Does time series momentum also exist outside traditional financial markets? Near-laboratory evidence from sports betting

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The presence of time series momentum in the returns of financial assets puzzles economists. We show that this anomaly is also present in sports betting, a seemingly unrelated market and a near-laboratory setting. We find both a statistically significant and economically meaningful difference between the returns of bets on recent winners compared to recent losers. These differences are not due to rational compensations for variance or skewness, but are in line with underreaction. The bookmakers do not appear to react efficiently to new information.

In this paper we document the existence of time series momentum in sports betting. We use a data set of hourly pre-game odds of 30 bookmakers on the outcomes of 17380 football (soccer) games played in 50 major football leagues between 2015 and 2016. First, we find evidence of return predictability based on past odds movements via a regression framework. More specifically, we find that outcomes of which the odds have decreased (and thus the probability of the underlying event has increased) generally have higher expected returns compared to outcomes of which the odds have increased (and thus the probability of the underlying event has decreased). Second, we deploy a time series momentum trading strategy which confirms the results from the regression analysis. The average returns of betting on odds which have been decreasing are statistically significantly higher compared to returns on bets with increasing odds. Furthermore, the differences are economically meaningful. For example, betting on home outcomes of which the odds have decreased by at least 10% in the runup to the game outperforms bets of which the odds have increased by at least 10% by 13.83 percentage points. These effects are robust for a battery of different design choices. It appears that bookmakers do not incorporate new information efficiently into their odds. However, although we find meaningful differences between returns on decreasing and increasing odds, they can only be exploited profitably in a small subset of our

implementations.

We argue that our results cannot be explained by rational risk premia as assets that have become more risky (higher odds, lower probability of the underlying event happening) have a lower return, while assets that have become less risky (lower odds, higher probability of the underlying event happening) enjoy a higher return. Furthermore, the results do not seem driven by a rational skewness compensation either. The explanation most consistent with the empirical observations is a behavioral underreaction model where information is only slowly absorbed into market prices. These results are consistent with earlier work in both experimental asset markets (Gillette, Stevens, Watts, & Williams, 1999; Kirchler, 2009; Page & Siemroth, 2021; Stevens & Williams, 2004; Weber & Welfens, 2007) and in empirical work on the cross-section of expected stock returns (Abarbanell & Bernard, 1992; Bernard & Thomas, 1989; Chan, Jegadeesh, & Lakonishok, 1996; Hui & Yeung, 2013).

The contribution of this paper is twofold. First, it adds to the sports betting literature by providing evidence of time series momentum in pre-game bookmaker odds. Second, it contributes to the broader asset pricing literature by providing an indication that time series momentum in financial markets could be driven at least partly by behavioral forces and by underreaction more specifically. The sports betting setting is an

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interesting empirical lab as terminal values of the assets, i.e. the outcomes of the bets, are observable and independent of bettor behavior (Moskowitz, 2021; Thaler & Ziemba, 1988). Furthermore, as we know the terminal values of the assets, we can distinguish between underreaction (which is characterized by a continued drift) and overreaction (which is characterized by a reversal). Generalizing results obtained in sports betting to capital markets should be done cautiously. However, similar patterns in seemingly unconnected markets could expose fundamental symmetries. A common criticism to behavioral theories is that "allowing for irrationality opens a Pandora's box of ad hoc stories that will have little out-of-sample predictive power" (Daniel, Hirshleifer, & Subrahmanyam, 1998, p. 1841). A general behavioral theory should be able to explain cognitive glitches irrespective of whether sports bets or capital market securities are involved.

The rest of this paper is structured as follows. Section 1 introduces the context. Section 2 discusses the institutional setting and the dataset. In Section 3, we carry out return predictability tests. In Section 4 time series momentum strategies are tested while Section 5 discusses the results and Section 6 concludes.

1. Context

Whether past returns predict future returns is a question that is probably older than financial economics itself. Early empirical work showed that the dependence of returns on their own past is "either extremely slight or else non-existent" (Fama, 1965, p. 90). Historical returns were believed to contain no information that could be profitably leveraged in a trading strategy as expected in an informationally efficient market. Since seminal work by Jegadeesh and Titman (1993) and more recently by Moskowitz, Ooi, and Pedersen (2012), interest in both cross-sectional and time-series momentum respectively has been rejuvenated. Fundamentally, both types of momentum refer to the observation that historical returns predict future returns. Momentum is typically cross-sectional, meaning that assets which have been outperforming relative to other assets keep on outperforming in the future. Time series momentum or trend momentum directly tries to predict future returns of an individual asset based on its past returns.

Significant cross-sectional and time series momentum premia have been found in major asset classes including stocks, government bonds, corporate bonds, currencies and commodities (Asness, Moskowitz, & Pedersen, 2013; Georgopoulou & Wang, 2016; Jostova, Nikolova, Philipov, & Stahel, 2013; Moskowitz et al., 2012). Momentum is also remarkably persistent over time as it shows up in long run historical data sets (Annaert & Mensah, 2014; Geczy & Samonov, 2016; Goetzmann & Huang, 2018). This meaningful return predictability based on past returns is awkward as it seems to imply that markets are not even weakly efficient.

Despite truckloads of empirical evidence on the existence of momentum, its origin puzzles financial economists and is still heavily debated. Multiple, sometimes mutually exclusive, explanations for this "premier anomaly" (Fama & French, 2008, p. 1653) have been proposed[1]. A first possibility is that momentum simply does not exist in the real world. Momentum could for example be the result of data mining (Jegadeesh & Titman, 2001), but this is very unlikely given the magnitude of the empirical evidence. Another possibility is that momentum profits exist on paper, but not in practice because of transaction costs (Lesmond, Schill, & Zhou, 2004; Patton & Weller, 2020).

The most common explanations however are either risk related or behavioral. A risk premium for assets that have been performing well would fit the standard asset pricing paradigm if good past performance increases an asset's risk, but this is counterintuitive (Lewellen, 2002)

although some rational stories have been proposed (Galariotis, 2013; Johnson, 2002; Li, 2018). Another explanation fitting the rational paradigm is that the momentum premium is a compensation for systematic skewness (Harvey & Siddique, 2000). Behavioralists argue that agents do not properly react to new information and that under- and/or overreaction to news could explain momentum (e.g. Barberis, Shleifer, and Vishny (1998), Daniel et al. (1998), Frazzini (2006)).

Empirically testing these theories is generally hindered by the joint hypothesis problem (Fama, 1991). If prices deviate from theoretical models, it is not clear whether the prices or the models are wrong, or both. To make matters worse, both risk and behavioral forces could be at work at the same time making it harder to distinguish between different alternatives. Betting markets could provide a way out of this gridlock (Moskowitz, 2021; Thaler & Ziemba, 1988). Betting markets have traditionally received substantial attention by economists because they can be regarded as "simple financial markets" (Sauer, 1998, p. 2021) These markets are interesting asset pricing labs for several reasons (Vandenbruaene, De Ceuster, & Annaert, 2022).

First, uncertainty is quickly resolved exogenously from bettor behavior and beliefs. Sports bets are typically short-term contracts with maturities of days to just minutes after which the terminal values of the assets are revealed. This allows researchers to detect systematic mispricing and makes betting markets "better suited for testing market efficiency and rationality" (Thaler & Ziemba, 1988, p. 162) compared to traditional financial markets. Furthermore, the short maturity of the contracts can enhance efficiency as agents can quickly get feedback on their decisions which experimental research shows is important to eliminate mispricing (Forsythe, Palfrey, & Plott, 1982; Haruvy, Lahav, & Noussair, 2007).

Second, bets take place in a vacuum, i.e. the payoffs are arguably uncorrelated with aggregate risks that drive the returns of traditional financial assets. This lack of correlation between the payoffs of bets and marginal utility means that the classic risk factors are not applicable to the pricing of sports bets (Moskowitz, 2021).

Third, as betting markets are real markets where real money is at risk, external validity concerns that tend to plague experimental results are alleviated. Moreover, the size of the available data, both cross-sectionally and in the time series, is multiple orders of magnitude larger than would be economically feasible in an experimental setting. As a result of these useful research characteristics, a sizable literature on the efficiency of sports betting markets has been developed.

The empirical work in sports betting dates back to Griffith (1949) who tried to uncover psychological biases by comparing market-implied probabilities in odds with their empirical counterparts. Since then, many researchers have studied the efficiency of betting markets, either via a regression framework to assess whether some variables are significantly correlated with betting returns or via a trading strategy that directly tests whether exploitable inefficiencies exist (Berkowitz, Depken II, & Gandar, 2015; Gray & Gray, 1997; Pankoff, 1968; Woodland & Woodland, 1994)[2]. Although individual papers sometimes find profitable strategies, the literature as a whole is mainly in line with market efficiency (Vandenbruaene et al., 2022).

An interesting example for our setting is Croxson and Reade (2014). Using data from betting exchange Betfair, they document that in-game odds move quickly and fully to their efficient levels when a goal is scored during a football game. Similarly, Gauriot and Page (2020) also use data from Betfair and find that although prices often update quickly and efficiently, underreaction can occur when information shocks are large.

