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Efficient Spread Betting Markets: A Literature Review

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Abstract

Are simple trading strategies profitable? It is a question that has been on the minds of academics and practitioners for decades. In this paper, we review the longstanding literature on trading strategies in spread betting (also known as handicap betting), a popular sports betting microstructure. We review over 600 strategy implementations and find that market efficiency and systematic misperceptions are not mutually exclusive per se. Predictable glitches occur, but they are too small to be profitably exploited which is consistent with efficient markets. Furthermore, while controlling for data mining issues is becoming mainstream in finance, it has not yet made its way into this literature. We provide evidence that the hurdle rate of $|z| > 3$ which has been put forward in the broader finance literature should also be used in betting market research.

JEL Classification

C12, G14, G40

Keywords

Market efficiency, sports betting, spread betting, handicap betting, literature review

In this paper we review the longstanding literature on simple rule-of-thumb or mechanical strategies in sports betting. The quest for profitable trading strategies receives substantial attention in the broader finance literature. Practitioners are interested in finding methods for accumulating wealth, while academics are interested in the informational efficiency implications of profitable strategies (or both). In an efficient market, asset prices summarize all available information such that simple trading rules cannot lead to risk-adjusted excess returns (Fama, 1970). The existence of persistently profitable strategies could, for example, expose significant behavioral biases which can have resource allocation implications. In financial markets, strategies that consist of sorting assets on price-to-fundamentals ratios (value) or on their past performance (momentum) are generally profitable (Asness, Moskowitz, & Pedersen, 2013). However, it is not clear whether these are genuine market inefficiencies or rational risk compensations. Sports betting markets, due to their design simplicity, provide more direct tests of market efficiency.

Sports betting markets have a long history[1] in both economics and psychology research as they are essentially “simple financial markets” (Sauer, 1998, p. 2021). In contrast to earlier, more general literature reviews (Sauer, 1998; Thaler & Ziemba, 1988) we focus on easily implementable mechanical strategies. We zoom in on such strategies as they provide a more direct test of market efficiency compared to tests based on regressions or on the statistical modeling of underlying game variables, which are also common in the literature. Furthermore, we concentrate on point spread betting (also known as handicap betting), the market microstructure where all bets have a winning probability of close to 50% by design. This setting has the methodological advantage that all the assets have identical risk-return characteristics (Dana & Knetter, 1994). Furthermore, as the returns of bets across different games are independent, the returns are iid[2]. With the risk explanation crossed out, persistently profitable trading rules that are easily implemented and based on public information are direct evidence of market inefficiencies.

We review more than 40 years of literature and over 600 strategy implementations and find evidence of statistically significant market inefficiencies. For example, the market quite persistently misestimates the probability that underdogs will beat the spread. Leveraging this information increases returns above that of a naïve, random trading strategy. At first sight, we also find economically significant market inefficiencies. However, the sports betting literature is plagued with type 1 error inconsistencies i.e. there are many examples of papers claiming to find inefficiencies that were later rebuked by out of sample tests. It is common practice to test a battery of strategies based on some easily observable variables for a wide range of parameter values while only vaguely referring to data mining issues. Furthermore, in the papers we review, statistical methods that control for the number of hypotheses tested were never used. The hurdle rates designed for single hypothesis testing (like $|z| > 1.96$) are routinely used in a multiple testing exercise. Our analyses based on three multiple testing adjustments (Bonferroni; Holm; Benjamini, Hochberg, and Yekutieli) indicate that a hurdle rate of $|z| > 3$, which was put forward by Harvey, Liu, and Zhu (2016) for research in equity markets and Benjamin et al. (2018) for research communities in general, should also be the hurdle rate for betting market research. Under this stricter hurdle rate, none of the reviewed strategies were significantly profitable after transaction costs, which is consistent with an efficient sports betting market. Lastly, we observe a strong inverse relationship between the profitability of a strategy and its sample size. This observation is again in line with an efficient market where inefficiencies are chance results.

The usual disclaimer for literature surveys applies. We summarize, interpret and discuss many important results, but this review is by no means a complete catalog of all papers that have been written on the subject. The rest of this paper is structured as follows. In section 1 we discuss the usefulness of sports betting as a research lab for finance. Section 2 introduces the point spread betting market microstructure. Section 3 discusses the methodology used to benchmark statistical and economic significance given the large number of tests conducted in the literature. Section 4 zooms in on individual strategies while section 5 zooms out and puts the results in context. A further discussion can be found in section 6 and section 7 concludes.

1. Sports betting as a research lab for finance

Empirical work in sports betting markets dates back to Griffith (1949). Since then, countless researchers have embraced the methodological advantages of sports betting markets to test their hypotheses. The links between sports betting markets and traditional financial markets like the stock market are clear. Both are competitive speculative markets in which a large number of participants collectively determine the prices of assets whose future payoffs are uncertain (Ali, 1979). Moreover, sports betting, like trading derivatives and active asset management, is a zero sum game (before commissions) (Levitt, 2004). However, sports betting markets have several features that make them interesting research labs in general and specifically allow for notably clean efficiency tests.

a) The assets are very simple. Sports bets are typically binary options that have a single positive payoff if the underlying event takes place. This payoff structure is very easy to understand for all parties involved which can ease efficiency. In a lab setting, Carlin, Kogan, and Lowery (2013) for example show that lower asset complexity leads to higher efficiency.
b) The assets have very short maturities of days to hours or even minutes. This relatively short time span allows individuals to quickly evaluate their investment decisions and can

enhance learning (Thaler & Ziemba, 1988). In experimental research, Forsythe, Palfrey, and Plott (1982) stress the importance of replication for asset prices to converge to a rational expectations equilibrium. Furthermore, the very short maturities virtually remove any necessity to incorporate the time value of money in analyses.

c) The assets' true values are exogenously revealed. The event outcomes are known ex post and are independent of the behavior of traders. This circumvents the dreaded joint hypothesis problem[3] as researchers can systematically compare market prices of assets with their true values (Campbell, Lo, & MacKinlay, 1997; Thaler & Ziemba, 1988).

d) The expected payoff of a sports bet at a particular point in time is idiosyncratic and does not comove with aggregate risk factors (Moskowitz, 2015; Snyder, 1978). This is very different from capital market assets where the returns are correlated with each other and the stochastic discount factor.

e) The information set relevant to the pricing of sports bets is much smaller compared to that of a multinational company which can enhance efficiency as the attention span of traders is limited (Hirshleifer, Lim, & Teoh, 2009; Simon, 1971).

f) The sports betting landscape consists of very different market microstructures (point spread betting, pari-mutuel betting, fixed odds betting…) in virtually any sport. This element coupled with the depth of historical data that is available[4] provides researchers a wealth of natural experiments (for recent examples, see Berkowitz, Depken II, and Gandar (2015), Brown (2014), Croxson and Reade (2014) or Mills and Salaga (2018)).

g) Many of the above features can be replicated in a lab setting, but the gain in controllability that experiments offer is at least partially offset by external validity concerns (Levitt &

List, 2007). In betting markets agents can be studied in their natural habitat, without being aware that they are observed and with real money at risk.

As a result, researchers have gratefully used these “market[s]-in-miniature” (Hausch & Ziemba, 1990, p. 61) in many topics including the market’s forecasting abilities (Asch, Malkiel, & Quandt, 1982; Griffith, 1949) arbitrage relations (Franck, Verbeek, & Nüesch, 2013; Marshall, 2009) testing prospect theory (Snowberg & Wolfers, 2010) or asset price clustering (Brown & Yang, 2016).

2. Point spread betting market microstructure

In spread betting, agents bet on whether a team is going to win by more or lose by less than the point spread. Point spreads are set by bookmakers i.e. market makers[5] who are the counterparty to all gamblers. The point spreads are set in proportion to the relative team qualities. This equalizes the probability of winning a bet on either team. As an example, suppose a very strong team plays against a very weak team. A simple bet on which team will win the game will heavily favor the stronger team. However, with a spread, the bookmaker can level the playing field by requiring not only that the stronger team wins, but that it wins by, for example, at least a 14-point difference. Bookmakers typically first announce their point spread a few days before the game (i.e. the opening spread). The spread can change because of i.a. game-related news or large volumes placed on one of the teams, right until the game is about to start (i.e. the closing spread). However, whenever a gambler makes a bet, the point spread quoted on the moment the bet is made is locked in. Subsequent spread changes only affect the gamblers who enter later. In contrast to pari-mutuel betting, a gambler knows all the conditions of the bet when it is made.

Point spread betting is arguably the most popular betting microstructure in the United States. Spread betting is mostly associated with American football and basketball where it is common to score many points in a game. The betting industry grafted onto these two sports is enormous. In 2020 for example, more than 10% of adult Americans indicated they would bet on the Super Bowl, the most important football game of the year, and in 2019, 20% of adult Americans indicated they would bet on March Madness, the NCAA men's basketball tournament (American Gaming Association, 2020)(American Gaming Association, 2019). The popularity of spread betting is sometimes explained by the increased thrill of betting on a score difference compared to betting on the outcome. Alternatively, under some circumstances it could be more profitable for a bookmaker to offer spread bets than to offer fixed odds bets (Bassett Jr, 1981). Research in these point spread betting markets dates back to Pankoff (1968) who explicitly introduced the efficiency jargon in the betting literature, inspired by his contemporaries Fama (1965) and Mandelbrot (1966).

If the spread indeed equalizes the win probabilities of bets on either team the fair odds would be 2. However, bookmakers are not in the business for the fun of it, so they charge a fee for their services just like market makers in traditional financial markets. Payout happens according to the 11 for 10 rule[6]. This means that an $11 winning bet only yields a profit of $10. This is below the fair payout, which allows the bookmaker to make a profit. A gambler who wants to break even must achieve a win fraction of at least $\frac{11}{21}$, approximately 52.4% (or alternatively, lose less than $1-\frac{11}{21}$, approximately 47.6%). This can be seen by solving

$$f \times 10 - (1 - f) \times 11 = 0 \quad (1)$$

to f, the fraction of winning bets.

If the total amount bet is perfectly balanced between the two teams, the bookmaker pays out $21 for every $22 it receives. Traditionally, bookmakers were understood to focus on achieving such a balance. By doing so, they take no risk as they can pay off the winning bets by the losing bets and collect a commission along the way. In this view, excessive volume placed on one team will induce the bookmakers to adjust the point spread in order to incentivize gamblers to bet on the other team. As a result, if the spread differs from the market's consensus, market forces will push the spread towards the equilibrium value. This also means that the point spread is not necessarily an unbiased predictor of the margin of victory. If the market's expectations are biased, bookmakers will anticipate and purposely bias the point spread to equalize the volumes bet on both sides to avoid having to take an active position in the game. As a result, the point spread will be a forecast of the market's expectation of the game outcome instead of the game outcome itself. More recent research however shows that bookmakers are not trying to nullify their risk in every game. Bookmakers can earn more when there are more losers whose stakes can be collected than winners who have to be paid. There is empirical evidence that bookmakers indeed maximize their profits by offering slightly biased lines, i.e. more than 50% of the volume on one side and take active positions in the game outcome as a result (Levitt, 2004; Paul & Weinbach, 2011; Strumpf, 2003). There is of course a limit to how far bookmakers can go with such practices as witty gamblers will quickly exploit flagrant profit opportunities.

It is worth mentioning that a strand of the spread betting literature examines the totals market where gamblers bet on the total number of points scored by the two teams combined. The efficiency of this market is beyond our scope. We refer interested readers to Paul and Weinbach (2002), Paul, Weinbach, and Wilson (2004) and DiFilippo, Krieger, Davis, and Fodor (2014).

3. Methodology

Spread betting brings about the methodological advantage that the probability of winning a series of bets can be modelled via a binomial distribution where successive outcomes are independent. In large samples, the binomial distribution can be conveniently approximated by the normal distribution. Two benchmarks are commonly used to evaluate the performance of trading strategies.

a) **Statistical efficiency:** the win fraction is indistinguishable from randomness (50%). Under the null, the point spreads reflect all information such that the expected return of every bet is equal.
b) **Economic efficiency:** the win fraction is not significantly higher than 52.4% (or lower than 47.6%). Under this null hypothesis expected returns do not have to be equal, but differences cannot be so large that profit opportunities arise.

The advantage of using these two benchmarks jointly is that both exploitable and unexploitable inefficiencies can be identified.

The benchmarks result in the following hypotheses and test statistics (Woodland & Woodland, 1997).

Hypothesis 1: the trading strategy is statistically efficient:

$$H_{0,1}: \pi = 0.5$$

$$H_{a,1}: \pi \neq 0.5,$$

where π is the win fraction. The test statistic is

$$Z_1 = \frac{(\hat{\pi} - 0.5)}{\sqrt{\frac{(0.5)(1-0.5)}{n}}},$$

where $\hat{\pi}$ is the empirical win fraction and n the number of bets.

Hypothesis 2: the trading strategy is economically efficient:

$$H_{0,2}: \pi = \frac{11}{21}$$

$$H_{a,2}: \pi > \frac{11}{21},$$

with a similar test statistic:

$$Z_2 = \frac{\left(\hat{\pi} - \frac{11}{21}\right)}{\sqrt{\frac{\frac{11}{21}\left(1 - \frac{11}{21}\right)}{n}}}.$$

In the discussion of the trading strategies, we will only report this second test statistic when the strategy is profitable (empirical win fraction larger than $\frac{11}{21}$), and we can reject the null of randomness (at the 5% significance level). For strategies with winning percentages significantly below 50%, we use the benchmark of $1 - \frac{11}{21} \approx 47.6\%$.

To further streamline the exhibition, we only present the *z*-statistics defined above in the analyses. Some older papers lack significance tests or use other methods including the test proposed by Tryfos, Casey, Cook, Leger, and Pylypiak (1984), which was shown to be slightly biased by Woodland and Woodland (1997), or use a likelihood ratio test (Even & Noble, 1992). In these cases, the above *z*-statistics are computed if the required data are provided. Furthermore, to save space and avoid data mining issues we only present consolidated results on the longest time period available in each paper and leave out the year by year analyses. Moreover, a small number of articles deploy strategies for which it is not clear that they can be implemented (strategies that rely on closing line information or strategies that assume more favorable point spreads could be obtained by setting up a betting syndicate that exploits price differences between different regions). These strategies are not included in this overview. Lastly, ties are excluded from the analyses as it is common bookmaker policy to simply refund bets in these scenarios (or avoid ties by non-integer point spreads).

