more extensive datasets, enabling a cross sectional analysis through multiple contracts such as Over/under, can circumvent omitted variable problems as they difference out. Confounding variables and price movements due to noninformation reasons compromises the validity of results for non-cross-sectional analysis in line with the above reasoning. The statistical insignificance within the results grants explanatory power to the requirement of performing the analysis through a cross sectional approach as the price movements caused by omitted variables is unobservable to a high extent and thereby unavoidable.

## Conclusion

This paper aims to implement the approach of (Moskowitz 2020) where sports betting markets are suggested to be a better laboratory environment for testing behavioral factors than the financial markets. I am able to find a general price movement within sports betting contracts corresponding to the irrational cognitive mechanism of overreaction where open-to-close price movements negatively predicts close-to-end returns.

By constructing momentum portfolio strategies in accordance with previous literature I am able to test the economic magnitude of behavioral mispricing models for various limits of momentum. I obtain results which conclude that for lesser or normal instances of momentum return predictability is statistically significant and is consistent with the hypothesis stating that investors drive prices in the direction of past performances which are reversed at the game’s outcome due to strong overreaction.

The main contribution I make is that my proposed method enables the direct comparison between economic magnitudes for various Portfolios once momentum is gradually tilted towards the extremes. I am able to deduce a suggestive pattern where investors continue to overreact and drive prices in the direction of past performance but to a much lesser extent as a result of potential fear of crashes similar to recent findings within financial markets.

As a general theme within the robustness section, the proposed method presents many interesting contributions to the literature in terms of possibility for analysis. However, the relative weaknesses of the results confirm the requirement for a more extensive dataset where multiple sports and contracts are implemented in order to avoid problems related to omitted variables. The limitation of the dataset causes a subsequent trade off within the chosen method of portfolio structuring which lower the reliability of results.

As I obtain non-significant results, I am unable to make any suggestive insights in regards to investor behavior within financial markets as well as confirming the recent findings stating that advanced asset pricing models still fail under more extreme portfolio tilts. I am still arguing for the positive contribution of this paper as there is reason to believe that many of the problems in terms of reliability could be managed by future researchers by performing the same analysis on a more extensive dataset.

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