Momentum strategies in sports betting have been tested previously

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[1] Many models are developed for momentum in the cross-sectional sense. However, they also pertain to individual assets and thus are relevant for time series momentum as well (Moskowitz et al., 2012).

[2] It is worth noting that parallel to the establishment of the empirical literature on sports bets, an experimental literature that uses the betting microstructures (like parimutuel betting) has been developed. See Noussair and Tucker (2013) for an overview.
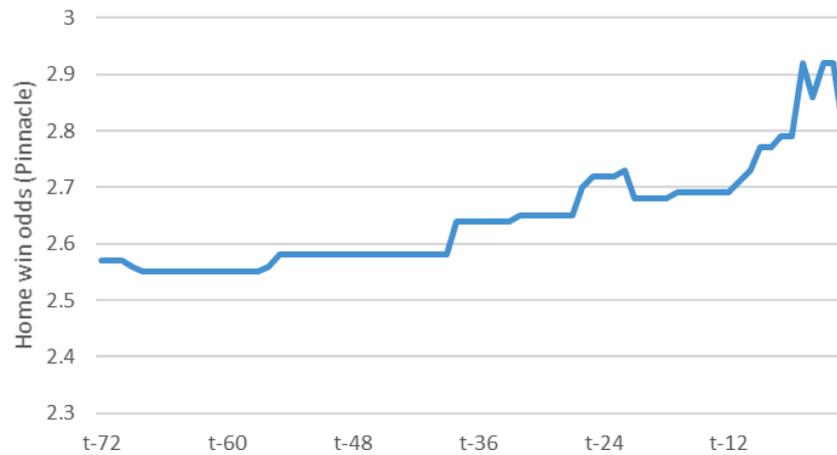
Fig. 1. Liverpool – Manchester city (2/3/2016), hourly pre-game home win odds as quoted by bookmaker Pinnacle.

(for an overview see Vandenbruaene et al. (2022)). However, almost all strategies that have been proposed take past game performance as the trading signal. For example, authors such as Vergin and Scriabin (1978), Tryfos, Casey, Cook, Leger, and Pylypiak (1984), Gandar, Zuber, O'Brien, and Russo (1988) or Vergin (2001) test whether betting on teams that beat their opponents by the largest amount in the last weeks can result in a profitable trading strategy. Such strategies are somewhat analogous to earnings momentum strategies in the traditional empirical work in finance and almost never significantly profitable.

Much less attention has been given to time series momentum strategies that take the evolution of the prices (the odds in a betting context) in the run-up to the game as the trading signal. There are a few notable exceptions[3] that use the evolution between the first odds (opening odds) and the last odds before the game starts (closing odds), but none of them evaluates the full time series of pre-game odds which is the focus of this paper and which much more closely resembles the time series momentum tests carried out with traditional financial assets.

2. Setting, Data & Descriptive Statistics

Contemporary European football betting is mainly organized via fixed-odds betting. This means that bookmakers offer odds for game outcomes on which gamblers can bet. An important characteristic of this microstructure is that the potential payouts are fixed and known when a bet is made, which is not the case in parimutuel betting popular in horse racing. This does not mean the odds cannot change over time, it just means that when a gambler chooses to place a bet, the odds at that time are locked in and known by the gambler. In this paper, we use the decimal/European odds convention. These decimal odds represent the payout on a winning unit bet. For example, a gambler betting 1 on the home team when the home team odds are 1.66 gets a payoff of 1.66 when the home team wins (i.e. a return of 66%) and a payoff of 0 when the home team does not win. Note that odds are inversely related to outcome probabilities: high (low) odds reflect a low (high) probability event.

More formally, let o_{ijmt} be the decimal odds for outcome i, set by bookmaker j, for game m at time t where $i = 1$ refers to a home win, $i = 2$ refers to a draw and $i = 3$ refers to an away win. The return on a home win bet r_{1jmt+1} is given as follows:

$$r_{1jmt+1} = \begin{cases} (o_{1jmt} - 1) & \text{if home goals} > \text{away goals (home win)} \\ -100\% & \text{if home goals} = \text{away goals (draw)} \\ -100\% & \text{if home goals} < \text{away goals (away win).} \end{cases}$$

The returns on draw and away win bets are analogous.

Sports bets can thus be regarded as European binary options where the underlying is the outcome of a game. A home bet is in the money whenever the number of home goals is strictly larger than the number of away goals. Also note that the inverse odds are essentially state prices in the Arrow and Debreu (1954) framework.

To make their business profitable, bookmakers charge a transaction cost for their services. This transaction cost is implicitly embedded into the odds, i.e. bookmakers skew the odds into their favor by setting them lower than they would be if the bets were fair. The property that transaction costs are directly embedded into the prices makes life easy for us as the returns on bets are already the post-transaction cost returns. These transaction costs should result in a positive expected return for the bookmaker and a negative expected return for the gambler.

Early literature usually assumed that bookmakers are merely balancing their books, such that they lock in a profit independent of the outcome of the game (see for example (Woodland & Woodland, 1991)). If the books are perfectly balanced, the winners can be paid by the losers while the bookmaker pockets a small transaction cost. In more recent work, Grant, Oikonomidis, Bruce, and Johnson (2018) classify bookmakers with this business model as "book-balancing bookmakers" (BBBs). Examples of BBBs in our sample include SBOBET, 188Bet and Pinnacle.

In seminal work however, Levitt (2004) argued that bookmakers can increase their profits if they exploit the preferences of their clients, i.e. making sure there are more losers than winners. Grant et al. (2018) classify bookmakers with this business model as "position-taking bookmakers" (PTBs). In contrast with book-balancing bookmakers who live off volume, position-taking bookmakers can achieve higher margins if they actively manage their client portfolio. As they take positions against their customers, they try to reduce their exposure to sophisticated gamblers by monitoring the behavior of their clients and limiting their action radius if they win too much (Franck, Verbeek, & Nüesch, 2013). Examples of PTBs in our sample include Ladbrokes, William Hill and Bet 365.

As mentioned earlier, the data set consists of time series of pre-game odds on 17380 football games[4]. The data set is collected by Kaunitz, Zhong, and Kreiner (2017) who use it to construct a betting strategy that exploits pricing differences between different bookmakers. A real-world implementation of their strategy yielded a return of 8.5%. However, they discontinued their strategy in a response to discriminatory practises of bookmakers to which we will come back later in the paper.

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[3] See for example Baryla Jr, Borghesi, Dare, and Dennis (2007), Crafts (1985), Gandar et al. (1988) or Shank (2018).

[4] The data are collected by Kaunitz et al. (2017) and are available on Kaggle: https://www.kaggle.com/austro/beat-the-bookie-worldwide-football-datas et#odds_series_b.csv.gz.

For each game in the data set, the home win, draw and away win odds of 30 bookmakers[5] are recorded every hour. In essence, we thus observe evaluations of the outcome probabilities of the games of 30 agents (bookmakers). Note that these evaluations are fully transparent as both bookmakers and gamblers can monitor the odds online in real-time, resulting in a competitive market. Each time series starts with the quoted odds 72 hours before the game and ends with the quoted odds 1 hour before the game. The bookmakers can update their odds as new information is released (like the starting line-up or the injury of a key player or because of significant volumes placed on one of the outcomes which can be an indication of the existence of insider information). As an example, Fig. 1 shows the time series of pre-game home win odds quoted by bookmaker Pinnacle for a game between Liverpool and Manchester City on 2 March 2016. The odds were revised from 2.57 to 2.79 in the 72 hours before the game.

The fundamental value of the assets (the bets) thus fluctuates over time and is driven by the relative strengths and weaknesses of the teams involved and not by the experimental design. This is different from related work on under- and overreaction in experimental asset markets where the fundamental values of the assets typically decline deterministically over time as is the case in the seminal model of Smith, Suchanek, and Williams (1988). As an exception to this design, Stöckl, Huber, and Kirchler (2015) run an experiment in which the fundamental values fluctuate randomly over time. They find that the assets are overvalued (undervalued) when the fundamental values predominantly decline (increase), which is also consistent with our results reported in Sections 3 and 4.

The games in the data set were played in 50 different football leagues[6] between September 2015 and November 2016. Table 1 reports the leagues and game-related summary statistics of the games in the sample. The number of games per league varies because of some missing values, but mainly because of differences in league organization like the number of teams in the league and the timing of the games. On average, we have just under 350 games per league. It is interesting to point to the well-documented home field advantage. In all but one of the leagues, the probability of a home win is larger than the probability of an away win. On average home wins occur 50% more often than away wins. Lastly, the mean number of goals per match is 2.62.

To make the time series in our sample more manageable, we summarize the odds of the 30 individual bookmakers into market odds $\overline{o}_{imt}$ which could be interpreted as the market price of the respective outcome[7]. These market odds are the trimmed cross-sectional average odds for outcome i over all bookmakers j for match m at time t. We remove the three bookmakers with the highest and lowest odds to prevent that our results are driven by extreme values that are potentially pricing errors. (Analyses with different trim choices are similar.)