Multiple Testing

We initially benchmark the test statistics against the common single hypothesis test values of $|z| > 1.96$ and $|z| > 1.64$ for the two- and one-tailed tests respectively. The strategy implementations with z-statistics that exceed these critical values are deemed statistically significant in the original studies. However, the trading strategy literature in spread betting is a textbook example of a situation where corrections for multiple testing are crucial to limit flagrant p-hacking. Scholars test hundreds of possible strategies, often without any theoretical underpinning. When enough strategies are tried out, significant results will be found even if the null is true, by construction of the hypothesis test (type 1 error). In this paper, we review 628 strategies, so the risk of many type 1 errors is very real. Moreover, when researchers find an interesting strategy, they often start digging in the periphery. As a result, many slight alterations of the same profitable strategy are proposed. Alternatively, some promising strategies are tested multiple times in similar or overlapping datasets (for example, first between 1970-1985, and in a later follow-up study between 1970-1995). Some implementations are so similar that the returns are almost identical and the z-statistics very highly correlated. An example from the reviewed strategies includes betting on home underdogs when the spread is 8.5 in the NBA between 1995-2002 and betting on home underdogs when the spread is 9 in the NBA between 1995-2002. If we count both these strategies, we are essentially double counting profitable strategies and will vastly overestimate the true degree of inefficiency. In contrast, strategies that are not deemed profitable are often not published (publication bias) and not further dissected which artificially suppresses the number of unprofitable strategies. As a result, we get a lopsided literature that is tilted in favor of profitability. A testable consequence of such a scenario is that we find pockets of profitability centered around a few strategies in a few samples that do not generalize out of their samples and find too few unprofitable strategies.

We try to alleviate the concern related to the number of proposed test by using multiple testing methodologies (we rely on Harvey et al. (2016) who propose a multiple testing framework for finance in general). The issue of correlated z-statistics is trickier, we propose a pragmatic approach that limits the overlap between strategies.

Taming the family-wise error rate and the false discovery rate

The significance level α controls the type 1 error rate in a single hypothesis test and is usually set to 5%. When multiple tests are carried out, α should be adjusted. If not, the probability of making a type 1 error, i.e. the family-wise error rate, quickly approaches 100%.

The most common approach to limiting the family-wise error rate to the usual 5% level is the Bonferroni adjustment which shrinks the original α by the number of tests:

$$\alpha^{Bonferroni} = \frac{\alpha}{N},$$

where N is the number of tested hypotheses. The objective of the Bonferroni adjustment is somewhat extreme (controlling the probability of making a single type 1 error), which results in harsh hurdle rates when the number of tests increases. In our case it would amount to rejecting the null of all implementations with z-scores above 3.95 for the two-sided tests as we have a sample of 628 hypotheses. Note that we implicitly assume here that all tests that were conducted are included in our sample. This is clearly not realistic but still a useful exercise as the results can be thought of as a lower bound for the hurdle rate. As an example, the hurdle rate would rise to 4.11 is we were to assume that we are only observing half of all conducted tests.

Another well-known method to control the family-wise error rate is Holm's adjustment, which sequentially tests all p-values against a dynamic benchmark. The algorithm consists of a few steps:

1) Order the p-values from small to large: $p_{(1)} \leq p_{(2)} \leq \cdots \leq p_{(i)} \leq \cdots \leq p_{(N)}$.
2) For each p-value (starting from the smallest), check if $p_i < \frac{\alpha}{N+1-i} = \alpha_i^{Holm}$.
3) Reject the respective null if the inequality holds. If the inequality does not hold, do not reject the respective hypothesis and all other hypotheses with larger p-values.

Holm's method is dynamic, i.e. the index number i in the denominator makes the hurdle rate different for every hypothesis, in contrast to the Bonferroni method. Note that for $i = 1$, $\alpha_i^{Holm} = \alpha^{Bonferroni}$. For $i = 2$, $\alpha_i^{Holm} > \alpha^{Bonferroni}$, making Holm's adjustment less stringent, leading to more rejections and all rejections via Bonferroni are also rejected via Holm.

A last method we deploy is the Benjamini, Hochberg, and Yekutieli (BHY) adjustment that is algorithmically somewhat similar to Holm's adjustment. In contrast to the previous two adjustments, BHY's targets the false discovery rate, i.e. the expected proportion of false discoveries, and makes sure it stays below α. It consists of the following steps:

a) Order the p-values from small to large: $p_{(1)} \leq p_{(2)} \leq \cdots \leq p_{(i)} \leq \cdots \leq p_{(N)}$.

b) Find the largest i such that: $p_i \leq \frac{i}{N \times c(N)} \alpha = \alpha_i^{BHY}$. (It can be shown that setting $c(N) = \sum_{j=1}^{N} \frac{1}{j}$ is suitable under arbitrary dependency among the test statistics.)

c) Reject the respective null hypotheses for p_k for $k = 1, \ldots, i$ and accept the other null hypotheses.

When we apply the multiple testing adjustments to our data, it is important to account for the correlation between z-statistics of the different hypotheses. Correlation among the *z*-statistics, which is certainly present, makes the multiple testing methods too stringent. Consider the extreme case where we test the same hypothesis 100 times. Instead of using the ordinary *p*-value hurdle rate of 5% which would be appropriate as we are essentially conducting a single hypothesis test, we would use $\frac{5\%}{100}$ under the Bonferroni adjustment, which is of course far too conservative.

In the remainder of this section, we apply the multiple testing adjustments to our data set to determine the appropriate critical values. As mentioned previously, the data set contains 628 strategy implementations, but many of these implementations test the same strategy (like for example betting on the home team). Moreover, the samples in which these different implementations of the same strategy are tested often overlap. To determine the appropriate critical values for the *z*-statistics given this dependence, we make a subsample of 85 strategy implementations. In this subsample, the dependence is removed to a large extent as we only include one implementation of each strategy per tournament (so we remove implementations of the same strategy in different periods). If the patterns in betting markets follow a stationary process, tests in different time periods measure the same phenomenon anyway. We do include implementations of the same strategy when tested in a different tournament because of the large institutional differences. If the strategy is tested for multiple parameter values, we still only include one implementation as implementations for subsequent parameter values are often highly correlated. We make two subsamples of 85 strategy implementations via the process described above, one with the smallest and one with the largest z-values per strategy and tournament. We compute the appropriate z-score benchmarks in both subsamples, which are shown in table 1.

[INSERT TABLE 1 HERE]

Table 1 provides us a number of different critical values which we can use as a benchmark. Note that all multiple test benchmarks are at least 3. Also note that the multiple test benchmarks are relatively robust to changes in the number of tested hypotheses. Even if we make the widely unrealistic assumption that only 20 hypothesis tests were ever carried out, the Bonferroni hurdle rate would already be above 3. As a result, using a multiple test hurdle rate of $|z| > 3$ is very reasonable (although it increases the probability of type 2 errors). This choice is both consistent with the analysis from table 1 and with the previous proposals of i.a. Harvey et al. (2016) and Benjamin et al. (2018).

4. Mechanical trading strategies

To make the trading strategy zoo more manageable we fit the reviewed strategies in the taxonomy shown below.

a) Game characteristics

1) **Home team** (betting on the home team)
2) **Underdog** (betting on the underdog, i.e. the team that receives a head start via the spread)
3) **Home underdog** (betting on the home underdog)

4) **Home favorite** (betting on the home favorite where the favorite is the team that receives a disadvantage via the point spread)
5) **Familiarity** (for example, betting on a team that plays on the surface it is used to)
6) **Fatigue** (for example, betting on a team on a road trip)
7) **Attention & Importance** (for example, betting on the home team in a playoff game)
8) **Absences** (for example, betting on a team with an absent top player)

b) Past performance

1) **Performance against the spread** (for example, betting on teams that beat the spread last game)
2) **Performance not against the spread** (for example, betting on teams that won their last 3 games)
3) **Spread movements** (for example, bet on teams that became larger underdogs between opening and closing spread)

We first distinguish between strategies based on current game characteristics (like the location of the game) and past performance (for example whether a team won the last game or not). The first four items of this first category are individual strategies as they are so common in the literature (home team, underdog, home underdog, home favorite). The next four are container items for strategies related to familiarity, fatigue, attention & importance and absences. The second category (past performance) contains the large family of momentum and contrarian strategies. We subset this category by performance against the spread, performance not against the spread and spread movements. The performance against the spread strategies are especially interesting as they take both the game outcomes and expectations (the spread) into account.

We collected the relevant papers by querying for “spread betting” and either “efficiency” or “efficient” in the EBSCO discovery service. This resulted in a sample of 157 papers. We removed all papers that did not implement strategies and further expanded our sample by reviewing the bibliographies of the relevant papers and the papers that cited the examined papers (backward/forward snowballing). This resulted in a final sample of 46 papers. The last query was carried out in October of 2020. In what follows we highlight the most important results per strategy family. To make the discussion digestible we will often refer to the appendix where interested readers can find additional strategies. In the tables, we will highlight strategy implementations that reject the null under the single hypothesis benchmark in bold and the strategies that reject the null under the multiple test benchmark in red.

4.1 Strategies based on game characteristics

4.1.1 home team.

Consistently betting on home teams is one of the simplest and most tested mechanical trading rules. The well-known home-field advantage posits that home teams win more often than visiting teams. In NLF games between 1981 and 2004 for example, the home team outscored the visiting team by 3 points on average (Borghesi, 2007a). Factors that drive this effect include familiarity with the venue, crowd behavior, travel fatigue and referee biases (see Jamieson (2010) for a review). If the market does not adequately reflect this home-field advantage into prices, inefficiencies can occur. Table 2 summarizes the studies that implement the strategy of consistently betting on home teams. The data sets include NFL games, NBA games, college football games, college basketball games and Australian Football League games between 1973 and 2017. Overall, the market correctly discounts the home-field advantage. The empirical win fractions are not consistently above or below 50% and for only two strategies that were profitable in sample, the null of randomness could be rejected at the single hypothesis benchmark (and even in different directions). Furthermore, the null of unprofitability is never rejected.

[INSERT TABLE 2 HERE]

4.1.2 underdog.

Another trading rule that requires almost no information is betting on the favorite or underdog. These are the teams that received a disadvantage or an advantage via the point spread respectively. Investigating this strategy seems meaningful as in other environments like pari-mutuel betting, it is a stylized fact that returns on favorites are much higher than returns on underdogs (Snowberg & Wolfers, 2010). However, it is worth repeating that in spread betting there are no real favorites or underdogs at the level of the bet. All bets have virtually the same risk-return characteristics, which is not at all the case in pari-mutuel betting or fixed-odds betting where you can regularly make bets at odds of 20 to 1 or more for example. Still, at the game level, the market could misestimate the winning probability of an underdog which can give rise to inefficiencies.

Table 3 summarizes the papers implementing the “bet on underdog” strategy. There appears to be an outspoken bias in favor of underdogs. Of the 22 implementations of this strategy, 20 find that underdogs win more than 50% of the time against the spread. Moreover, the null of randomness is rejected in 9 cases at the single test benchmark and once at the multiple test benchmark. Unprofitability is only once rejected at the single test benchmark.

The market appears to systematically underestimate the quality of underdogs such that the return of a strategy that bets on these teams will be higher than that of a naïve, random strategy. However, the bias is generally too small to be profitably exploited. A possible explanation of the tendency to underbet underdogs is that it is more fun to bet on and root for the team that is likely to win

(Paul & Weinbach, 2005a). As the best performing teams receive most media attention, it could also be the case that the volume of news coverage biases gamblers into overestimating the favorites.

[INSERT TABLE 3 HERE]

Motivated by better than even winning probabilities of the unconditional underdog strategy, many researchers implement underdog strategies conditional on some point spread PS. Predicting the score difference in a game between two very unevenly matched teams might be harder which could induce further biases (Vergin & Scriabin, 1978). The results of these conditional underdog strategies are similar to the unconditional underdog strategy. For 46 out of 51 implementations, the underdog beats the spread in more than 50% of the games. Furthermore, the null of randomness is rejected in 17 cases at the single test benchmark and twice at the multiple test benchmark. The null of unprofitability is never rejected at the multiple test benchmark. The supporting tables can be found in the appendix subsection on underdogs.

4.1.3 home underdog.

Meshing home team and underdog information results in the strategy that most systematically rejects the nulls of both randomness and unprofitability at the single test benchmark. In total, 45 home underdog implementations are reviewed (both unconditional shown in table 4 and conditional on the point spread, shown in appendix). The null of randomness is rejected 22 times at the single test benchmark and 6 times at the multiple test benchmark. Betting on home underdogs was even significantly profitable (at the single test benchmark) in NFL games between 1973 and 1987. However, in more recent periods, the win fraction is below 50%. It seems that this inefficiency has faded over time, an observation also made by Gray and Gray (1997) when they study the returns of the strategy season by season. At the multiple testing benchmark, the strategy was never profitable.

[INSERT TABLE 4 HERE]

Several explanations for the home underdog bias have been proposed. First, large home underdogs are the worst teams in the league and bettors may be hesitant to bet on such low-quality teams. Second, when away favorites are leading by a comfortable margin, they might relax their performance and substitute their best players off the field to avoid injury and fatigue. As a result, the favorite wins the game, but does not cover the spread. This effect is arguably larger for away teams as home crowds will be disappointed if their team does not fully commit or if key players stop playing early. Some even go further and hint that this observation might be consistent with point shaving: corruption where players maximize their utility by both winning the game while at the same time receiving a bribe to fail to cover the spread (Wolfers, 2006). Ashman, Bowman, and Lambrinos (2010) further add that bad teams have little opportunities in a season to get recognized. They might be extra motivated when they get to play a big team at home to prove what they are worth, leading to an unexpectedly good performance.

For completeness, we include the papers implementing the "bet on home favorites" strategy in appendix. The null of randomness is never rejected.

4.1.4 familiarity.

In this section we review strategies that try to exploit differences in familiarity with game circumstances between the teams.

Boulier, Stekler, and Amundson (2006) try to exploit differences in playing field surfaces in NFL games (turf versus grass). The authors propose the strategy of betting on the home team when it hosts a visiting team that is used to playing on a different surface. The strategy is profitable in sample and randomness is rejected at the single test benchmark, but not at the multiple test benchmark as shown in row 1 of table 5.

Borghesi (2007a) investigates whether temperature information can be profitably exploited. To control for the temperature teams are familiar with, the author constructs a temperature acclimatization advantage variable. For example, if a team from Miami plays an away game in New England in December, it is clearly less familiar with the game conditions. One of the strategies he proposes is betting on home teams in the coldest quartile of game day temperatures conditional on the acclimatization advantage, shown in table rows 2 to 5 of table 5. It appears that the market does not fully incorporate the acclimatization difficulties that occur on the coldest game days when the acclimatization difficulties for the visiting team are the largest. The null of randomness of this strategy implemented for NFL games between 1981-2004 is decisively rejected at the single test benchmark, but again not at the multiple test benchmark. The author also tests the converse strategy of betting on home teams in the warmest quartile of games conditional on the acclimatization advantage, but no statistically significant results are found (see in appendix under the familiarity subsection).

Familiarity with the climate is further investigated by Kuester and Sanders (2011). They find that betting on teams from arid regions when they host teams from humid regions is profitable and the null of unprofitability is even rejected at the single test benchmark, but again not at the multiple test benchmark as shown in row 6 of table 5. Just like the strategy of Borghesi (2007a) discussed above, the performance of this strategy is also not symmetric. For the converse strategy of betting on teams from humid regions when they host teams from arid regions, the null of randomness is not rejected at the single test benchmark. The difference could be explained by aridity being more performance adverse and harder to acclimatize to. Aridity is also correlated with for example altitude, which has a large impact on the oxygen uptake of the athlete. (A few extensions of the strategy can be found in appendix).

We finish this section with Shank (2019), who studies the performance of home teams in divisional NFL games. The NFL schedule stipulates that each team plays its divisional rivals twice a year, while they are only guaranteed to play teams outside their division once every three or four years. As a result, the familiarity with divisional rivals' coaches, players, tactics etc., is much higher, to which the market can misreact. Indeed, home teams only cover in 47% of divisional games between 2003-2016, rejecting the null of randomness at the single test benchmark, but not at the multiple test benchmark as shown in row 8 of table 5.

[INSERT TABLE 5 HERE]

4.1.5 fatigue.

Fatigue is another major factor that can impact game performance and must be accounted for in the point spread. Lacey (1990) and Vergin (1998) devise strategies where the location of a team's previous game proxies for fatigue. Home teams that played at home in the previous game are supposedly well rested while away teams that also played away in their previous game traveled more. The strategies are shown in the first four rows of table 6 and are never profitable nor significantly different from randomness.

Sung and Tainsky (2014) investigate whether the bye-week induces inefficiencies. An NFL season consists of 17 weeks where each team plays only 16 games. This means that every team gets one week off each season (between the fourth and tenth week of the season). The bye-week gives players and staff the time to unwind and rest. The authors build their hypotheses on the strand of the psychology literature that established a positive relationship between days off and subsequent performance. As a result, if the betting market does not accurately estimate the value of the bye-week, the performance of teams that took a week off might be underestimated. They propose a battery of strategies of which we highlight a selection in rows 5 to 8 of table 6 (rest shown in appendix). Interestingly, the null of unprofitability is rejected for two strategies at the single test benchmark: betting on the favorite after it had a bye-week and betting on the away favorite after it had a bye-week. This last strategy has an empirical win fraction of over 73%. Betting on underdogs after their bye-weeks was never profitable. The authors hypothesize that rest affects strong teams and weaker teams differently. However, if we benchmark the results at the more appropriate multiple test critical values, none of the strategies are statistically significant.

Ashman et al. (2010) test whether player fatigue is correctly priced in NBA point spreads. As NBA teams often face games on consecutive nights, fatigue is more of an issue for basketball players compared to athletes in other sports. Table 6 rows 9 to 11 show the result of betting on the home team when respectively the visiting team, both teams and home team had back-to-back games. Randomness is rejected for home teams playing back-to-back games at the multiple test benchmark. Apparently, the betting market does not fully recognize that fatigue at least partially cancels out the home field advantage.

Ashman et al. (2010) further dissect the results from this last strategy conditional on the number of days of rest the away team had shown in rows 12 to 20 of table 6. Furthermore, in rows 13, 16 and 19 the sample is limited to games where the home team traveled one or two time zones eastwards between their back-to-back games. Underperformance arising from eastward travel is in line with Jehue, Street, and Huizenga (1993) who find that West Coast teams perform badly when they travel to the east. Home team underperformance is statistically significant at the multiple test benchmark when the visiting team rested for one or two games. Inspired by the above results, Ashman et al. (2010) further condition the strategies on other game related information (shown in appendix in the fatigue subsection). The results are qualitatively similar.

[INSERT TABLE 6 HERE]

We end this section with Schnyzer and Hizgilov (2018) who specifically focus on the effect of jet lag induced fatigue. They study the Australian Football League, which has the methodological advantage that many games take place on neutral grounds. Jet lag has been shown to worsen the performance of athletes, but the question of course is whether the betting market efficiently incorporates this information into prices (Jehue et al., 1993). Results of several strategies conditional on the jet lag of the visiting team are shown in table 6 rows 21 to 28. Interestingly, there appears to be no jet lag effect on neutral grounds, but there appear to be jet lag effects on the non-neutral grounds (relative to the single test benchmark only). The authors argue that the jet lag effect on non-neutral grounds is just a home team bias.

4.1.6 attention & Importance.

Another common input to trading strategies is the importance of a game and the attention it receives. Amoako-Adu, Marmer, and Yagil (1985) and Vergin and Sosik (1999) propose the strategy of betting on all home teams in Monday night NFL games. For a long time, Monday night games were the only games broadcasted in prime time leading to substantial media and fan attention. These spotlights can be a strong incentive for teams to perform better and these games tend to attract more casual bettors. As depicted in table 7, Monday night home team bets had a win fraction of 68% between 1979-1981 and 60% between 1976-1996, leading to statistically significant profits in both periods at the single test benchmark, but not at the multiple test benchmark (although the null of randomness is rejected at the multiple test benchmark). Shank

(2018) extends the strategy as it is now common practice to also broadcast games in prime time on Thursday, Saturday and Sunday night. Although the return of betting on home teams in prime-time games is higher compared to that of the regular Sunday games (compare row 5 and 6 of table 7), the null of randomness is not rejected.

In a similar vein, Vergin and Sosik (1999), Gandar, Zuber, and Lamb (2001) and Borghesi (2007b) test betting on playoff games for the NFL and the NBA. These games, like the prime-time games, receive considerably more attention and attract a large amount of casual, less informed, bettors. Furthermore, these games often involve teams that rarely play against each other and can take place on a neutral location, which could complicate the pricing. Lastly, the stakes are especially high in these games as losing teams are eliminated. The strategy of Vergin and Sosik (1999) and Borghesi (2007b) to bet on home teams in playoff games rejects the null of unprofitability at the single test benchmark (but randomness is not rejected at the multiple test benchmark). The similar strategy of betting on home underdogs in playoff games is also significantly profitable at the single test benchmark and has an astounding empirical win fraction of over 70%. Surprised by these results, Gandar et al. (2001) revisit the strategies in a large sample of NBA games, in NFL games beyond the sample used by Vergin and Sosik (1999) and in MLB games (these results are not shown due to the different microstructure of baseball betting). None of these datasets contain evidence that betting on playoff home games is significantly different from randomness, “the bias found by Vergin and Sosik was short-lived” (Gandar et al., 2001, p. 451).

Hickman (2020) focusses on NCAA basketball “March Madness” games. March Madness is a 6-round single-elimination postseason tournament with 64 teams. As these games are played on neutral courts the home/away distinction cannot be made. However, all teams in the tournament are divided into seeds where seed 1 represents the best teams and seed 16 the worst, based on the opinion of a selection committee. Hickman (2020) tests whether consistently betting on the higher-seeded team in March Madness games results in profits as shown in table 7 (rows 18 to 21). The null of randomness can never be rejected, additional results are shown in appendix, none of them are statistically significant.

We end this section by looking at potential psychological factors that make teams perform differently in the weeks leading up to, or after an important game. Lacey (1990) investigates whether strategies that bet on teams in games before or after divisional games result in profits. Teams might underperform in the week preceding a divisional game as they are already preparing for the divisional game (looking past their opponents) and after a divisional game as a result of the aftermath of a big win or loss. However, as summarized in table 7 (row 22 and 23), the profits of these strategies do not differ from randomness.

[INSERT TABLE 7 HERE]

4.1.7 absences

Dare, Dennis, and Paul (2015) investigate betting market efficiency in the NBA when players are absent because of for example injury, sickness, suspension or personal reasons. Table 8 shows the results of the strategy of betting on the team with most absences. To further refine the strategy, it is also tested conditional on the value of the payer(s) that is (are) absent, indicated by the Approximate Value (AV) index, which is proportional to the quality of the player (see the paper for more information on how to compute this metric). The results in table 8 show that betting on teams that miss players wins more than half of the time and the null of randomness can be rejected in 1 case (only at the single test benchmark). The analysis is repeated for home teams and away teams (tables shown in appendix). Home teams with absent players consistently cover more than 50%, although randomness is never rejected. For away teams the evidence is mixed.

Colquitt, Godwin, and Shortridge (2007) investigate the role of coaching changes on betting markets. Inspired by the literature on CEO turnover and subsequent stock price behavior, they investigate whether betting markets react efficiently when a team changes its coach. As shown in table 8 row 7, when an inexperienced coach takes over, the betting market underestimates the team's ability as these teams cover 63% of the time, which is statistically profitable (again, only at the single test benchmark). The effect fades quickly in the next games. When an experienced coach takes over, randomness is never rejected. Further results with respect to the runup to a coaching change are reported in appendix, the null of randomness is never rejected.

[INSERT TABLE 8 HERE]

4.2 Strategies based on past performance

In this section we summarize the large family of both momentum and contrarian trading rules. Momentum strategies extrapolate past performance into the future, while contrarian strategies do just the opposite. These strategies are especially interesting as they are also intensely studied in the mainstream finance literature. Momentum especially is considered to be the "premier anomaly" (Fama & French, 2008, p. 1653). Stocks that have outperformed in the past 3 to 12 months continue to outperform in the near future. Such profitable momentum strategies are awkward as they seem to imply that markets are not even weakly efficient. To make momentum profits compatible with the neoclassical rational framework risks would have to increase after good past performance, which is counterintuitive (Lewellen, 2002) although several attempts for risk based explanations have been made (Galariotis, 2013; Johnson, 2002; Li, 2018). Contrarian strategies found their way into the broader finance literature via seminal work of De Bondt and Thaler (1985). Stocks that have performed relatively well in a 2 to 5-year period relatively underperform the following years and vice versa. This phenomenon is most readily explained by investor overreaction to news which is corrected in the long run but others point to varying risk-premia (Chan, 1988; Fama & French, 1996). As the risk-return profile of all spread bets is equal by construction as discussed previously, any risk explanation can be quickly ruled out in our context. If profitable momentum betting strategies would be found, we could more confidently point to behavioral explanations.

4.2.1 performance against the spread.

A first straightforward strategy consists of betting on the team that beat the spread by the largest average amount in the last *k* weeks. This is the team that outperformed the most, relative to the expectations. If momentum (contrarian) patterns would exist, we would expect this team to overperform (underperform) in the future. As shown in table 9 rows 1-4, the evidence is mixed. In the early days (1969-1981) the momentum strategy was generally profitable in sample (although randomness was never rejected) while later periods are consistent with a profitable contrarian strategy but the null of unprofitability is only once rejected at the single test benchmark.

A variation on the same theme is not just betting on the one team that outperformed the most, but on all teams that are on win streaks against the spread as shown in table 9 rows 5-10. The evidence here is mostly consistent with contrarian strategies and the null of randomness is rejected for 1 implementation at the multiple test benchmark.

[INSERT TABLE 9 HERE]

The appendix contains 145 additional implementations based on performance against the spread including Camerer (1989) and Paul, Weinbach, and Humphreys (2014) who further refine the strategies shown in table 9 by also looking at the performance of the opponents in the last games. The null of randomness is never rejected at the multiple test benchmark.

4.2.2 performance not against the spread.

Next to momentum and contrarian strategies against the point spread, it is also common to define strategies relative to past game performance not against the point spread as shown in table 10. Rows 1-4 implement the strategy of betting on the team that beat its opponents by the largest average amount last weeks. However, for none of the 22 strategies the null of randomness is rejected at the multiple test level.

Fodor, DiFilippo, Krieger, and Davis (2013) implement a longer-term contrarian strategy that exploits the sticky preferences of gamblers. They find that teams that qualified for the playoffs in the prior season are overrated by the market in the first game of the following season. Between seasons, teams can drastically change their lineup, coaches and tactics, which can have a large impact on their subsequent performance. However, gamblers' perceptions are still anchored to the successful campaign of the last season. These sticky preferences can be exploited by betting against teams that qualified for the playoffs last season when they face a team that did not qualify in the first week of the new season as shown in row 5 of table 10. The strategy results in a win fraction of over 64% and the null of unprofitability is rejected at the single test benchmark, but not at the multiple test benchmark. The effect vanishes as expected in the second week of a new season as gamblers update their beliefs. (The authors also show the results for the strategy beyond game 6, these results are left to the appendix).