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[5] These bookmakers are: Interwetten, bwin, bet-at-home, Unibet, Expekt, 10Bet, William Hill, bet365, Pinnacle Sports, DOXXbet, Betsafe, Betway, 888sport, Ladbrokes, Betclic, Sportingbet, myBet, Betsson, 188BET, Jetbull, Paddy Power, Tipico, Coral, SBOBET, BetVictor, 12BET, Titanbet, youwin, ComeOn, Betfair Sports.

[6] Notice that the data set of Kaunitz et al. (2017) contains more than 50 leagues. We opted to select 50 major leagues based on the UEFA and FIFA rankings as liquidity and media coverage typically decreases in lower leagues. We are confident that the proposed sample is a good reflection of the global football sports betting market. Furthermore, missing values can occur as for example some bookmakers are quicker to offer odds on games than others who only start offering odds closer to the start of the game. Missing values are not systematically treated by removing all rows that contain a missing value or replace them by for example the mean. When an analysis is carried out, for example the momentum trading strategy, only the odds that are available at the required moment are taken into account, the missing values are ignored.

[7] These market odds are not directly tradable. In our trading strategies, we will use these market odds as an information signal but make bets on odds of individual bookmakers to make sure the strategies are implementable.

Table 1
Descriptive statistics of the data set.

	League	Number of games	Home win %	Draw %	Away win %	Mean goals per match
1	Argentina: Primera Division	510	46.86%	28.43%	24.71%	2.32
2	Austria: Tipico Bundesliga	206	47.57%	24.27%	28.16%	2.61
3	Belarus: Vysshaya Liga	274	38.69%	28.10%	33.21%	2.45
4	Belgium: Jupiler League	341	49.85%	24.63%	25.51%	2.88
5	Belgium: Proximus League	294	41.84%	25.85%	32.31%	2.94
6	Brazil: Série A	499	52.51%	24.05%	23.45%	2.45
7	Bulgaria: A PFG	122	46.72%	25.41%	27.87%	2.37
8	Chile: Primera Division	288	44.79%	27.78%	27.43%	2.88
9	China: Super League	273	49.08%	26.01%	24.91%	2.65
10	Colombia: Liga Aguila	523	48.57%	27.53%	23.90%	2.37
11	Croatia: 1. HNL	209	43.06%	27.27%	29.67%	2.23
12	Cyprus: First Division	286	41.96%	26.22%	31.82%	2.69
13	Czech Republic: Synot liga	186	51.61%	22.58%	25.81%	2.76
14	Denmark: Superliga	260	45.38%	25.00%	29.62%	2.76
15	Ecuador: Serie A	311	47.59%	26.05%	26.37%	2.63
16	England: Championship	654	43.43%	28.59%	27.98%	2.46
17	England: League One	661	42.81%	25.26%	31.92%	2.66
18	England: League Two	652	38.50%	26.53%	34.97%	2.67
19	England: Premier League	434	43.32%	27.42%	29.26%	2.75
20	France: Ligue 1	443	45.15%	27.31%	27.54%	2.58
21	France: Ligue 2	451	40.80%	32.59%	26.61%	2.29
22	Germany: 2. Bundesliga	359	43.73%	27.02%	29.25%	2.69
23	Germany: Bundesliga	355	46.48%	23.38%	30.14%	2.81
24	Greece: Super League	287	47.04%	27.53%	25.44%	2.23
25	Israel: Ligat ha'Al	278	38.85%	28.06%	33.09%	2.31
26	Italy: Serie A	457	45.73%	25.60%	28.67%	2.62
27	Italy: Serie B	587	46.51%	29.98%	23.51%	2.40
28	Japan: J-League	373	37.80%	23.86%	38.34%	2.61
29	Kazakhstan: Premier League	229	50.22%	19.65%	30.13%	2.49
30	Mexico: Primera Division	407	44.23%	29.24%	26.54%	2.81
31	Netherlands: Eredivisie	386	43.26%	25.65%	31.09%	2.90
32	Norway: Tippeligaen	299	46.82%	24.75%	28.43%	2.82
33	Paraguay: Primera Division	303	37.29%	23.43%	39.27%	2.97
34	Poland: Ekstraklasa	346	42.20%	28.61%	29.19%	2.64
35	Portugal: Primeira Liga	357	42.58%	24.09%	33.33%	2.66
36	Romania: Liga 1	304	41.78%	28.29%	29.93%	2.52
37	Russia: Premier League	283	45.94%	28.62%	25.44%	2.33
38	Scotland: Premiership	261	40.23%	25.29%	34.48%	2.83

(continued on next page)

Table 1 (*continued*)

	League	Number of games	Home win %	Draw %	Away win %	Mean goals per match
39	Serbia: Super Liga	346	45.95%	26.30%	27.75%	2.38
40	Slovakia: Fortuna liga	236	51.27%	22.03%	26.69%	2.56
41	Slovenia: Prva liga	213	35.21%	27.70%	37.09%	2.43
42	South Korea: K-League Classic	290	38.62%	28.28%	33.10%	2.65
43	Spain: Primera Division	344	48.55%	23.55%	27.91%	2.79
44	Spain: Segunda Division	423	43.74%	31.68%	24.59%	2.21
45	Sweden: Allsvenskan	288	46.53%	22.57%	30.90%	3.10
46	Switzerland: Super League	208	47.12%	25.00%	27.88%	3.24
47	Turkey: Super Lig	351	47.86%	25.64%	26.50%	2.64
48	Ukraine: Pari-Match League	212	40.57%	23.11%	36.32%	2.65
49	Uruguay: Primera Division	291	39.18%	25.77%	35.05%	2.57
50	USA: MLS	430	51.40%	27.91%	20.70%	2.81
	Sum	17380				
	Average	347.60	44.53%	26.19%	29.28%	2.62

Table 2

Summary statistics for all market odds, home win market odds, draw market odds and away win market odds. The market odds are the trimmed hourly cross-sectional averages of the odds (3 highest and lowest odds are removed).

	All market odds	Home win market odds	Draw market odds	Away win market odds
N	3,559,957	1,186,728	1,186,471	1,186,758
Mean	3.34	2.46	3.58	3.98
Median	3.15	2.15	3.34	3.29
Standard deviation	1.92	1.39	0.82	2.70
Skewness	4.97	4.65	4.91	4.19
Kurtosis	49.04	37.40	40.47	30.61
Minimum	1.020	1.02	1.60	1.02
Maximum	55.94	33.76	18.74	55.94

Table 2 reports summary statistics of the market odds $\overline{o}_{imt}$. We have approximately three million market odds observations distributed uniformly across the three outcome categories (home win, draw, away win). Note that the mean and median home odds (2.46 and 2.15) are significantly lower than the corresponding away odds (3.98 and 3.29), which reflects the strong home field advantage. Furthermore, it is worth pointing to the standard deviations and the extrema of the different odds categories. Draw market odds live in the smallest interval while away win market odds vary most wildly.

Table 3 provides summary statistics of both absolute and percentage hourly market odds changes, the latter will be our variable of interest in the next section. First, notice that on average market odds do not change. The mean and median values are all very close to zero, both for absolute and percentage changes. However, from time to time very dramatic odds changes occur between two consecutive odds, as indicated by the extreme values on the last two rows of the two panels in Table 3. Double digit percentage increases and decreases in the market odds occur for all outcome categories.

The dynamism in pre-game odds is more pronounced when we consider the total change between the opening odds and the closing odds as depicted in Fig. 2. From these figures, we learn that bookmakers do not systematically revise their odds in either direction in the runup to a

Table 3

Summary statistics for changes in all market odds, home win market odds, draw market odds and away win market odds. The changes are the percentage and absolute change in market odds, which are the trimmed hourly cross-sectional averages of the odds (3 highest and lowest odds are removed).

	All market odds	Home win market odds	Draw market odds	Away win market odds
N percentage changes	3,507,701	1,169,309	1,169,053	1,169,339
Mean percentage changes	0.02%	0.01%	0.01%	0.03%
Median percentage changes	0.00%	0.00%	0.00%	0.00%
Standard deviation percentage changes	0.96%	0.94%	0.53%	1.27%
Skewness percentage changes	9.54	7.76	5.65	8.85
Kurtosis percentage changes	998.42	772.83	399.83	739.52
Minimum percentage change	-53.57%	-53.57%	-25.85%	-52.00%
Maximum percentage change	185.93%	133.08%	55.95%	185.93%
N absolute changes	3,507,701	1,169,309	1,169,053	1,169,339
Mean absolute changes	0.00	0.00	0.00	0.00
Median absolute changes	0.00	0.00	0.00	0.00
Standard deviation absolute changes	0.06	0.04	0.02	0.08
Skewness absolute changes	6.05	7.02	3.85	4.40
Kurtosis absolute changes	1915.86	3657.17	621.90	895.92
Minimum absolute change	-8.52	-8.52	-1.86	-8.00
Maximum absolute change	8.69	6.27	2.50	8.69

game. This could be an indication that without the arrival of new information, the odds 72 hours before the start are equally indicative of the outcome of the game as the odds just an hour before the game as would be expected in an efficient market.