In a follow-up study, Bennett (2019) analyzes these sticky preferences in the college football setting. More specifically, he tests whether betting against teams in the top of the Associated Press poll (a prestigious ranking) last season is profitable in the first game of a new season. The results are shown in row 6 of table 10 and the null of unprofitability can be rejected for top 10 teams, but again only at the single test benchmark. The overvaluation does not exist for the lower ranked teams (11 to 25).

Relatedly, J. Davis, McElfresh, Krieger, and Fodor (2015) analyze how information of this first game of a new season is used to make decisions related to the second game of a new season. They analyze the performance of the underdog in the second game of a season conditional on the outcome of the first game as shown in table 10 row 7. In 1 of 5 strategies, statistical efficiency is rejected at the multiple test benchmark. The authors hypothesize that the lack of information (only 1 game played) makes it especially hard to establish efficient point spreads.

Lacey (1990), Vergin (1998) and Vergin (2001) test the contrarian strategy of betting against teams that won their previous game by a large margin. Results are shown in the final rows of table 10. Eight out of nine strategies are profitable in sample although the null of randomness is only once rejected at the single test benchmark and never at the multiple test benchmark. Interestingly, the profitability of the strategies rises almost monotonically with the size of the win in the previous game. Results of the converse strategy of betting on teams that lost by a large margin are shown in appendix. The null of randomness is never rejected.

More strategies can be found in appendix. The null of randomness is never rejected at the multiple test benchmark in 47 additional implementations.

[INSERT TABLE 10 HERE]

4.2.3 spread movements.

We end the past performance discussion by reviewing the strategies that use movements of the point spread as their trading signal. Gandar, Zuber, O'Brien, and Russo (1988) propose the strategy of systematically betting on the team that became more of an underdog between the opening and closing line, i.e. the team the market assigns diminishing winning probabilities to. Such a strategy would be profitable if market movements are mainly driven by investor irrationality instead of efficient reactions to news. This strategy of betting against the market is profitable as shown in table 11 and the null of randomness is quite strongly rejected at the single test benchmark, but again not at the multiple test benchmark.

Gandar, Dare, Brown, and Zuber (1998) and Shank (2018) also implement strategies that look at the difference between opening and closing point spreads. Interestingly, they find that when the home team becomes more of a favorite, its chances of beating the spread go down as shown in table 11. Conversely, when the home team becomes more of an underdog its chances go up. These are signals that the point spread might overreact to the arrival of news and that gamblers can exploit this by betting in the opposite direction. The null of randomness is rejected once at the multiple test benchmark in 20 line movement strategies shown in table 11. The appendix contains 26 additional strategies. The null of randomness is never rejected at the multiple test benchmark.

[INSERT TABLE 11 HERE]

5. Review

In this section we summarize the reviewed strategies (both the strategies discussed in the main text and those in appendix). Table 12 shows a high-level overview of the effectiveness of the 628 strategy implementations reviewed in this paper. Over 50% were profitable in their sample (i.e. the empirical win fraction fell outside the 47.6%-52.4% interval). Profitable strategies were found in every sport and every strategy family. The null of randomness could be rejected for 18% of the implementations at the single test benchmark, but only for 3% at the multiple test benchmark. The null of unprofitability was rejected for 7% of the strategies at the single test benchmark, but never at the multiple test benchmark. It is worth noting that 40% of all unprofitability rejections at the single test benchmark originate from just three papers (namely Ashman et al. (2010), Paul and Weinbach (2005a) and Vergin and Sosik (1999)). Most rejections both in relative and absolute terms occur in the home underdog category. Also note that the significance of the momentum and contrarian strategies that receive a lot of attention in the mainstream finance literature is very limited.

[INSERT TABLE 12 HERE]

[INSERT FIGURE 1 HERE]

Figure 1 visualizes all strategy implementations. The top left panel plots the empirical win fractions and the absolute value of the Z_1 statistics. The vast majority of implementations are located in the bottom left or bottom right quadrants which represent the implantations whose track records are indistinguishable from randomness. The implementations in the top right corner are the most interesting. These strategies are profitable in sample and reject the null of randomness at the multiple test benchmark. The red dots represent the implementations that reject the null of unprofitability at the single test benchmark. As mentioned previously, the null of unprofitability was never rejected at the multiple test benchmark. The top right panel of figure 1 is a funnel plot, a scatter diagram of the empirical win fractions and the square root of the sample size. Funnel plots are often used in meta-analyses to summarize estimates and detect publication bias (Stanley & Doucouliagos, 2010). The funnel is centered right at 50% and shows a clear relationship between profitability and sample size. The strategies tested in the largest samples are unprofitable, the smaller the sample, the higher the likelihood of finding a profitable strategy[7]. This is consistent with an efficient market where deviations from randomness are chance results.

The bottom left and right panels of figure 1 display histograms of the absolute values of the Z_1 and Z_2 statistics respectively. Interestingly, the number of strategies with test statistics between 0 and 1 is much lower compared to what we would expect under the null.

To conclude the analysis, some of the individual strategies might strongly challenge the notion of market efficiency in sports betting. However, when the evidence is placed in the broader context and we account for the large data mining exercise that has been conducted over the decades, the evidence is consistent with the null of an efficient market. A last argument in favor of market efficiency next to the size of the z-statistics is the unpredictability of their signs. There are many examples of z-statistics flipping sign when the exact same strategy is tested in another sample. Moreover, sometimes the null of randomness is even rejected in the two opposite directions (see for example the home team strategy). This of course creates a clairvoyance issue with respect to the sign as it is a priori not clear in which direction we should implement the strategy when we want to exploit any bias. This point echoes Fama (1998), who argues that biases in both directions are consistent with the efficient market hypothesis where anomalies are chance results.

6. Discussion

Market efficiency in betting markets has been studied for decennia but there is still no clear consensus. The efficiency literature is especially susceptible to data mining issues which stand in the way of more definitive conclusions. It is common practice to devise a battery of strategies based on some easily observable variables without (or only a vague) reference to the underlying logic or psychological mechanisms that would make such strategies a priori interesting to investigate. “What bias are we testing for today?” Sauer (2005, p. 418) somewhat ironically asks when discussing the staleness in the literature, to which we can easily add “which subsample should we investigate today?”.

A general problem for behavioral trading strategies is that "each strategy can be defended persuasively on reasonably plausible a *priori* grounds" (Tryfos et al., 1984, p. 129). Indeed, a momentum strategy betting on teams which have been performing well can sensibly be defended by underreaction. The market does not yet fully appreciate the recent increase in team quality, such that assets on this team can be bought at discount prices. However, the diametrically opposite contrarian strategy of betting on teams that have been performing badly could also sound reasonable if we embed it in a story where the market overreacts and underestimates the true ability of the team. This point echoes the common criticism to the behavioral project: "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). If a sensible story can be made for any strategy it appears that they all deserve to be closely investigated, which induces data mining concerns.

In defense of the anomaly dredging endeavors, efficiency requires that all information is properly discounted. Consistently testing any imaginable strategy in any subsample you can get your hands on seems warranted. Such practices can inductively expose unexpected behavioral glitches. However, in these cases, it is vital to properly subject the results to multiple testing methods. If not, we end up with a literature without a clear consensus and profitable strategies which are merely type 1 errors. An issue that is further amplified by the tendency of journals to publish significant results (Harvey, 2017). An interesting area for future research would be to test all proposed strategies both out of sample and post publication. For equities, McLean and Pontiff (2016) and Jacobs and Müller (2020) find that many claimed anomalies disappear over time.

Another interesting area for future research is the origin of the persistent biases. The most frequently used explanation is that the observed regularities are behavioral glitches. However, we should keep in mind that the observed perceived biases might just be rational, a point that is often overlooked in papers that claim to find inefficiencies. "Are we observing an inefficient market or simply one in which the tastes and preferences of the market participants lead to the observed results?" (Gabriel & Marsden, 1990, p. 885). If consumption benefits between betting on favorites and underdogs for example are large enough, rational utility maximizers will be bribed into giving up expected returns, a point that echoes the utility of gambling model (Conlisk, 1993; Humphreys, Paul, & Weinbach, 2013). Although the spread betting microstructure controls for risk-return differences that are expected to drive decision making in a mean-variance framework, agents could also derive consumption benefits from other asset characteristics. Distinguishing between misperceptions (biases) and non-risk-return related consumption benefits (which fit the rational framework) remains empirically difficult, but findings could spill over to the cross-section of expected stock returns (for example to explain the returns on glamour stocks). Consumption benefit differentials driving the decisions of agents in a spread betting context would of course be bad news for the cleanliness of this microstructure as an asset pricing lab. We would again be entangled in a joint-hypothesis problem in the attempt to construct a model that captures the non-risk-return related consumption benefits of the different assets.

7. Conclusion

In this review we examine over 600 betting strategies tested over 40 years. We operate in the spread betting context that has the nice characteristic that all assets have the same risk-return profile such that differences in returns between assets or strategies cannot be attributed to risk. Many of the reviewed strategies, when discussed individually, would point in the direction of severe market inefficiencies. However, placing these results in the bigger context takes the sting out.

We document a number of persistent biases, most notably the underdog bias, that could be levered to raise returns of a betting strategy above that of a naïve, random strategy. We find that 3% of the strategy implementations reject the null of randomness under the multiple test benchmark. However, these biases are too small to be profitably exploited. We find that 7% of strategies are significantly profitable under the common single hypothesis benchmark. This could lead researchers to conclude ample profit opportunities exist. However, when we factor in the large number of hypotheses tested over the last decades, we have to move the hurdle rate to at least $|z| > 3$ under which the null of unprofitability is never rejected. Furthermore, we observe a strong inverse relationship between the profitability of a strategy and its sample size, which is again in line with an efficient market where inefficiencies are chance results.

Both data mining and the publication bias most likely lead to more reports of statistically significant trading strategies than actually exist. It is reasonable to assume that our reported profitability rate is an upper bound. The fact that we find no significantly profitable strategies, even with a scientific process that could tilt the evidence in its direction, is a strong argument to not reject the null of market efficiency.

A counter argument that could be made is that successful traders never reveal their secrets. It might well be that the discoverers of highly profitable trading strategies choose to monetize their findings instead of publishing them in a journal. This might lead us to overestimate the true degree of efficiency. However, given the scrutiny betting strategies received over the last decades, it is not very likely that many profitable strategies would go unnoticed.

Footnotes

1. Betting arguably even lies at the origin of modern probability theory. Mathematicians Blaise Pascal and Pierre de Fermat developed fundamental probability concepts while discussing a game of chance (Devlin, 2010). Furthermore, via the solutions of the St. Petersburg paradox, which involves a theoretical lottery, many core economic concepts like utility functions and expected utility maximization were introduced (Bernoulli, 1954; Smith, 1971)

2. Note that this is generally not the case in other betting market microstructures like pari-mutuel or fixed odds betting. In these markets, assets with very different risk-return profiles coexist. This induces a need to adjust for the risk-return differences between the assets as agents generally seem to prefer lottery-like assets with a low probability of a high return over assets with a high probability of a low return (Bird & McCrae, 1987). This empirical regularity is called the "favorite-longshot bias".

3. Testing efficiency in stock markets is a notoriously fishy undertaking. Market prices can never be compared with the true value of stocks as the latter are never revealed. Researchers can resort to models that generate theoretical prices and compare these to market prices. However, when discrepancies arise, it is not clear whether the market prices are wrong or whether the model that generates theoretical prices is wrong, or both. This fundamental untestability of efficiency in stock markets is called the joint hypothesis problem.

4. See jonasvdb.info for an overview of data sources.

5. Jaffe and Winkler (1976) discuss the similarities between market makers in financial and sports betting markets and their relationship with investors. Furthermore, it is important to appreciate that the risk bookmakers take is categorically different from that of other gambling establishments like

casinos. While the latter exploit the law of large numbers to secure asymptotically certain profits, bookmakers can suffer large losses when they systematically misestimate game outcome probabilities or bettor behavior. While the outcome probabilities for a casino game like roulette are common knowledge, pricing a sports bet is much harder. This introduces incentives for sports bettors to gather information as they do not just rely on luck (like their roulette colleagues), but also on their ability to correctly estimate game outcome probabilities (Figlewski, 1979). (Or at least it appears. In an efficient market, the marginal profits to analyzing information are again zero.)

6. Levitt (2004) notes that a "major puzzle in this industry is the rarity of price competition, i.e., the vig is almost universally 10%". This point is further explored by Sandford and Shea (2013). They attribute it to the first mover disadvantage bookmakers have when setting their lines. Gamblers can consequently make their bets with information bookmakers did not have when they set their lines. More recently however, bookmaker competition starts to bring down the commission charged (Berkowitz, Depken II, & Gandar, 2018). Papers in which the authors state the 11 for 10 commission structure did not apply (which were very few) were not included in this review to keep the hurdle rate constant.

7. The symmetry of the funnel is often inspected in meta-studies to detect possible publication bias. If for example only negative effect sizes are published because a negative sign is more intuitive or in line with theory, the funnel will be asymmetric (for example, see Havranek, Irsova, and Zeynalova (2018) on the relationship between tuition fees and college enrollment). In our case symmetry is less of a concern as it is not the sign of the effect that indicates profitability, but the absolute deviation from 50%.

Tables

Table 1: Z-score hurdle rates under different testing methods (naïve single testing, the Bonferroni adjustment, Holm's adjustment and Benjamini, Hochberg, and Yekutieli's adjustment). For the dynamic methods (Holm and BHY) the hurdle rate represents the z-score the first insignificant strategy should achieve in order to reject its null.

Testing method	**Min one sided**	**Max one sided**	**Min two sided**	**Max two sided**
Naïve single test	1.64	1.64	1.96	1.96
Bonferroni adjustment	3.24	3.24	3.44	3.44
Holm's adjustment	3.24	3.23	3.44	3.43
BHY adjustment	3.68	3.31	3.85	3.50

Table 2: Overview of papers implementing "bet on home team" strategy.

Authors	**Data set**	$\hat{\pi}$	Z_1	Z_2
Lacey (1990)	NFL 1984-1986	0.476	-1.234	
Golec and Tamarkin (1991)	NFL 1973-1987	0.515	1.709	
Golec and Tamarkin (1991)	College football 1973-1987	0.498	-0.251	
Oorlog (1995)	NBA 1989-1991	0.486	-1.312	
Gray and Gray (1997)	NFL 1976-1994	0.504	0.383	
Vergin (1998)	NFL 1984-1995	0.489	-1.087	
Vergin and Sosik (1999)	NFL 1981-1996	0.499	-0.153	
Gandar et al. (2001)	NBA 1981-1997	0.495	-1.202	
Kochman and Goodwin (2004)	NFL 1998-2002	0.500	0.026	
Kochman and Goodwin (2004)	Preseason NFL 1998-2002	0.438	**-2.121**	-1.315
Boulier et al. (2006)	NFL 1994-2000	0.513	0.854	
Borghesi (2007b)	NFL 1981-2000	0.502	0.324	
Sung and Tainsky (2014)	NFL 2002-2009	0.485	-1.307	
Paul, Weinbach, and Wilson (2014)	NFL 2007-2011	0.482	-1.262	
Sinkey and Logan (2014)	College football 1985-2008	0.511	**2.749**	
Humphreys, Paul, and Weinbach (2014)	College basketball 2007-2008	0.495	-0.565	
Coleman (2017)	College football 2004-2011	0.504	0.509	
Shank (2018)	NFL 2009-2017	0.489	-0.951	
Schnyzer and Hizgilov (2018)	Australian Football League 2001-20016	0.533	**2.949**	0.818
Shank (2019)	NFL 2003-2016	0.487	-1.500	

Table 3: Overview of papers implementing "bet on underdog" strategy.

Authors	**Data set**	$\hat{\pi}$	Z_1	Z_2
Vergin and Scriabin (1978)	NFL 1969-1974	0.515	0.968	
Tryfos et al. (1984)	NFL 1969-1981	0.526	**2.563**	0.223
Golec and Tamarkin (1991)	NFL 1973-1987	0.524	**2.742**	0.068
Golec and Tamarkin (1991)	College football 1973-1987	0.504	0.678	
Oorlog (1995)	NBA 1989-1991	0.501	0.087	
Gray and Gray (1997)	NFL 1976-1994	0.526	**3.303**	0.276
Paul, Weinbach, and Weinbach (2003)	College football 1976-2000	0.503	0.695	
Kochman and Goodwin (2004)	NFL 1998-2002	0.531	**2.394**	0.545
Kochman and Goodwin (2004)	Preseason NFL 1998-2002	0.581	**2.704**	**1.913**
Paul and Weinbach (2005a)	NBA 1995-2002	0.501	0.261	
Paul and Weinbach (2005b)	College basketball 1996-2004	0.496	-1.255	
Borghesi, Paul, and Weinbach (2009)	NFL 1981-2004	0.518	**2.687**	
Borghesi et al. (2009)	College football 1982-2004	0.510	**2.198**	
Borghesi et al. (2009)	AFL 1998-2006	0.538	**2.413**	0.914
Sung and Tainsky (2014)	NFL 2002-2009	0.507	0.631	
Paul, Weinbach, and Wilson (2014)	NFL 2007-2011	0.505	0.344	
Sinkey and Logan (2014)	College football 1985-2008	0.508	1.875	
Humphreys et al. (2014)	College basketball 2007-2008	0.490	-1.215	
(J. L. Davis & Krieger, 2017)	NFL 1995-2014	0.503	0.460	
(J. L. Davis & Krieger, 2017)	Preseason NFL 1995-2014	0.524	1.656	
(J. L. Davis & Krieger, 2017)	NBA 2005-2014	0.501	0.221	
(J. L. Davis & Krieger, 2017)	Preseason NBA 2005-2014	0.542	**2.421**	1.045

Table 4: Overview of papers implementing "bet on home underdog" strategy.

Authors	**Data set**	$\hat{\pi}$	Z_1	Z_2
Amoako-Adu et al. (1985)	NFL 1979-1981	0.599	**2.743**	**2.085**
Golec and Tamarkin (1991)	NFL 1973-1987	0.556	**3.743**	**2.156**
Golec and Tamarkin (1991)	College football 1973-1987	0.503	0.341	
Oorlog (1995)	NBA 1989-1991	0.479	-0.988	
Gray and Gray (1997)	NFL 1976-1994	0.546	**3.347**	1.627
Vergin and Sosik (1999)	NFL 1981-1996	0.525	1.613	
Gandar et al. (2001)	NBA 1981-1997	0.493	-0.945	
Paul et al. (2003)	College football 1976-2000	0.503	0.340	
Paul and Weinbach (2005b)	College basketball 1996-2004	0.497	-0.407	
Borghesi (2007b)	NFL 1981-2000	0.532	**2.341**	0.572
Borghesi et al. (2009)	NFL 1981-2004	0.530	**2.490**	0.521
Borghesi et al. (2009)	College football 1982-2004	0.522	**2.946**	
Borghesi et al. (2009)	AFL 1998-2006	0.522	0.728	
Sung and Tainsky (2014)	NFL 2002-2009	0.512	0.591	
Paul, Weinbach, and Wilson (2014)	NFL 2007-2011	0.481	-0.786	
Sinkey and Logan (2014)	College football 1985-2008	0.519	**2.696**	
Humphreys et al. (2014)	College basketball 2007-2008	0.465	**-1.989**	-0.626
Shank (2018)	NFL 2009-2017	0.490	-0.516	
Shank (2019)	NFL 2003-2016	0.485	-0.992	

Table 5: Overview of papers implementing "bet conditional on familiarity characteristics" strategies.

	Authors	Data set	Conditioning	$\hat{\pi}$	Z_1	Z_2
1	Boulier et al. (2006)	NFL 1994-2000	Bet on home team when it hosts a team that plays on a different surface (grass/turf) in its own venue	0.534	**1.970**	0.593
2	Borghesi (2007a)	NFL 1981-2004	Q1 acclimatization advantage (highest)	0.565	**2.416**	1.530
3			Q2 acclimatization advantage	0.540	1.413	
4			Q3 acclimatization advantage	0.515	0.571	
5			Q4 acclimatization advantage (lowest)	0.547	1.565	
6	Kuester and Sanders (2011)	College football 2000-2006	Bet on teams from arid regions when they host teams from humid regions	0.566	**2.653**	**1.704**
7			Bet on teams from humid regions when they host teams from arid regions	0.498	-0.440	
8	Shank (2019)	NFL 2003-2016	Bet on divisional game home team	0.469	**-2.170**	-0.481

Table 6: Overview of papers implementing "bet conditional on fatigue characteristics" strategies.

	Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
1	Lacey (1990)	NFL 1984-1986	Bet on home team after previous home game	0.478	-0.596	
2			Bet on away team after previous away game	0.516	0.435	
3	Vergin (1998)	NFL 1984-1995	Bet on home team after previous home game	0.498	-0.110	
4			Bet on away team after previous away game	0.513	0.692	
5	Sung and Tainsky (2014)	NFL 2002-2009	Bet on favorites that had a bye-week	0.625	**2.915**	**2.363**
6			Bet on underdogs that had a bye-week	0.445	-1.144	
7			Bet on away favorites that had a bye-week	0.732	**2.967**	**2.663**
8			Bet on home favorites that had a bye-week	0.448	-0.855	
9	Ashman et al. (2010)	NBA 1990-2009	Bet on home team in the second game of back-to-back games for the away team	0.506	0.873	
10			Bet on home team in the second game of back-to-back games for both teams	0.499	-0.048	
11			Bet on home team in the second game of back-to-back games for the home team	0.459	**-3.086**	-1.312
Rows 12-20 show the strategy "bet on home teams in the 2nd game of back-to-back games for the home team" conditional on the days of rest the away team had (0, 1 or 2, >2) and on whether the home team travelled one or two time zones to the east between their back-to-back games (E) or not (No E).						
12			0	0.499	-0.048	
13			0 E	0.491	-0.330	
14			0 No E	0.501	0.107	
15			1 or 2	0.455	**-3.162**	-1.508
16			1 or 2 E	0.424	**-2.442**	**-1.684**
17			1 or 2 No E	0.463	**-2.298**	-0.827
18			>2	0.486	-0.374	
19			>2 E	0.310	**-2.469**	**-2.163**
20			>2 No E	0.540	0.940	
Rows 21-28 show the strategy "bet on visiting team" conditional on the jet lag (time difference).						
21	Schnyzer and Hizgilov (2018)	Australian Football League 2001-2016	Gain 2+ hours	0.458	-1.414	
22			Gain 1 hour	0.571	1.000	
23			No change	0.454	**-2.547**	-1.221
24			Lose 1 hour	0.533	0.516	
25			Lose 2+ hours	0.431	**-2.256**	-1.477
26			Gain 2+ hours or lose 2+ hours	0.445	**-2.585**	-1.462
27			Lose 2+ hours neutral field	0.545	0.302	
28			Gain 2+ hours or lose 2+ hours neutral field	0.583	0.577	

Table 7: Overview of papers implementing "bet conditional on attention characteristics" strategies.

	Authors	Data set	Conditioning	$\hat{\pi}$	Z_1	Z_2
1	Amoako-Adu et al. (1985)	NFL 1979-1981	Home team Monday night	0.682	**2.412**	**2.099**
2	Vergin and Sosik (1999)	NFL 1976-1996	Home team Monday night	0.608	**3.837**	**2.997**
3			Home team Monday night underdog	0.667	**3.464**	**2.973**
4			Home team Monday night favorite	0.571	1.801	
5	Shank (2018)	NFL 2009-2017	Home team Prime time	0.520	0.852	
6			Home team Not prime time	0.481	-1.504	
7	Vergin and Sosik (1999)	NFL 1976-1996	Home team Playoff	0.586	**2.304**	**1.665**
8	Gandar et al. (2001)	NFL 1997-1999	Home team Playoff	0.446	-0.930	
9		NBA 1981-1997	Home team Playoff	0.511	0.728	
10	Borghesi (2007b)	NFL 1981-2000	Home team Playoff	0.592	**2.507**	**1.863**
11	Vergin and Sosik (1999)	NFL 1976-1996	Home team Playoff underdog	0.737	**2.065**	**1.859**
12	Gandar et al. (2001)	NFL 1997-1999	Home team Playoff underdog	0.412	-0.728	
13		NBA 1981-1997	Home team Playoff underdog	0.543	1.093	
14	Borghesi (2007b)	NFL 1981-2000	Home team Playoff underdog	0.778	**2.357**	**2.157**
15	Vergin and Sosik (1999)	NFL 1976-1996	Home team Playoff favorite	0.577	1.794	
16	Gandar et al. (2001)	NFL 1997-1999	Home team Playoff favorite	0.456	-0.662	
17		NBA 1981-1997	Home team Playoff favorite	0.505	0.297	
18	Hickman (2020)	March Madness 1996-2019	Bet on the higher-seeded team	0.494	-0.466	
19			Bet on higher-seeded team in round 1	0.497	-0.144	
20			Bet on higher-seeded team in round 2	0.507	0.255	
21			Bet on higher-seeded team in rounds 3-6	0.473	-0.979	
22	Lacey (1990)	NFL 1984-1986	Bet on teams on the week before a divisional game	0.513	0.482	
23			Bet on teams on the week after a divisional game	0.506	0.224	

Table 8: Overview of papers implementing "bet conditional on absences" strategies.

	Authors	Data set	Conditioning	$\hat{\pi}$	Z_1	Z_2
Rows 1-5 show the strategy "bet on team with most absences" conditional on the AV. (AV is the total Approximate Value of the players who are absent. The higher the AV, the more valuable players are missing. When both teams have absences, the AV is the difference between the values of players missing for each team).						
1	Dare et al. (2015)	NBA 1996-2005	unconditional	0.513	1.925	
2			AV≥ 5	0.517	**2.105**	
3			AV ≥ 10	0.511	0.905	
4			AV ≥ 15	0.520	0.887	
5			AV ≥ 20	0.525	0.665	
Rows 6-11 show the strategy "bet on team with a new coach" conditional on the time after the change (1-3 to 7-9 games) and on whether the new coach has previous experience as a NBA head coach (EX) or not (N EX).						
6	Colquitt et al. (2007)	NBA 1988-2002	1-3, EX	0.547	0.808	
7			1-3, N EX	0.631	**2.400**	**1.966**
8			4-6, EX	0.525	0.447	
9			4-6, N EX	0.565	1.193	
10			7-9, EX	0.481	-0.333	
11			7-9, N EX	0.481	-0.333	

Table 9: Overview of papers implementing "bet conditional on performance against the spread" strategies.