However, notice that remarkable changes in odds, both in relative and absolute terms, occur. For percentage changes, we witness extrema as low as -71.78% and as high as 248.74%, in absolute terms, changes in market odds of -14.33 to 22.56 are observed which are clearly economically meaningful (remember that these market odds are already trimmed to minimize pricing errors in the data). As shown in Fig. 3, in absolute value terms, the odds[8] tend to change the most in the hours just before the game. This is intuitively reasonable as important information like starting line-ups is released close to the start of the game.

3. Return predictability

In an efficient betting market, information is instantaneously and adequately incorporated into the pre-game odds. In such a market, past price movements do not predict future returns. To test for return pre-

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[8] Fig. 3 is based on away market odds. The dynamics in home and draw market odds are almost identical.
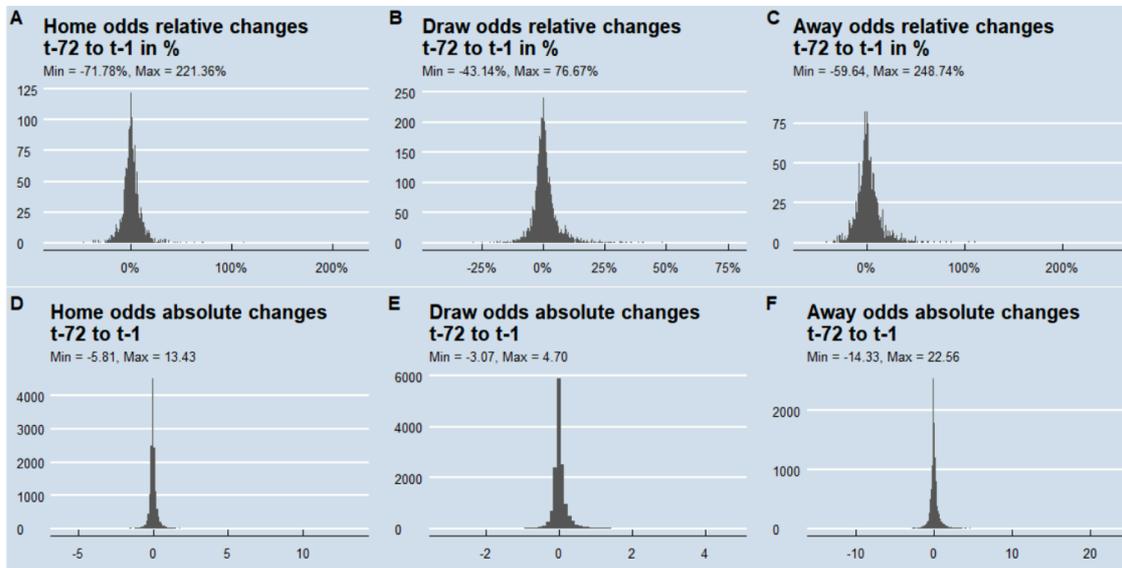
Fig. 2. Histograms of the percentage changes in market odds from t-72 to t-1 per outcome category (home win, draw, away win) are shown in panels A to C while histograms of absolute changes are shown in panels D to F.
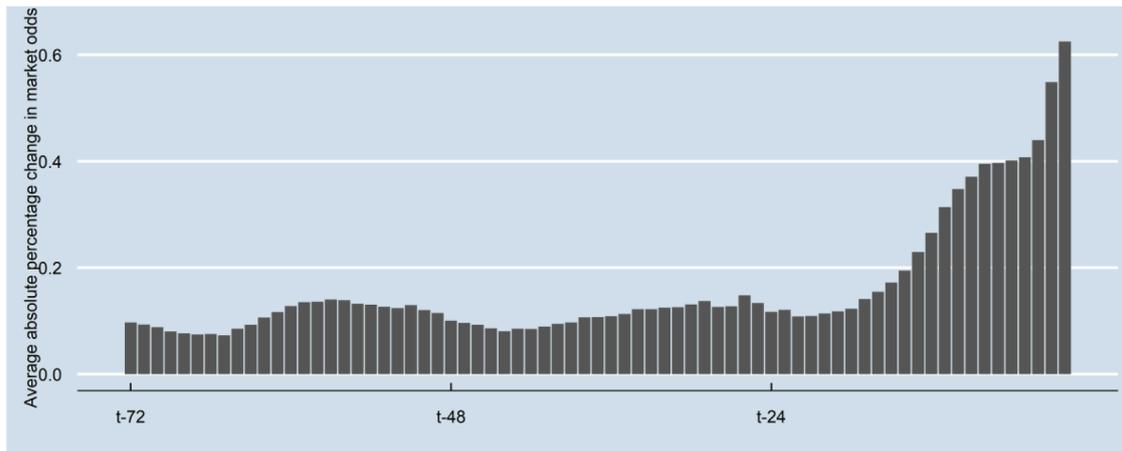

Fig. 3. Average of the absolute value of the percentage changes in away market odds per hour.

dictability, we estimate the following equation:

$$r_{imt} = \alpha_k + \beta_k \Delta \bar{o}_{imt-k}^{t-1} + \beta_m League_m + \varepsilon_{imt} \qquad (1)$$

where r_{imt} is the return achieved by betting on the market odds for outcome i in match m at time t. We will refer to the period between t and the end of the game as the investment window. $\Delta \bar{o}_{imt-k}^{t-1}$ represents the relative change in market odds between $t-k$ and $t-1$, referred to as the information window, for outcome i in match m with $k > 1$. We end the information window at $t-1$ instead of t to avoid information spillovers[9]. We control for the league the game is played in as bookmakers could charge different transaction costs in leagues that receive a lot of attention like the English Premier League versus more humble competitions like the Vysshaya Liga in Belarus.

In an efficient market, we expect β_k to be indistinguishable from zero.

Hypothesis 1a. $\beta_k = 0$: Efficient sports betting market.

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[9] For robustness, we repeat the analysis with an information window ending at t-2. The results are similar and shown in appendix.

Alternatively, bookmakers do not incorporate information efficiently into their odds. In this case, odds change too little or too much depending on whether bookmakers under- or overreact. Because terminal values of sports bets are observable (we know the outcome of the game), we can easily distinguish between under- and overreaction. Suppose important information 24 hours before the game induces the home odds to decline, as depicted in panel A of Fig. 4. This means the probability of a home win has gone up. In an efficient market, the odds move from o_a to o_b. If bookmakers underreact to the news, the odds will not move down by the full extent but end up at o_{b1}. These odds are a good deal for gamblers as they are higher than they should be, these odds are too high given the outcome probability. If bookmakers overreact to news, the odds will move to o_{b2}. These odds are not a good deal for gamblers as they are lower than they should be given the outcome probability. Analogously, in panel B of Fig. 4 information 24 hours before the game induces the home odds to increase. This means that the probability of a home win has decreased. In an efficient market the home odds move from o_a to o_b. If bookmakers underreact, the odds will not move up by the full extent and end up at o_{b1}. These odds are a bad deal as they are lower than they should be. If bookmakers overreact to news, the odds will move to o_{b2}. These odds are a good deal as they are higher than they should be.
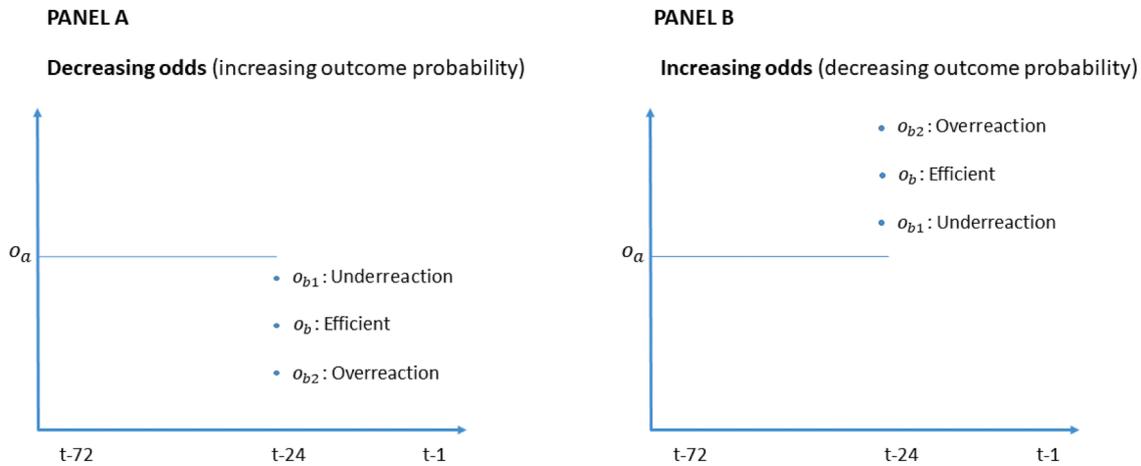
PANEL A

Decreasing odds (increasing outcome probability)

PANEL B

Increasing odds (decreasing outcome probability)

Fig. 4. Efficient (o_b), under- (o_{b_1}) and overreaction (o_{b_2}) to news at t-24

Table 4

Overview of the $\widehat{\beta_k}$ coefficients and t statistics of regression (1). The table shows the number of regressions with coefficients and t-stats in the respective range.

Coefficient	Home	Draw	Away	t-stat	Home	Draw	Away
b > 0.1	123	72	95	t > 1.96	0	0	0
0 < b < 0.1	58	18	41	-1.96 < t < 1.96	2026	1451	2111
-0.1 < b < 0	259	13	182	-2.5 < t < -1.96	267	594	205
-0.5 < b < -0.1	1551	181	1800	-3 < t < -2.5	120	375	103
-1 < b < -0.5	286	1062	293	-4 < t < -3	67	65	65
b < -1	208	1139	74	t < -4	5	0	1

We can conclude that if $\beta_k > 0$ in equation (1), a past increase (decrease) of the odds increases (decreases) subsequent returns. This happens when bookmakers overreact. If $\beta_k < 0$ in equation (1), a past increase (decrease) in the odds decreases (increases) subsequent returns. This happens when bookmakers underreact. We summarize this in the following hypotheses.

Hypothesis 1b. $\beta_k > 0$: Inefficient sports betting market where agents overreact

Hypothesis 1c. $\beta_k < 0$: Inefficient sports betting market where agents underreact

To avoid data mining issues, we run regression (1) for all possible information and investment windows, i.e. all $t - k$ to $t - 1$ intervals that are feasible. By doing this we get a full overview of the possible combinations of information and investment windows and avoid cherry-picking values for k and t that work by accident. Note that we have 72 hourly odds observations per game, resulting in $\frac{72 \times 71}{2} = 2556$ unique information windows. As we require at least 1 hour between the end of the information window and the start of the investment window, 71 information windows become uninvestable, resulting in 2485 regressions. We estimate heteroskedasticity and autocorrelation consistent standard errors via the Newey-West procedure[10].

Table 4 summarizes the results of the regressions. We estimate the regressions for home, draw and away odds individually to bypass the correlation between odds on the same game (i.e. if home odds move

down, away odds have to move up to keep the transaction cost constant). Overall, the evidence is heavily tilted towards market inefficiencies induced by underreaction. $\widehat{\beta_k}$ is negative in over 93% of cases for home odds, draw odds and away odds. Moreover, it is not uncommon to observe coefficients smaller than -1, meaning that a change in odds results in a more than proportional change in returns. This is especially the case for draw odds where almost 50% of coefficients are smaller than -1. Next to being economically significant, many of the coefficients are also statistically significant. The number of t-stats smaller than -1.96 hovers between 15% and 42% and extreme t-stats under -4 are observed. Furthermore, none of the positive t-stats is larger than 1.96.

An objection that can be made is that we run many regressions and that our regressions are clearly not independent. In terms of statistical significance, Chen (2020) shows[11] that for an arbitrary correlation structure the expected number of rejections of the null is given by:

$$E[Number\ of\ observed(|t_i| > \bar{t})] = Np(|Z| > \bar{t}), \qquad (2)$$

where t_i are the t-statistics of N tests, $\bar{t}$ is a critical value and Z a standard normal random variable. For the common critical value of $\bar{t} = -1.96$, we would only expect $2485 \times 0.05 = 124$ rejections of the null per odds category. In contrast, we respectively find 459, 1034 and 374 such results. The results are even more extreme when we would consider the observed number of t-stats below -3 or -4 compared to what we would expect. Another way to place the results in context is by applying the Bonferroni correction for multiple hypothesis tests. In this case, we scale the significance level α by the number of tests: $\alpha^{Bonferroni} = \frac{\alpha}{N}$. As we run 2485 regressions, we evaluate the results at $\alpha^{Bonferroni} = 2 \times 10^{-5}$, which corresponds to a t-stat of -4.26. Given that we observe t-stats smaller than this extreme value for both home and away odds, these results are statistically significant even when we take the large number of tests into account. Similar results are obtained via other popular multiple hypotheses tests like the Holm correction or the Benjamini, Hochberg and Yekutieli (BHY) correction. Notice furthermore that the Bonferroni correction is especially harsh in our context as many of our t-stats are highly correlated. For example, suppose we run two regressions of which the underlying data is almost perfectly correlated. This would result in $\alpha^{Bonferroni} = \frac{0.05}{2}$ which is clearly too extreme as we essentially run the same regression twice. As a result, the Bonferroni hurdle rate we apply is an extreme upper bound to test statistical significance in our context.

In summary, the results make a case for significant return predictability driven by underreaction, or in other words:

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[10] For the lag parameter, we use $T^{1/4} = 72^{1/4} \approx 3$. The results for other standard error estimation choices (e.g. clustering by league) are similar as shown in appendix.

[11] Under the assumption that the marginal distribution of t-statistics is standard normal under the null.

Table 5

Overview of the $\widehat{\beta_k}$ coefficients and t statistics of regression (4). The table shows the number of regressions with coefficients and t-stats in the respective range.

Coefficient	**Home**	**Draw**	**Away**	t-stat	**Home**	**Draw**	**Away**
b > 0.1	20	144	61	t > 1.96	0	1	0
0 < b < 0.1	4	18	13	-1.96 < t < 1.96	1598	1419	1725
-0.1 < b < 0	6	18	7	-2.5 < t < -1.96	575	594	445
-0.5 < b < -0.1	55	103	94	-3 < t < -2.5	249	349	185
-1 < b < -0.5	223	148	255	-4 < t < -3	63	113	111
b < -1	2177	2054	2055	t < -4	0	9	19

$$E\left(r_{imt}\,\middle|\,\Delta\overline{o}_{imt-k}^{t-1}\rangle 0\right)\left\langle E\left(r_{imt}\,\middle|\,\Delta\overline{o}_{imt-k}^{t-1} < 0\right). \tag{3}$$

Note that these results are hard to reconcile with a rational risk story. The returns increase on bets for which the odds have decreased, i.e. which became less risky. For bets that have become riskier, the returns go down. This is the opposite of what one would expect in a framework where predictable patterns in returns must be induced by risk factors.

As a robustness exercise we follow Moskowitz et al. (2012) and estimate a variation to regression (1) where we check whether just the sign of the past returns contains predictive information.

$$r_{imt} = \alpha_k + \beta_k sign\left(\Delta\overline{o}_{imt-k}^{t-1}\right) + \beta_m League_m + \varepsilon_{imt} \tag{4}$$

The results of regression (4) are displayed in Table 5 and are in line with the earlier discussion.

A valid remark that could be made is that the aggregation of odds into market odds as described above can create an artificial momentum effect. Indeed, if some bookmakers are later to update their odds than others, average odds could seem to underreact to information while none of the individual bookmakers underreact. We can distinguish between bookmakers underreaction to information (i.e. not fully updating their odds to an efficient level) and just being late (i.e. updating their odds to the efficient level, but with a lag compared to others) by rerunning the analysis for each bookmaker individually. If the momentum effect we notice at a market level is driven by the underreaction of individual bookmakers, we must see a predictability pattern in the odds of the individual bookmakers as well.

Table 6 shows the relative frequencies of the coefficients and t-statistics of the regressions on the individual bookmaker level aggregated over all bookmakers. Notice that the evidence is weaker but it points in the same direction: much more (less) t-statistics < -1.96 (>1.96) than would be expected under the null and a large majority of coefficients smaller than 0.

Table 7 shows the percentage of t-statistics < -1.96 of the $\widehat{\beta_k}$ coefficients per bookmaker. It is interesting to see that not all bookmakers underreact to the same extent. Eleven of the bookmakers in the sample have values that do not deviate from what we would expect under a null of market efficiency. Furthermore, it is hard to point to a variable that differentiates the underreacting bookmakers from the rest. For example, both position-taking bookmakers (PTBs) and book-balancing bookmakers (BBBs) appear in the category of bookmakers that most heavily

underreact. Moreover, both traditional bookmakers like Ladbrokes (which dates back to 1886) as well as online disrupters like Interwetten (founded in 1990) appear to underreact.

4. Momentum portfolios

In the previous section we put forward evidence that bookmakers underreact to new information which is in line with earlier research in experimental asset markets (e.g. Kirchler (2009); Weber and Welfens (2007)). In this section, we move beyond and analyze whether the documented return predictability can be monetized in a real betting market via a time series momentum strategy. To do so, we make two portfolios, one for "winners" and one for "losers". We define winners as the bets of which the odds have decreased i.e. the probabilities of the underlying events have increased. Losers are defined as the bets of which the odds have increased i.e. the probabilities of the underlying events have decreased. In an efficient market betting on winners will yield the same return as betting on losers as all bets are priced correctly. However, if bookmakers underreact, the returns on winners are expected to be higher than the returns on losers as prices do not respond swiftly but continue to drift towards their efficient levels.

In Fig. 5, we show in blue the mean return across all *M* games for every hour *t* and every odds type *i* for all observations. That is, every blue dot is:

$$\frac{1}{M}\sum_{m=1}^{M} r_{imt},$$

for its respective value of *i* and *t*. Similarly, the mean returns for the observations of which the odds decreased between $t-2$ and $t-1$ are shown in red. That is, every red dot is:

$$\frac{1}{M}\sum_{m=1}^{M} r_{imt}\,\middle|\,\Delta\overline{o}_{imt-2}^{t-1} < 0$$

for its respective value of *i* and *t*. Lastly, the mean returns for the ob-

Table 7

The columns indicate the percentage of t-statistics < -1.96 of the $\widehat{\beta_k}$ coefficients per bookmaker.