	Authors	Data set	k=1	k=2	k=3	k=4	k=5	k=6
Rows 1-4 show the strategy "each week, bet on team that beat the spread by the largest average amount last k weeks".								
1	Vergin and Scriabin (1978)	NFL 1969-1974	$\hat{\pi}$: 0.526 Z_1: 0.453	$\hat{\pi}$: 0.569 Z_1: 1.179	$\hat{\pi}$: 0.538 Z_1: 0.620	$\hat{\pi}$: 0.627 Z_1: 1.953	$\hat{\pi}$: 0.528 Z_1: 0.412	$\hat{\pi}$: 0.521 Z_1: 0.289
2	Tryfos et al. (1984)	NFL 1969-1981	$\hat{\pi}$: 0.517 Z_1: 0.455	$\hat{\pi}$: 0.541 Z_1: 1.031	$\hat{\pi}$: 0.531 Z_1: 0.742	$\hat{\pi}$: 0.526 Z_1: 0.602	$\hat{\pi}$: 0.537 Z_1: 0.812	$\hat{\pi}$: 0.523 Z_1: 0.475
3	Gandar et al. (1988)	NFL 1980-1985	$\hat{\pi}$: 0.488 Z_1: -0.221	$\hat{\pi}$: 0.416 Z_1: -1.481	$\hat{\pi}$: 0.380 Z_1: **-2.018** Z_2: -1.618	$\hat{\pi}$: 0.409 Z_1: -1.477	$\hat{\pi}$: 0.508 Z_1: 0.130	
4	Vergin (2001)	NFL 1981-1995	$\hat{\pi}$: 0.493 Z_1: -0.204	$\hat{\pi}$: 0.418 Z_1: **-2.328** Z_2: **-1.654**	$\hat{\pi}$: 0.418 Z_1: **-2.255** Z_2: -1.602	$\hat{\pi}$: 0.468 Z_1: -0.841	$\hat{\pi}$: 0.457 Z_1: -1.100	
Rows 5-10 show the strategy "bet on teams that beat the spread last k games".								
5	Lacey (1990)	NFL 1984-1986	$\hat{\pi}$: 0.508 Z_1: 0.398	$\hat{\pi}$: 0.422 Z_1: **-2.795** Z_2: **-1.945**				
6	Oorlog (1995)	NBA 1989-1991	$\hat{\pi}$: 0.500 Z_1: -0.031					
7	Vergin (1998)	NFL 1984-1995	$\hat{\pi}$: 0.500 Z_1: -0.020	$\hat{\pi}$: 0.482 Z_1: -1.109				
8	Paul and Weinbach (2005a)	NBA 1995-2002		$\hat{\pi}$: 0.460 Z_1: **-4.359** Z_2: **-1.738**		$\hat{\pi}$: 0.462 Z_1: **-1.981** Z_2: -0.775		
9	Paul, Weinbach, and Humphreys (2011)	NBA 2003-2009		$\hat{\pi}$: 0.499 Z_1: -0.117		$\hat{\pi}$: 0.508 Z_1: 0.500		
10	Sinkey and Logan (2014)	College football 1985-2008		$\hat{\pi}$: 0.500 Z_1: -0.067				

Table 10: Overview of papers implementing "bet conditional on performance not against the spread" strategies.

	Authors	Data set	k=1	k=2	k=3	k=4	k=5	k=6
Rows 1-4 show the strategy "each week, bet on team that beat its opponents by the largest average amount last k weeks".								
1	Vergin and Scriabin (1978)	NFL 1969-1974	$\hat{\pi}$: 0.462 Z_1: -0.679	$\hat{\pi}$: 0.563 Z_1: 1.068	$\hat{\pi}$: 0.603 Z_1: 1.638	$\hat{\pi}$: 0.667 Z_1: **2.517** Z_2: **2.160**	$\hat{\pi}$: 0.608 Z_1: 1.540	$\hat{\pi}$: 0.523 Z_1: 0.302
2	Tryfos et al. (1984)	NFL 1969-1981	$\hat{\pi}$: 0.483 Z_1: -0.455	$\hat{\pi}$: 0.525 Z_1: 0.636	$\hat{\pi}$: 0.510 Z_1: 0.249	$\hat{\pi}$: 0.550 Z_1: 1.136	$\hat{\pi}$: 0.538 Z_1: 0.825	$\hat{\pi}$: 0.528 Z_1: 0.583
3	Gandar et al. (1988)	NFL 1980-1985	$\hat{\pi}$: 0.433 Z_1: -1.265	$\hat{\pi}$: 0.392 Z_1: -1.913	$\hat{\pi}$: 0.457 Z_1: -0.717	$\hat{\pi}$: 0.500 Z_1: 0.000	$\hat{\pi}$: 0.483 Z_1: -0.263	
4	Vergin (2001)	NFL 1981-1995	$\hat{\pi}$: 0.509 Z_1: 0.265	$\hat{\pi}$: 0.470 Z_1: -0.844	$\hat{\pi}$: 0.440 Z_1: -1.664	$\hat{\pi}$: 0.443 Z_1: -1.508	$\hat{\pi}$: 0.459 Z_1: -1.038	
Row 5 shows the strategy "bet against teams that qualified for the playoffs last season when they face a team that did not qualify in game k of the next season".								
5	Fodor et al. (2013)	NFL 2004-2012	$\hat{\pi}$: 0.644 Z_1: **2.213** Z_2: **1.850**	$\hat{\pi}$: 0.500 Z_1: 0.000	$\hat{\pi}$: 0.507 Z_1: 0.120	$\hat{\pi}$: 0.475 Z_1: -0.391	$\hat{\pi}$: 0.424 Z_1: -1.231	$\hat{\pi}$: 0.544 Z_1: 0.662
Row 6 shows the strategy "bet on teams in top of AP poll in first game of next season when playing against a team not in the top 25" strategy. The strategy is further conditioned on the top team being the favorite (F) and whether the top team is part of the top 25, top 10 or top 11-25.								
			Top 25	**Top 25 F**	**Top 10**	**Top 10 F**	**Top 11-25**	**Top 11-25 F**
6	Bennett (2019)	College football 2008-2016	$\hat{\pi}$: 0.425 Z_1: **-1.971** Z_2: -1.344	$\hat{\pi}$: 0.436 Z_1: -1.645	$\hat{\pi}$: 0.373 Z_1: **-2.305** Z_2: **-1.873**	$\hat{\pi}$: 0.385 Z_1: **-2.038** Z_2: -1.619	$\hat{\pi}$: 0.471 Z_1: -0.588	$\hat{\pi}$: 0.484 Z_1: -0.308

	Authors	Data set					
Row 7 shows the strategy "bet on underdog in the second game of a season conditional on the performance in the first game".							
			Both teams won first game	**Favorite won first game underdog lost**	**Favorite lost first game underdog won**	**Both teams lost first game**	**All games**
7	J. Davis et al. (2015)	NFL 1997-2012	$\hat{\pi}$: 0.585 Z_1: 1.236	$\hat{\pi}$: 0.435 Z_1: -1.193	$\hat{\pi}$: 0.463 Z_1: -0.469	$\hat{\pi}$: 0.707 Z_1: **3.151** Z_2: **2.792**	$\hat{\pi}$: 0.540 Z_1: 1.234

	Authors	Data set			
Rows 8-10 shows the strategy "bet against teams that won their previous game by k points or more".					
			k=10	**k=15**	**k=20**
8	Lacey (1990)	NFL 1984-1986	$\hat{\pi}$: 0.539 Z_1: 1.335	$\hat{\pi}$: 0.561 Z_1: 1.714	$\hat{\pi}$: 0.590 Z_1: **1.992** Z_2: 1.467
9	Vergin (1998)	NFL 1984-1995	$\hat{\pi}$: 0.526 Z_1: 1.809	$\hat{\pi}$: 0.527 Z_1: 1.492	$\hat{\pi}$: 0.524 Z_1: 1.051
10	Vergin (2001)	NFL 1981-1995	$\hat{\pi}$: 0.522 Z_1: 1.674	$\hat{\pi}$: 0.526 Z_1: 1.584	$\hat{\pi}$: 0.536 Z_1: 1.769

Table 11: Overview of papers implementing "bet conditional on spread movements" strategies.

	Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
1	Gandar et al. (1988)	NFL 1980-1985	Bet on the team that becomes less favored (more of an underdog) over the course of the week's betting	0.549	**2.909**	1.503
The next rows show the strategy "bet on home team when the spread for the home team moves by k points".						
2	Gandar et al. (1998)	NBA 1985-1994	k≤-4	0.464	-0.378	
3			k=-3	0.493	-0.117	
4			k=-2	0.429	**-2.583**	**-1.719**
5			k=-1	0.510	0.689	
6			k=0	0.510	0.886	
7			k=1	0.490	-0.692	
8			k=2	0.480	-0.719	
9			k=3	0.364	**-2.216**	**-1.831**
10			4≤k	0.579	0.688	
11	Shank (2018)	NFL 2009-2017	k≤-4	0.421	-1.192	
12			k≤-3	0.464	-0.895	
13			k≤-2	0.489	-0.388	
14			k≤-1	0.437	**-3.064**	**-1.901**
15			k≤0	0.479	-1.188	
16			k=0	0.495	-0.200	
17			0<k	0.497	-0.179	
18			1≤k	0.498	-0.082	
19			2≤k	0.475	-0.900	
20			3≤k	0.514	0.329	
21			4≤k	0.608	1.540	

Table 12: General overview of the effectiveness of the reviewed strategies. The second column shows the number of strategy implementations. The third column shows the number of profitable strategies ($\hat{\pi} > 0.524$ or $\hat{\pi} < 0.476$) while columns four and five show the rejections of the null of randomness and the null of unprofitability respectively, both at the single test benchmark and at the multiple test benchmark (between brackets).

Sample	**n**	**Profitable in sample**	**Randomness rejected z>|1.96| (z>|3|)**	**Unprofitability rejected z>|1.64| (z>|3|)**
Full	628	324	113 (17)	45 (0)
Sports				
AFL	4	3	3 (0)	1 (0)
Australian Football League	9	9	4 (0)	0 (0)
College basketball	15	5	2 (0)	0 (0)
College football	87	28	17 (0)	5 (0)
NBA	176	93	36 (8)	19 (0)
March Madness	35	13	0 (0)	0 (0)
NFL	290	164	45 (9)	19 (0)
Preseason NFL	7	5	3 (0)	1 (0)
Preseason NBA	5	4	3 (0)	0 (0)
Strategies				
Home team	20	3	3 (0)	0 (0)
Underdog	73	37	26 (3)	2 (0)
Home underdog	45	29	22 (6)	10 (0)
Home favorite	18	1	0 (0)	0 (0)
Familiarity	18	11	5 (0)	1 (0)
Fatigue	48	35	18 (3)	8 (0)
Attention & Importance	61	31	8 (2)	8 (0)
Absences	24	8	3 (0)	1 (0)
Past performance against the spread	177	85	12 (1)	5 (0)
Past performance not against the spread	95	58	11 (1)	6 (0)
Spread movements	49	26	5 (1)	4 (0)

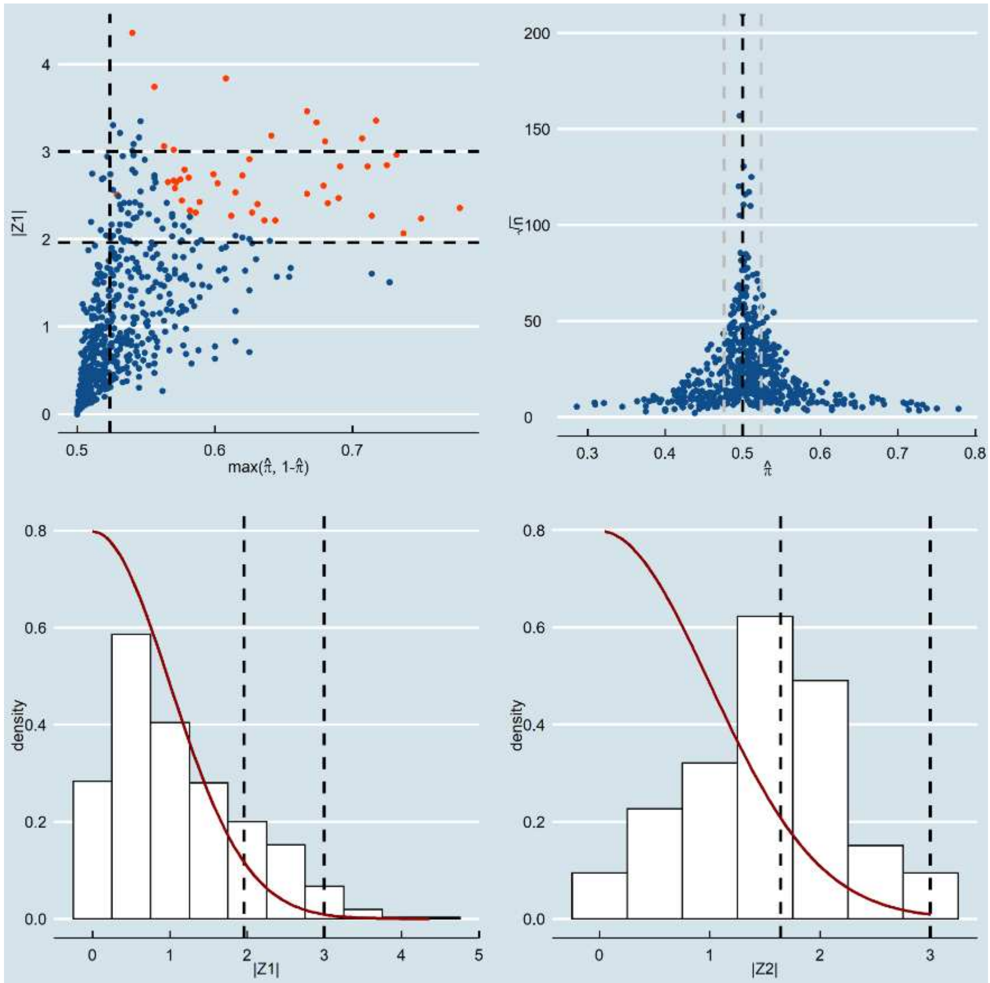

Figure 1: top left panel: scatterplot of the strategy implementations. The horizontal axis represents the empirical win fractions. The black dashed lines represent critical values (1.96 and 3 for the horizontal axis and 0.524 for the vertical axis). The red dots represent the strategy implementations that reject the null of unprofitability under the single test benchmark. Top right panel: funnel plot with the empirical win fractions on the horizontal axis and the square root of the sample size on the vertical axis. Bottom left and right panels show histograms of the absolute value of the Z1 statistics and the Z2 statistics respectively for the full sample of strategy implementations. The vertical blue lines show the critical values, i.e. 0.476 and 0.524 for in-sample profitability and 1.96 and 1.64 for the z-statistics. The red line is the folded standard normal distribution.

(Online) Appendix A: additional tables and results

Game characteristics

Underdog

Table A summarizes papers implementing the "bet on the underdog" strategy, conditional on some point spread *PS*. Note that there does not appear to exist a clean relation between the point spread cutoff value and the empirical win fraction, nor statistical significance. However, the tendency to underestimate conditional underdogs is clear as 46 out of 51 implementations indicate underdogs win more than 50% of the time.

Table A: Overview of papers implementing "bet on underdog conditional on the point spread (PS)" strategy.

Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Vergin and Scriabin (1978)	NFL 1969-1974	PS>5	0.546	**2.388**	1.153
		0<PS≤5	0.456	-1.655	
		5<PS≤10	0.543	1.735	
		10<PS≤15	0.530	0.882	
		15<PS	0.640	**1.980**	**1.645**
Tryfos et al. (1984)	NFL 1969-1981	PS>5	0.540	**3.010**	1.224
		0<PS≤5	0.506	0.410	
		5<PS≤10	0.536	**2.169**	0.709
		10<PS≤15	0.539	1.564	
		15<PS	0.589	1.687	
Gandar et al. (1988)	NFL 1980-1985	PS>5	0.502	0.091	
		0<PS≤5	0.543	**2.248**	0.999
		5<PS≤10	0.511	0.440	
		10<PS≤15	0.537	0.611	
		15<PS	0.375	-0.707	
Vergin (2001)	NFL 1969-1995	PS>5	0.531	**3.215**	0.713
Paul et al. (2003)	College football 1976-2000	7 < PS	0.503	0.467	
		28 < PS	0.538	**2.161**	0.817
Paul and Weinbach (2005b)	College basketball 1996-2004	10 < PS	0.506	0.930	
		20 < PS	0.529	1.652	
Borghesi et al. (2009)	NFL 1981-2004	7 < PS	0.525	1.813	
	College football 1982-2004	7 < PS	0.507	1.163	
	AFL 1998-2006	7 < PS	0.572	**2.653**	**1.776**
Humphreys et al. (2014)	College basketball 2007-2008	10 < PS	0.496	-0.279	
		12 < PS	0.507	0.364	
(J. L. Davis & Krieger, 2017)	NFL 1995-2014	PS>3	0.503	0.390	
		0<PS≤3	0.503	0.246	
		PS>5	0.504	0.423	

		0<PS≤5	0.502	0.235	
(J. L. Davis & Krieger, 2017)	Preseason NFL 1995-2014	PS>3	0.532	1.469	
		0<PS≤3	0.517	0.914	
		PS>5	0.577	**2.154**	1.492
		0<PS≤5	0.514	0.872	
(J. L. Davis & Krieger, 2017)	NBA 2005-2014	PS>3	0.499	-0.095	
		0<PS≤3	0.506	0.613	
		PS>5	0.498	-0.326	
		0<PS≤5	0.505	0.676	
	Preseason NBA 2005-2014	PS>3	0.556	**2.701**	1.557
		0<PS≤3	0.510	0.312	
		PS>5	0.569	**2.287**	1.498
		0<PS≤5	0.529	1.352	
Paul and Weinbach (2005a)	NBA 1995-2002	PS>8.5	0.509	0.800	
		PS>9	0.506	0.555	
		PS>9.5	0.510	0.770	
		PS>10	0.525	1.902	
		PS>10.5	0.530	**2.094**	0.458
		PS>11	0.532	**2.010**	0.494
		PS>11.5	0.537	**2.162**	0.776
		PS>12	0.541	**2.238**	0.941
		PS>12.5	0.556	**2.728**	1.561
		PS>13	0.552	**2.287**	1.247

Home underdog

Table B summarizes conditional home underdog strategies. The performance of the strategy in NBA games is striking. In these cases, there exists an almost monotonic relationship between performance and the point spread. For the largest home underdogs, empirical win fractions of over 70% are observed.

Table B: Overview of papers implementing "bet on home underdog" strategy.

Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Paul et al. (2003)	College football 1976-2000	PS>7	0.517	1.607	
		PS>28	0.571	1.648	
Paul and Weinbach (2005b)	College basketball 1996-2004	PS>10	0.454	**-2.303**	-1.106
Borghesi (2007b)	NFL 1981-2000	PS>2	0.540	**2.792**	1.139
		PS>8	0.547	1.264	
Borghesi et al. (2009)	NFL 1981-2004	PS>7	0.524	0.790	
Borghesi et al. (2009)	College football 1982-2004	PS>7	0.521	**2.041**	
Borghesi et al. (2009)	AFL 1998-2006	PS>7	0.625	**2.000**	1.621
Humphreys et al. (2014)	College basketball 2007-2008	PS>10	0.433	-1.373	
		PS>12	0.417	-1.291	
Shank (2018)	NFL 2009-2017	PS>3	0.493	-0.323	
		PS>6	0.541	1.109	
		PS>10	0.630	1.769	
Paul and Weinbach (2005a)	NBA 1995-2002	PS>8.5	0.545	1.624	
		PS>9	0.555	1.788	
		PS>9.5	0.569	**2.032**	1.330
		PS>10	0.602	**2.639**	**2.028**
		PS>10.5	0.641	**3.182**	**2.646**
		PS>11	0.674	**3.336**	**2.883**
		PS>11.5	0.680	**3.118**	**2.708**
		PS>12	0.717	**3.357**	**2.991**
		PS>12.5	0.711	**2.832**	**2.516**
		PS>13	0.725	**2.846**	**2.548**
Ashman et al. (2010)	NBA 1990-2009	PS>11	0.571	**2.162**	1.437
		PS>12	0.620	**2.729**	**2.191**
Vergin and Sosik (1999)	NFL 1981-1996	PS=0	0.522	0.361	

Home favorite

For completeness, we mention the results of the strategy of betting on home favorites in table C.

The null of randomness is never rejected.

Table C: Overview of papers implementing "bet on home favorite" strategy.

Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Golec and Tamarkin (1991)	NFL 1973-1987	Unconditional	0.493	-0.642	
	College football 1973-1987	Unconditional	0.495	-0.595	
Oorlog (1995)	NBA 1989-1991	Unconditional	0.486	-1.097	
Vergin and Sosik (1999)	NFL 1981-1996	Unconditional	0.486	-1.358	
Gandar et al. (2001)	NBA 1981-1997	Unconditional	0.496	-0.841	
Sung and Tainsky (2014)	NFL 2002-2009	Unconditional	0.484	-1.181	
Paul, Weinbach, and Wilson (2014)	NFL 2007-2011	Unconditional	0.483	-0.989	
Sinkey and Logan (2014)	College football 1985-2008	Unconditional	0.497	-0.513	
Humphreys et al. (2014)	College basketball 2007-2008	Unconditional	0.503	0.275	
Shank (2018)	NFL 2009-2017	Unconditional	0.487	-0.956	
Shank (2019)	NFL 2003-2016	Unconditional	0.488	-1.122	
Humphreys et al. (2014)	College basketball 2007-2008	PS≤ -12	0.486	-0.759	
		PS≤ -10	0.497	-0.164	
Shank (2018)	NFL 2009-2017	PS≤ -10	0.517	0.487	
		PS≤ -7	0.490	-0.445	
		PS≤ -4	0.494	-0.354	
		PS≤ -2	0.485	-0.997	
		PS = 0	0.549	0.700	

Familiarity

Borghesi (2007a) investigates whether temperature information can be profitably exploited. As a first exploration, he computes the empirical win fractions for the home team conditional on the temperature of the game as shown in the first four rows of table D. Interestingly, the home team covers significantly more than expected in the coldest games at the single test benchmark, but never at the multiple test benchmark. Rows 5 to 8 of table D contain the strategy of betting on home games in the hottest quartile of game day temperatures conditional on the acclimatization advantage (the converse of the strategy discussed in the main text). Kuester and Sanders (2011) further investigate climate acclimatization challenges. For completeness, we include row 9 and 10 of table D where the subsamples contain games between arid region teams or between humid region teams (so no acclimatization challenges). The strategies are not profitable in sample and the null of randomness is never rejected.

Table D: Overview of papers implementing "bet on home team conditional on familiarity" strategies.

Authors	Data set	Conditioning	$\hat{\pi}$	Z_1	Z_2
Borghesi (2007a)	NFL 1981-2004	Q1 temperature (hottest)	0.473	-1.300	
		Q2 temperature	0.483	-1.565	
		Q3 temperature	0.501	0.053	
		Q4 temperature (coldest)	0.541	**2.960**	1.240
		Q1 temperature (hottest) and Q1 acclimatization advantage (highest)	0.475	-0.811	
		Q1 temperature (hottest) and Q2 acclimatization advantage	0.434	-1.543	
		Q1 temperature (hottest) and Q3 acclimatization advantage	0.518	0.381	
		Q1 temperature (hottest) and Q4 acclimatization advantage (lowest)	0.470	-0.492	
Kuester and Sanders (2011)	College football 2000-2006	Both teams from arid regions	0.498	-0.116	
		Both teams from humid regions	0.507	0.749	

Fatigue

Additional bye-week related strategies by Sung and Tainsky (2014) and other tests of the "betting on the home team in the second game of back-to-back games when the away team had 1 or 2 days of rest" by Ashman et al. (2010) are shown in table E. Furthermore, Oorlog (1995) investigates whether betting on a team playing the last game of a road trip can be profitable. Inefficiencies could arise if the market misestimates the effect of road wear on team performance. Coleman (2017) tests whether betting on a favored home team in the latter half of the season when it hosts a visiting team that travelled one time zone to the east is profitable. This strategy seems promising based on his elaborate regression results. Although the null of randomness is rejected relative to the single test benchmark, the null of unprofitability is not.

Table E: Overview of papers implementing "bet conditional on fatigue characteristics" strategies.

	Authors	Data set	Conditioning	$\hat{\pi}$	Z_1	Z_2
1	Sung and Tainsky (2014)	NFL 2002-2009	home team after it had a bye-week	0.536	0.851	
2			away team after it had a bye-week	0.551	1.063	
3			home favorite after it had a bye-week	0.579	1.539	
4			home underdog after it had a bye-week	0.452	-0.617	
Rows 5-8 display the strategy "bet on the home team in the second game of back-to-back games for the home team when the visiting team had 1 or 2 days of rest" conditional on other info.						
5	Ashman et al. (2010)	NBA 1990-2009	both teams played away last game	0.470	-1.361	
6			the home team played away and away team played at home last game	0.443	**-2.649**	-1.536
7			he home team played at home while the away team played away last game	0.395	-1.889	
8			both teams played at home last game	0.500	0.000	
Rows 9-14 display the strategy "bet home team in back-to-back games when the visiting team is not having back-to-back games" conditional on whether it travelled one or two time zones to the east between back-to-back games (E) or not (No E) and other info.						
9			home team is an underdog	0.430	**-3.021**	**-1.998**
10			the home team is an underdog (E)	0.388	**-2.266**	**-1.785**
11			home team is an underdog (No E)	0.442	**-2.214**	-1.312
12			home team is a favorite	0.470	-1.798	
13			home team is a favorite (E)	0.411	**-2.426**	**-1.781**
14			home team is a favorite (No E)	0.485	-0.784	
Rows 15-18 display the strategy "bet on the home underdog in the second game of back-to-back games for the home team when the visiting team had 1 or 2 days of rest" conditional on other info.						
15			both teams played away last game	0.448	-1.412	
16			home team played away and the away team played at home last game	0.424	**-1.982**	-1.360
17			the home team played at home and the away team played away last game	0.286	**-2.268**	**-2.018**
18			both teams played at home last game	0.500	0.000	
19	Oorlog (1995)	NBA 1989-1991	bet on teams on the last game of a road trip	0.543	1.952	
20	Coleman (2017)	College football 2004-2013	bet on favored home teams in the latter half of the season when they host a visiting team that travelled one time zone to the east	0.554	**1.964**	1.092

Attention & Importance

Hickman (2020) also tests whether the market correctly estimates the quality of the teams per seed.

The proposed strategy is to bet on a team when it plays a team from another seed. As shown in table F, in none of the 16 cases, the null of randomness is rejected. Furthermore, Hickman (2020) tests whether conference affiliation of the teams can be profitably exploited. A number of variations are shown in table 18 but randomness can never be rejected.

Relatedly, Moore and Francisco (2019) investigate the performance of Power Five (P5)/Automatic Qualifying (AQ) college football teams when playing against a Football Championship Subdivision (FCS) team. The authors dissect the strategy by dividing the P5/AQ sample per conference. The P5/AQ sample includes the Southeastern Conference (SEC), the Atlantic Coast Conference (ACC), the Big Ten, the Big Twelve and the Pacific 10/Pacific 12 and the Big East until 2012. It is worth noting that the SEC is considered the best conference in college football. Results conditional on the conference are shown in table F. Interestingly, the strategy of betting against SEC teams when they play against an FCS team rejects the null of unprofitability (only at the single test benchmark). The authors hypothesize that SEC teams might save their best players for next games when playing against FCS teams, or simply lack motivation.

Table F: Overview of papers implementing "bet conditional on attention and importance characteristics" strategies.