<5%	5% < x < 10%	10% < x < 15%	15% < x < 20%	< 20%
Unibet	bet365	Pinnacle Sports	Interwetten	bet-at-home
Expekt	888sport	Betway	Bwin	Ladbrokes
10Bet	Paddy Power	Tipico	Sportingbet	myBet
William Hill	SBOBET	youwin		188BET
DOXXbet	BetVictor			Coral
Betsafe	12BET			
Betclic	ComeOn			
Betsson				
Jetbull				
Titanbet				
Betfair Sports				

Table 6

Overview of the $\widehat{\beta_k}$ coefficients and t statistics of regression (1) at the individual bookmaker level ($r_{imt} = \alpha_k + \beta_k\Delta o_{imt-k}^{t-1} + \beta_m League_m + \varepsilon_{imt}$). The table shows the number of regressions with coefficients and t-stats in the respective range.

Coefficient	**Home**	**Draw**	**Away**	t-stat	**Home**	**Draw**	**Away**
b > 0.1	27.22%	29.35%	19.88%	t > 1.96	0.65%	1.62%	1.20%
0 < b < 0.1	9.47%	4.42%	7.10%	-1.96 < t < 1.96	91.93%	88.35%	85.49%
-0.1 < b < 0	11.43%	5.26%	12.18%	-2.5 < t < -1.96	4.07%	6.14%	7.45%
-0.5 < b < -0.1	35.7%	22.04%	38.33%	-3 < t < -2.5	1.81%	2.41%	3.38%
-1 < b < -0.5	8.67%	17.89%	15.30%	-4 < t < -3	1.18%	1.17%	1.89%
b < -1	7.51%	21.04%	7.21%	t < -4	0.37%	0.31%	0.60%

Fig. 5. Mean returns for every t leading up to the game. Mean returns per hour for all observations in blue, mean returns for the observations of which the odds decreased between t-2 and t-1 in red and the mean returns for the observations of which the odds increased between t-2 and t-1 in green. The black dots are the group means and the black bars the 99% confidence intervals.

servations of which the odds increased between $t-2$ and $t-1$ are shown in green. That is, every green dot is:

$$\frac{1}{M} \sum_{m=1}^{M} r_{imt} \mid \Delta \overline{o}_{imt-2}^{t-1} \rangle 0$$

for its respective value of i and t. We compute the returns at t instead of $t-1$ to prevent information spillovers. The group means are shown in black in Fig. 5 together with their 99% confidence intervals. Notice that the mean returns of the observations with decreasing odds are systematically higher than the unconditional means, which are again higher

than the means of the observations with increasing odds. Furthermore, the differences between the means of the increasing and decreasing odds are statistically significant for home odds, draw odds and away odds (the t-statistics are respectively -8.72, -3.29 and -7.34). These results are consistent with the regression analysis from the previous section and again point in the direction of underreaction.

To further investigate whether the differences are exploitable, we set up the following trading strategy. We compute odds changes $\Delta \overline{o}_{imt-k}^{t-1}$ for all feasible values for t and k and generate a trading signal whenever $|\Delta \overline{o}_{imt-k}^{t-1}| > |c|$ for the first time in the respective time series i.e. at the

Table 8
Performance of the momentum strategies when bets are made at the best available odds. c is a critical value for the relative change in odds during the time series. For example, c = -5% means betting on all odds that have decreased by at least 5% in the runup to the game. The difference in means is tested via t-tests, the difference in variances is tested via the non-parametric Fligner-Killeen test, the difference in the skewness is tested via a bootstrap setup. The stars indicate whether the results are significant at the 10%, 5% and 1% level respectively.

c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
Panel A: HOME ODDS													
-5%	6901	4.54%	139.95%	1.93	5%	7573	-3.15%	144.83%	2.00	7.69%	0.12% ***	2.60%**	79.40%
-10%	2877	8.80%	154.98%	2.39	10%	3756	-5.03%	158.36%	2.41	13.83%	0.04% ***	0.32%***	94.60%
-15%	1282	10.03%	174.24%	2.83	15%	2070	-6.54%	173.01%	2.54	16.57%	0.74% ***	0.58%***	68.00%
-20%	645	11.09%	178.23%	2.36	20%	1202	-3.37%	195.44%	3.09	14.46%	10.86%	2.84%**	4.40%**
Panel B: DRAW ODDS													
-5%	2842	-1.97%	181.65%	1.75	5%	4224	-6.42%	182.15%	1.82	4.45%	31.38%	96.53%	73.00%
-10%	657	-4.88%	200.63%	2.21	10%	1660	-9.60%	190.10%	1.90	4.72%	60.44%	72.43%	80.00%
-15%	226	-0.38%	216.95%	2.08	15%	748	-18.98%	186.74%	2.08	18.60%	24.47%	15.13%	50.60%
-20%	82	17.93%	239.01%	1.85	20%	370	-21.51%	188.03%	2.17	39.44%	16.42%	5.75%*	41.80%
Panel C: AWAY ODDS													
-5%	8520	-2.08%	188.79%	2.82	5%	9746	-8.69%	191.83%	3.33	6.61%	1.93% **	0.32%***	35.80%
-10%	4200	-2.08%	192.60%	2.83	10%	5668	-11.19%	208.80%	4.76	9.11%	2.50% **	0.04%***	28.80%
-15%	2137	-0.45%	201.62%	2.74	15%	3548	-10.11%	233.31%	5.31	9.66%	9.93%*	0.06%***	7.80%*
-20%	1093	2.70%	204.44%	2.37	20%	2413	-11.38%	222.65%	3.16	14.08%	6.64%*	0.15%***	0.00%***

Table 9

Performance of the momentum strategies when bets are made at the 4th highest odds. c is a critical value for the relative change in odds during the time series. For example, c = -5% means betting on all odds that have decreased by at least 5% in the runup to the game. The difference in means is tested via t-tests, the difference in variances is tested via the non-parametric Fligner-Killeen test, the difference in the skewness is tested via a bootstrap setup. The stars indicate whether the results are significant at the 10%, 5% and 1% level respectively.

c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
Panel A: HOME ODDS													
-5%	6732	-0.03%	131.70%	1.76	5%	7396	-6.78%	136.63%	1.80	6.75%	0.28%***	9.21%*	55.60%
-10%	2807	1.97%	142.03%	2.13	10%	3675	-9.37%	147.37%	2.23	11.34%	0.17%***	2.90%**	59.30%
-15%	1243	0.04%	154.71%	2.64	15%	2026	-12.25%	157.72%	2.16	12.29%	2.88%**	4.05%**	25.30%
-20%	625	-2.90%	151.75%	2.03	20%	1174	-10.63%	175.27%	2.77	7.73%	32.99%	15.17%	98.40%
Panel B: DRAW ODDS													
-5%	2741	-6.57%	172.11%	1.64	5%	4061	-10.99%	173.09%	1.77	4.42%	30.05%	99.92%	79.80%
-10%	644	-11.27%	185.99%	2.06	10%	1609	-15.13%	179.43%	1.89	3.86%	65.35%	74.05%	25.80%
-15%	216	-12.95%	194.49%	2.07	15%	723	-23.59%	174.73%	2.04	10.64%	47.11%	37.97%	44.40%
-20%	76	-7.37%	201.88%	1.94	20%	359	-24.73%	178.43%	2.11	17.36%	48.89%	34.54%	68.80%
Panel C: AWAY ODDS													
-5%	8237	-7.22%	175.23%	2.63	5%	9472	-14.01%	177.41%	3.25	6.79%	1.06%**	0.24%***	84.70%
-10%	4086	-8.29%	176.91%	2.67	10%	5543	-17.06%	189.15%	4.09	8.77%	1.96%**	0.07%***	81.60%
-15%	2085	-7.91%	183.40%	2.56	15%	3472	-16.61%	210.17%	4.92	8.70%	10.54%	0.15%***	95.70%
-20%	1064	-5.69%	185.13%	2.31	20%	2354	-17.87%	201.00%	2.94	12.18%	8.32%*	0.33%***	99.60%

Table 10

Performance of the momentum strategies when bets are made at median odds. c is a critical value for the relative change in odds during the time series. For example, c = -5% means betting on all odds that have decreased by at least 5% in the runup to the game. The difference in means is tested via t-tests, the difference in variances is tested via the non-parametric Fligner-Killeen test, the difference in the skewness is tested via a bootstrap setup. The stars indicate whether the results are significant at the 10%, 5% and 1% level respectively.

c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
Panel A: HOME ODDS													
-5%	6901	-4.52%	124.32%	1.59	5%	7573	-10.60%	129.97%	1.65	6.08%	0.41%***	17.99%	77.00%
-10%	2877	-3.80%	131.57%	1.96	10%	3756	-13.77%	138.72%	1.96	9.97%	0.28%***	6.03%*	91.80%
-15%	1282	-5.92%	140.63%	2.31	15%	2070	-16.97%	147.13%	2.01	11.05%	3.00%**	4.99%**	69.30%
-20%	645	-8.13%	137.47%	1.75	20%	1202	-16.38%	158.14%	2.33	8.25%	24.43%	13.28%	1.40%**
Panel B: DRAW ODDS													
-5%	2842	-10.34%	164.07%	1.59	5%	4224	-14.20%	164.98%	1.64	3.86%	33.43%	82.73%	64.80%
-10%	657	-16.41%	173.02%	2.00	10%	1660	-18.22%	170.40%	1.81	1.81%	82.03%	95.72%	74.30%
-15%	226	-17.22%	174.84%	1.86	15%	748	-28.25%	163.91%	1.99	11.03%	39.97%	31.31%	60.40%
-20%	82	-6.09%	184.12%	1.65	20%	370	-30.16%	165.71%	2.07	24.07%	27.79%	14.00%	29.60%
Panel C: AWAY ODDS													
-5%	8520	-12.72%	163.75%	2.49	5%	9746	-18.94%	164.44%	2.71	6.22%	1.06%**	0.36%***	50.60%
-10%	4200	-15.25%	162.32%	2.49	10%	5668	-22.84%	170.65%	2.88	7.59%	2.46%**	0.20%***	39.80%
-15%	2137	-16.40%	164.24%	2.38	15%	3548	-23.92%	183.07%	3.28	7.52%	10.94%	0.37%***	7.00%*
-20%	1093	-15.28%	164.42%	2.18	20%	2413	-25.19%	181.05%	2.77	9.91%	10.96%	0.66%***	1.40%**

smallest possible value for $t-1$ where the critical value condition is met. If the condition is met, we bet at three different odds

1. The most favorable odds offered by the bookmakers in the sample at time t.

2. The 4th most favorable odds at time t (we remove the 3 highest odds to prevent that our results are driven by pricing errors)

3. The median odds at time t

This setup eliminates information spillovers in both the information

Table 11

Performance of the momentum strategies applied to the time series of odds of individual bookmakers. For example, c = -5% means betting on all odds that have decreased by at least 5% in the runup to the game. The difference in means is tested via t-tests, the difference in variances is tested via the non-parametric Fligner-Killeen test, the difference in the skewness is tested via a bootstrap setup. The stars indicate whether the results are significant at the 10%, 5% and 1% level respectively.

Panel A: HOME ODDS													
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	160487	-6.17%	124.20%	1.72	5%	171066	-7.70%	133.33	1.76	1.53%	0.06% ***	0.01%***	69.30%
-10%	64638	-7.25%	131.88%	2.05	10%	83604	-9.56%	146.98	2.11	2.31%	0.15% ***	74.19%	68.70%
-15%	27294	-9.25%	142.48%	2.43	15%	43373	-11.48%	158.52	2.37	2.23%	5.26%*	2.99%**	36.50%
-20%	11931	-13.24%	150.20%	2.77	20%	23769	-11.42%	172.34	2.66	-1.82%	30.54%	30.15%	28.90%
Panel B: DRAW ODDS													
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	91024	-9.59%	160.06%	1.46	5%	114674	-10.68%	166.52%	1.55	1.09%	13.18%	0%***	99.90%
-10%	19571	-13.97%	169.96%	1.87	10%	38809	-14.16%	177.94%	1.89	0.19%	90.48%	7.3%*	67.70%
-15%	6289	-14.48%	180.97%	2.12	15%	16552	-16.42%	188.33%	2.17	1.94%	47.58%	58.66%	74.40%
-20%	2157	-13.05%	191.75%	2.28	20%	7319	-18.22%	200.61%	2.48	5.17%	27.64%	8.49%*	93.10%
Panel C: AWAY ODDS													
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	200146	-13.40%	162.94%	2.65	5%	221185	-15.56%	169.36%	2.77	2.16%	0%***	0%***	84.60%
-10%	97698	-15.54%	168.68%	3.08	10%	133291	-17.38%	181.44%	3.11	1.84%	1.17% **	0%***	58%
-15%	49888	-16.97%	176.34%	3.24	15%	82901	-19.85%	192.47%	3.45	2.88%	0.54% ***	0%***	84.10%
-20%	24039	-18.44%	179.72%	3.3	20%	52673	-20.44%	204.77%	3.72	2.00%	17.07%	0%***	94.40%

window and investment window and is implementable in real time. Furthermore, the market odds are not directly tradable, so we only use these odds to generate a trading signal and trade at odds offered directly in the market.

Summary statistics of the momentum strategy with the best odds, 4th best odds and median odds are shown in Tables 8, 9 and 10 respectively. We consider 4 different values for |c| (5, 10, 15 & 20) for home odds, draw odds and away odds, resulting in 12 different "momentum portfolios" per table. First, note again that in every case, the mean returns on bets of which odds have decreased are larger than the mean returns on bets of which the odds have increased. This is consistent with our previous analyses and with underreaction. This difference is often substantial and statistically significant. For example, bets of which the odds have decreased by at least 10% in the runup to a game outperform bets of which the odds have increased by at least 10% by 13.83 percentage points (t-stat of 3.57) when bets are made at the best odds. Second, 6 implementations of the strategy betting at best odds are profitable after transaction costs (Table 8) and 2 implementations stay profitable when betting at the 4th highest odds (Table 9). However, when bets are made at median odds (Table 10), none of the implementations have a positive mean return.

An objection that could be made is that the differences in returns are rational risk compensations. In this scenario, strategies that are riskier should yield higher returns. However, this explanation seems unlikely as the variances of the returns of bets on decreasing odds are lower than those of the increasing odds in 8 out of 12 strategies and the differences are often statistically significant. Another argument that could be brought forward is that the differences in returns are the result of a skewness preference of gamblers. Empirical work on stock markets is often consistent with the hypothesis that investors like stocks with positive skewness (lottery-like characteristics) and are willing to pay a premium for them (Annaert, De Ceuster, & Verstegen, 2013). However, this explanation is not supported by our data as the skewness values of the returns of the different portfolios are seldomly statistically different from each other.

In a final analysis, we repeat the momentum trading strategy but only look at the odds time series of individual bookmakers, both to generate the trading signal and select the corresponding odds at which the bets are made. In contrast with previous analyses, we thus do not use the market odds anymore to identify trading opportunities but look at changes in the time series of individual bookmakers. Furthermore, we do not place bets at the best odds available in the cross-section but at the odds offered by the respective bookmaker an hour later.

The results are shown in Table 11. In 11 of the 12 strategy implementations, the returns of "winners" are higher than those of "losers" and these differences are often highly statistically significant. This is in line with the previous analyses. However, none of the implementations are profitable. In appendix, we find similar results when we repeat the analysis with an information window ending at $t - 2$ and $t - 3$ respectively (i.e. a gap of 2 and 3 hours between the end of the information period and the execution of the bet).

5. Discussion

We document a strong time series momentum effect in betting markets that appears to be driven by underreaction of bookmakers. Although underreaction is indeed a prevalent behavioral fallacy in the literature, many behavioral models involve both underreaction and overreaction (e.g. Barberis et al. (1998) or Daniel et al. (1998)). There are a number of reasons why we could fail to document overreaction in our setting. First, underreaction simply appears to be a more persistent anomaly than overreaction. For example, Lin and Rassenti (2012) find that underreaction drifts substantially outnumber overreaction reversals in an experimental asset market. Similarly, Stevens and Williams (2004) find that underreaction is a common behavioral glitch and document that agents underreact to both negative and positive information in a controlled experimental setting. In their study, 24.8% of subjects underreacted to information more than 50% of the time while 0% of subjects overreacted more than 50% of the time, leading them to conclude that they do not find evidence of systematic overreaction. This is consistent with Weber and Welfens (2007) who also find evidence of stock price underreaction but not of overreaction in an experimental

Table 12

Overview of the $\widehat{\beta_k}$ coefficients and t statistics of regression (1). The table shows the number of regressions with coefficients and t-stats in the respective range.

Coefficient	Home	Draw	Away	t-stat	Home	Draw	Away
b > 0.1	123	72	95	t > 1.96	1	0	0
0 < b < 0.1	58	18	41	-1.96 < t < 1.96	2041	1265	2042
-0.1 < b < 0	259	13	182	-2.5 < t < -1.96	270	494	249
-0.5 < b < -0.1	1551	181	1800	-3 < t < -2.5	125	377	111
-1 < b < -0.5	286	1062	293	-4 < t < -3	47	337	75
b < -1	208	1139	74	t < -4	1	12	8

Table 13

Overview of the $\widehat{\beta_k}$ coefficients and t statistics of regression (1). The table shows the number of regressions with coefficients and t-stats in the respective range.

Coefficient	Home	Draw	Away	t-stat	Home	Draw	Away
b > 0.1	133	71	100	t > 1.96	1	0	0
0 < b < 0.1	51	21	44	-1.96 < t < 1.96	2022	1249	2012
-0.1 < b < 0	241	12	194	-2.5 < t < -1.96	245	463	225
-0.5 < b < -0.1	1519	179	1733	-3 < t < -2.5	113	378	105
-1 < b < -0.5	275	1026	276	-4 < t < -3	33	315	67
b < -1	198	1106	68	t < -4	1	10	6

setting.

Second, many behavioral models consist of short-term underreaction followed by longer-term overreaction. As our time series only contain 72 hourly observations, they might be too short to pick up reversal patterns. In the seminal work by De Bondt and Thaler (1985) for example, the observed overreaction effect is strongest between 3 and 5 years after portfolio formation. Such a timeframe is clearly of a different order of magnitude than we have in our data (and that of previous experimental work). In related work, Moskowitz (2021) finds evidence consistent with overreaction in a US sample of sportsbets. However, his momentum signals are related to the past performance of teams up to the last 8 games which is again a much longer timeframe than the one we consider in this study.

It is worth hypothesizing why we document underreaction whereas related work like Croxson and Reade (2014) finds that odds generally update efficiently. A first reason might be the market microstructure. Croxson and Reade (2014) use data from betting exchange Betfair, while we rely on bookmaker odds. Betting exchanges where prices are directly determined by supply and demand have been shown to produce more accurate odds compared to bookmakers (Franck, Verbeek, & Nüesch, 2010).

A second reason might be the salience and transparency of the information. Croxson and Reade (2014) study the reaction of in-game odds to goals being scored, which are very and transparent events and broadcasted worldwide. The information that moves the odds in the 72 hours leading up to the game is much less transparent (for example

rumors on players being injured). A more extreme version of this argument is potential insider trading or match fixing. Under this hypothesis, it is not the bookmakers who underreact to information, but information itself reaching the market only gradually. This could be the case when there are insiders with private information who gradually build up their stakes in order not to move market prices too much with their transactions. Although the topic of potential insider trading has a tradition in the betting literature (see for example Crafts (1985), Schnytzer and Shilony (1995) or Shin (1991)) these studies mostly focus on horse racing. Football is due to its nature as a team sport and the media scrutiny it receives probably less susceptible to insider trading or match fixing which could make it less likely that it is the main driver of the ubiquitous momentum effect that we document.

To end the discussion, it should be noted that although we document some strategies that appear profitable, it is not sure whether they can also be exploited. Franck et al. (2013) and Kaunitz et al. (2017) for example document discrimination of bookmakers against successful clients. The maximum stakes of gamblers who win consistently can be reduced or their accounts can be simply suspended. This limits the potential profitability of running a momentum betting strategy. In addition, any profitability is conditional on the best odds being quoted correctly and available to place bets at.

6. Conclusion

Does time series momentum also exist outside traditional financial markets? If we look at pre-game sports bet odds, the answer is yes. The expected returns of "winners" are economically and statistically significantly higher than those of "losers". This result is robust to a battery of different design choices. Furthermore, we add to the growing evidence that agents systematically underreact to new information. The momentum patterns that we document are consistent with a prolonged drift towards efficient asset values.

Can we further generalize our results? It is obvious that betting markets are in many respects very different than traditional financial markets. However, the fact that we document a similar momentum pattern in a seemingly unrelated environment can reveal a fundamental human behavioral glitch. Especially because it is consistent with earlier results in experimental asset markets.

Disclosure statement

The authors know of no other conflicts of interests related to this manuscript to disclose.

Data availability statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/austro/beat-the-booki e-worldwide-football-dataset.

Data availability

Data will be made available on request.

Appendix

In Table 12, we show the results of regression (1) where the standard errors are clustered by league. The results are similar to those in the main text.

In the main text, we defined the information window as $\Delta\overline{o}_{imt-k}^{t-1}$, representing the relative change in market odds between $t-k$ and $t-1$ with $k > 1$. As a robustness exercise, we change the gap between the information window and investment window from 1 to 2 hours: $\Delta\overline{o}_{imt-k}^{t-2}$ with $k > 3$. The results are shown in Table 13 and are similar to those discussed in the main text.

Table 14 and 15 show the performance of the momentum strategy that bets on the time series of odds of individual bookmakers but now with lags

Table 14

Performance of the momentum strategies applied to the time series of odds of individual bookmakers with a lag of 2 hours between the end of the information window and the execution of the bet. For example, c = -5% means betting on all odds that have decreased by at least 5% in the runup to the game. The difference in means is tested via t-tests, the difference in variances is tested via the non-parametric Fligner-Killeen test, the difference in the skewness is tested via a bootstrap setup. The stars indicate whether the results are significant at the 10%, 5% and 1% level respectively.

| Panel A: HOME ODDS | | | | | | | | | | | | | |
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	147623	-6.27%	124.60%	1.76	5%	157365	-7.71%	134.35%	1.76	1.44%	0.22%***	0.00%***	51.00%
-10%	56385	-7.36%	132.96%	2.11	10%	73957	-9.93%	148.58%	2.14	2.57%	0.10%***	54.08%	61.40%
-15%	23520	-9.83%	143.50%	2.46	15%	37525	-12.65%	159.80%	2.39	2.82%	2.43%**	0.26%***	31.30%
-20%	10202	-14.66%	149.94%	2.82	20%	20445	-12.71%	173.21%	2.67	-1.95%	30.80%	22.58%	22.80%
Panel B: DRAW ODDS													
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	82458	-9.89%	160.52%	1.49	5%	106946	-10.51%	166.81%	1.55	0.62%	41.36%	0.00%***	99.40%
-10%	17179	-13.44%	171.71%	1.89	10%	34765	-14.42%	178.05%	1.91	0.98%	54.72%	29.59%	65.10%
-15%	5441	-14.64%	183.58%	2.18	15%	14360	-16.56%	188.53%	2.20	1.92%	51.35%	52.57%	59.40%
-20%	1851	-8.97%	197.56%	2.25	20%	6132	-17.51%	203.53%	2.52	8.54%	10.58%	2.06%**	96.90%
Panel C: AWAY ODDS													
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	185759	-13.56%	163.85%	2.75	5%	208905	-15.92%	169.95%	2.78	2.36%	0.00%***	0.00%***	54.90%
-10%	86140	-15.04%	171.70%	3.27	10%	122038	-17.54%	182.89%	3.15	2.50%	0.14%***	0.00%***	30.70%
-15%	43093	-16.44%	179.73%	3.34	15%	74549	-20.09%	194.07%	3.47	3.65%	0.11%***	0.00%***	73.60%
-20%	20642	-18.58%	181.96%	3.39	20%	46824	-20.22%	206.79%	3.70	1.64%	30.40%	0.00%***	86.70%

Table 15

Performance of the momentum strategies applied to the time series of odds of individual bookmakers with a lag of 3 hours between the end of the information window and the execution of the bet. For example, c = -5% means betting on all odds that have decreased by at least 5% in the runup to the game. The difference in means is tested via t-tests, the difference in variances is tested via the non-parametric Fligner-Killeen test, the difference in the skewness is tested via a bootstrap setup. The stars indicate whether the results are significant at the 10%, 5% and 1% level respectively.

| Panel A: HOME ODDS | | | | | | | | | | | | | |
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	139046	-6.07%	124.94%	1.73	5%	147873	-7.52%	135.12%	1.78	1.45%	0.29%***	0.02%***	74.20%
-10%	51568	-6.91%	133.38%	2.08	10%	67574	-10.09%	149.85%	2.25	3.18%	0.01%***	10.39%	93.10%
-15%	21161	-1.00%	142.72%	2.37	15%	33818	-12.08%	161.30%	2.43	11.08%	12.31%	1.49%**	67.40%
-20%	8992	-1.55%	146.96%	2.57	20%	18208	-12.08%	174.76%	2.82	10.53%	8.77%*	62.19%	90.00%
Panel B: DRAW ODDS													
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	77046	-9.91%	160.91%	1.51	5%	100651	-10.30%	167.17%	1.56	0.39%	61.22%	0.00%***	98.50%
-10%	15654	-13.12%	172.73%	1.91	10%	31589	-14.02%	178.97%	1.93	0.90%	60.03%	33.93%	64.20%
-15%	4928	-15.57%	183.52%	2.22	15%	12692	-16.94%	188.92%	2.25	1.37%	65.99%	65.02%	61.40%
-20%	1662	-8.09%	200.69%	2.27	20%	5288	-17.45%	204.77%	2.59	9.36%	9.91%*	2.19%**	97.50%
Panel C: AWAY ODDS													
c	Number of bets	Mean return	Standard deviation	Skewness	c	Number of bets	Mean return	Standard deviation	Skewness	Difference means	p-value means	p-value variances	p-value skewness
-5%	175312	-13.75%	164.51%	2.83	5%	200255	-16.19%	170.53%	2.82	2.44%	0.00%***	0.00%***	44.10%
-10%	79087	-14.97%	173.35%	3.41	10%	114476	-17.74%	184.16%	3.21	2.77%	0.07%***	0.00%***	21.60%
-15%	39061	-16.85%	181.56%	3.48	15%	68956	-20.23%	195.14%	3.48	3.38%	0.43%***	0.00%***	51.30%
-20%	18494	-19.45%	183.49%	3.60	20%	42903	-20.11%	208.42%	3.79	0.66%	69.95%	0.00%***	75.20%

of 2 and 3 hours respectively between the end of the information window and the execution of the bet. The results are similar to those discussed in the main text.

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