Authors	Data set	Conditioning	$\hat{\pi}$	Z_1	Z_2
Hickman (2020)	March	bet on seed 1 teams (against a differently seeded team)	0.507	0.260	
	Madness	bet on seed 2 teams (against a differently seeded team)	0.444	-1.944	
	1996-2019	bet on seed 3 teams (against a differently seeded team)	0.520	0.656	
		bet on seed 4 teams (against a differently seeded team)	0.498	-0.064	
		bet on seed 5 teams (against a differently seeded team)	0.490	-0.283	
		bet on seed 6 teams (against a differently seeded team)	0.497	-0.073	
		bet on seed 7 teams (against a differently seeded team)	0.517	0.447	
		bet on seed 8 teams (against a differently seeded team)	0.536	0.936	
		bet on seed 9 teams (against a differently seeded team)	0.486	-0.329	

		bet on seed 10 teams (against a differently seeded team)	0.500	0.000	
		bet on seed 11 teams (against a differently seeded team)	0.532	0.801	
		bet on seed 12 teams (against a differently seeded team)	0.566	1.578	
		bet on seed 13 teams (against a differently seeded team)	0.462	-0.825	
		bet on seed 14 teams (against a differently seeded team)	0.425	-1.554	
		bet on seed 15 teams (against a differently seeded team)	0.529	0.594	
		bet on seed 16 teams (against a differently seeded team)	0.500	0.000	
		bet on higher seed when it comes from a major conference (ACC, Bog 10, Big 12, Big East, Pac-12, SEC)	0.510	0.558	
		bet on higher seed when lower seed comes from a major conference (ACC, Bog 10, Big 12, Big East, Pac-12, SEC)	0.491	-0.186	
		bet on higher seed when both teams come from a major conference (ACC, Bog 10, Big 12, Big East, Pac-12, SEC)	0.471	-1.318	
		bet on higher seed when both teams do not come from a major conference (ACC, Bog 10, Big 12, Big East, Pac-12, SEC)	0.504	0.086	
		bet on teams from the ACC conference (intra-conference games excluded)	0.447	-1.895	
		bet on teams from the Big 10 conference (intra-conference games excluded)	0.539	1.423	
		bet on teams from the Big 12 conference (intra-conference games excluded)	0.502	0.057	
		bet on teams from the Big East conference (intra-conference games excluded)	0.511	0.384	
		bet on teams from the Pac-12 conference (intra-conference games excluded)	0.525	0.768	
		bet on teams from the SEC conference (intra-conference games excluded)	0.507	0.236	
		bet on the higher-seeded team when PS≤ -20	0.478	-0.470	
		bet on the higher-seeded team when -20 <PS≤ -10	0.500	0.000	
		bet on the higher-seeded team when -10 <PS≤ -5	0.499	-0.045	
		bet on the higher-seeded team when -5 <PS≤ 0	0.480	-0.839	
		bet on the higher-seeded team when PS>0	0.527	0.612	
Moore and Francisco (2019)	College football 2003-2018	bet on P5/AQ teams when playing an FCS team	0.499	-0.052	
		bet on ACC teams when playing an FCS team	0.568	1.279	
		bet on Big 10 teams when playing an FCS team	0.533	0.516	
		bet on Big 12 teams when playing an FCS team	0.473	-0.405	
		bet on Big East teams when playing an FCS team	0.455	-0.522	
		bet on PAC 10/12 teams when playing an FCS team	0.520	0.283	
		bet on SEC teams when playing an FCS team	0.385	**-2.535**	**-2.011**

Absences

Dare et al. (2015) further condition their strategy on home teams and away teams respectively as shown in table G.

To investigate how the market deals with potential rumors on coaching changes, Colquitt et al. (2007) also investigate the runup to the change. As shown in table G, there is no evidence betting markets are not efficient in the games leading up to a coaching change.

Table G: Overview of papers implementing "bet conditional on absence characteristics" strategies.

Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Dare et al. (2015)	NBA 1996-2005	bet on home teams with the most absences	0.511	1.122	
		bet on home teams with the most absences AV ≥ 5	0.509	0.798	
		bet on home teams with the most absences AV ≥ 10	0.517	0.949	
		bet on home teams with the most absences AV ≥ 15	0.558	1.830	
		bet on home teams with the most absences AV ≥ 20	0.543	0.778	
		bet on away teams with the most absences	0.485	-1.602	
		bet on away teams with the most absences AV ≥ 5	0.475	**-2.167**	-0.101
		bet on away teams with the most absences AV ≥ 10	0.494	-0.347	
		bet on away teams with the most absences AV ≥ 15	0.518	0.561	
		bet on away teams with the most absences AV ≥ 20	0.490	-0.198	
Colquitt et al. (2007)	NBA 1988-2002	bet on the team that will hire a new coach games 1-3 before change	0.500	0.000	
		bet on the team that will hire a new coach games 4-6 before change	0.481	-0.477	
		bet on the team that will hire a new coach games 7-9 before change	0.491	-0.236	

Performance against the spread

Camerer (1989) and Paul, Weinbach, and Humphreys (2014) further refine the strategy shown in table 9 by conditioning on the performance of the opposing team against the spread. Table H shows the strategy of betting on teams on win streaks while table I shows the opposite strategy of betting on teams that are on losing streaks. The evidence is mixed, i.e. the empirical win fractions are not consistently smaller or larger than 50%, furthermore, the null of randomness is only once rejected at the single test benchmark.

Table H: Overview of papers implementing "bet on teams that are on a k game winning streak against the spread when playing a team on a shorter winning streak/losing streak against the spread" strategy.

Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Camerer (1989)	NBA 1983-1986	k=1, shorter winning streak	0.520	0.532	
		k=2, shorter winning streak	0.510	0.381	
		k=3, shorter winning streak	0.466	-1.104	
		k=4, shorter winning streak	0.459	-1.031	
		k=5, shorter winning streak	0.461	-0.792	
		k=6, shorter winning streak	0.426	-1.152	
		k=7, shorter winning streak	0.476	-0.309	
		k=8, shorter winning streak	0.345	-1.671	
		k ≥ 9, shorter winning streak	0.421	-0.973	
		k=1, losing streak	0.520	0.532	
		k=2, losing streak	0.520	0.523	
		k=3, losing streak	0.452	-1.159	
		k=4, losing streak	0.529	0.542	
		k=5, losing streak	0.480	-0.283	
		k=6, losing streak	0.514	0.169	
		k=7, losing streak	0.556	0.471	
		k=8, losing streak	0.400	-0.632	
		k ≥ 9, losing streak	0.444	-0.471	
Paul, Weinbach, and Humphreys (2014)	NFL 2005-2010	k=1, shorter winning streak	0.495	-0.164	
		k=2, shorter winning streak	0.490	-0.277	
		k=3, shorter winning streak	0.495	-0.097	
		k=4, shorter winning streak	0.520	0.283	
		k=5, shorter winning streak	0.478	-0.295	
		k=1, losing streak	0.492	-0.282	
		k=2, losing streak	0.519	0.434	
		k=3, losing streak	0.393	-1.664	
		k=4, losing streak	0.500	0.000	
		k=5, losing streak	0.455	-0.426	

Table I: Overview of papers implementing "bet on teams that are on a k game losing streak against the spread when playing a team on a shorter losing streak/winning streak against the spread" strategy.

Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Camerer (1989)	NBA 1983-1986	k=1, shorter losing streak	0.532	0.836	
		k=2, shorter losing streak	0.519	0.667	
		k=3, shorter losing streak	0.520	0.635	
		k=4, shorter losing streak	0.538	0.955	
		k=5, shorter losing streak	0.449	-1.010	
		k=6, shorter losing streak	0.596	1.457	
		k=7, shorter losing streak	0.444	-0.667	
		k=8, shorter losing streak	0.750	**2.236**	**2.025**
		k ≥ 9, shorter losing streak	0.615	1.177	
		k=1, winning streak	0.532	0.836	
		k=2, winning streak	0.532	0.836	
		k=3, winning streak	0.519	0.440	
		k=4, winning streak	0.536	0.655	
		k=5, winning streak	0.500	0.000	
		k=6, winning streak	0.654	1.569	
		k=7, winning streak	0.400	-0.775	
		k=8, winning streak	0.727	1.508	
		k ≥ 9, winning streak	0.615	0.832	
Paul, Weinbach, and Humphreys (2014)	NFL 2005-2010	k=1, shorter losing streak	0.491	-0.325	
		k=2, shorter losing streak	0.551	1.569	
		k=3, shorter losing streak	0.550	1.044	
		k=4, shorter losing streak	0.558	0.832	
		k=5, shorter losing streak	0.654	1.569	
		k=1, winning streak	0.491	-0.333	
		k=2, winning streak	0.529	0.676	
		k=3, winning streak	0.536	0.535	
		k=4, winning streak	0.556	0.577	
		k=5, winning streak	0.714	1.604	

Table J contains additional performance against the spread strategies of which we highlight a few. Woodland and Woodland (2000) and Sinkey and Logan (2014) investigate whether profitable strategies can be found at the intersection between past performance against the spread and other game variables (favorite/underdog or home/away). Vergin (2001) tests whether the performance against the spread in a previous season contains useful information. Kochman, Goodwin, and Gilliam (2017) test whether teams that have a very lopsided record against the spread in the beginning of the season regress to the mean in terms of performance against the spread. More specifically they propose the strategy of betting on all teams that lost at least 4 out of the 5 first games against the spread and betting against all teams that won at least 4 of their first 5 games against the spread. The null of randomness is never rejected.

Table J: Overview of papers implementing "bet conditional on performance against the spread characteristics" strategies.

Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Vergin and Scriabin (1978)	NFL 1969-1974	bet on teams that had a winning point spread record the year before	0.506	0.322	
Vergin and Scriabin (1978)	NFL 1969-1974	bet against teams that had a losing point spread record the year before	0.495	-0.266	
Gandar et al. (1988)	NFL 1980-1985	bet the underdog against a favored team that, as a favorite in the previous week, covered the spread by at least 10 points	0.581	**2.089**	1.476
Lacey (1990)	NFL 1984-1986	bet on teams that failed to beat the spread last two games	0.425	**-2.683**	**-1.834**
Vergin (1998)	NFL 1984-1995	bet on teams that failed to beat the spread last two games	0.507	0.423	
Sinkey and Logan (2014)	College football 1985-2008	bet on teams that failed to beat the spread last two games	0.495	-0.687	
Oorlog (1995)	NBA 1989-1991	bet on teams that have a better win record against the spread for the season to date	0.512	1.111	
Oorlog (1995)	NBA 1989-1991	in the second half of the season, bet on the team with the better win record against the spread in the first half of the season	0.510	0.643	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that covered last game	0.507	0.545	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that covered at least 2 consecutive games	0.501	0.077	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that covered at least 3 consecutive games	0.498	-0.055	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that covered at least 4 consecutive games	0.535	0.884	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that failed to cover last game	0.525	1.864	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that failed to cover at least 2 consecutive games	0.523	1.238	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that failed to cover at least 3 consecutive games	0.515	0.579	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that failed to cover at least 4 consecutive games	0.503	0.074	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that won and covered last game	0.511	0.777	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that won and covered at least 2 consecutive games	0.521	0.994	

Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that won and covered at least 3 consecutive games	0.469	-0.927	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that won and covered at least 4 consecutive games	0.480	-0.400	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that lost or tied and failed to cover last game	0.527	1.844	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that lost or tied and failed to cover at least 2 consecutive games	0.526	1.233	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that lost or tied and failed to cover at least 3 consecutive games	0.504	0.128	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that lost or tied and failed to cover at least 4 consecutive games	0.495	-0.097	
Vergin (2001)	NFL 1981-1995	bet against teams that covered the spread by 10 points or more last game	0.513	0.930	
Vergin (2001)	NFL 1981-1995	bet against teams that covered the spread by 15 points or more last game	0.518	1.010	
Vergin (2001)	NFL 1981-1995	bet against teams that covered the spread by 20 points or more last game	0.526	1.107	
Vergin (2001)	NFL 1981-1995	bet on teams that failed to cover the spread by 10 points or more last game	0.511	0.825	
Vergin (2001)	NFL 1981-1995	bet on teams that failed to cover the spread by 15 points or more last game	0.531	1.704	
Vergin (2001)	NFL 1981-1995	bet on teams that failed to cover the spread by 20 points or more last game	0.525	1.067	
Vergin (2001)	NFL 1981-1995	bet against teams that had a net winning record against the spread of at least 4 games last season	0.537	1.630	
Vergin (2001)	NFL 1981-1995	bet against teams that had a net winning record against the spread of at least 5 games last season	0.542	1.660	
Vergin (2001)	NFL 1981-1995	bet against teams that had a net winning record against the spread of at least 6 games last season	0.517	0.484	
Vergin (2001)	NFL 1981-1995	bet against teams that had a net winning record against the spread of at least 7 games last season	0.567	1.555	
Vergin (2001)	NFL 1981-1995	bet against teams that had a net winning record against the spread of at least 8 games last season	0.558	0.762	
Vergin (2001)	NFL 1981-1995	bet on teams that had a net losing record against the spread of at least 4 games last season	0.497	-0.134	
Vergin (2001)	NFL 1981-1995	bet on teams that had a net losing record against the spread of at least 5 games last season	0.513	0.504	
Vergin (2001)	NFL 1981-1995	bet on teams that had a net losing record against the spread of at least 6 games last season	0.561	1.480	
Vergin (2001)	NFL 1981-1995	bet on teams that had a net losing record against the spread of at least 7 games last season	0.560	1.342	

Vergin (2001)	NFL 1981-1995	bet on teams that had a net losing record against the spread of at least 8 games last season	0.622	1.640	
Vergin (2001)	NFL 1981-1995	each week, bet on the team that lost against the spread by the largest average amount last week	0.505	0.137	
Vergin (2001)	NFL 1981-1995	each week, bet on the team that lost against the spread by the largest average amount last 2 weeks	0.500	0.000	
Vergin (2001)	NFL 1981-1995	each week, bet on the team that lost against the spread by the largest average amount last 3 weeks	0.531	0.866	
Vergin (2001)	NFL 1981-1995	each week, bet on the team that lost against the spread by the largest average amount last 4 weeks	0.445	-1.445	
Vergin (2001)	NFL 1981-1995	each week, bet on the team that lost against the spread by the largest average amount last 5 weeks	0.529	0.723	
Paul and Weinbach (2005a)	NBA 1995-2002	bet against teams that are not on a >2 game losing streak against the spread versus teams on >2 game losing streaks against the spread	0.514	1.530	
Paul and Weinbach (2005a)	NBA 1995-2002	bet against teams that are not on a >4 game losing streak against the spread versus teams on >4 game losing streaks against the spread	0.512	0.640	
Paul et al. (2011)	NBA 2003-2009	bet against teams on a 2-game loss streak against the spread	0.498	-0.235	
Paul et al. (2011)	NBA 2003-2009	bet against teams on a 4-game loss streak against the spread	0.513	0.848	
Sinkey and Logan (2014)	College football 1985-2008	bet on home teams that beat the spread last two games	0.516	1.680	
Sinkey and Logan (2014)	College football 1985-2008	bet on underdogs that beat the spread last two games	0.489	-1.209	
Sinkey and Logan (2014)	College football 1985-2008	bet on home favorites that beat the spread last two games	0.498	-0.139	
Sinkey and Logan (2014)	College football 1985-2008	bet on home underdogs that beat the spread last two games	0.524	1.414	
Sinkey and Logan (2014)	College football 1985-2008	bet on home teams that failed to beat the spread last two games	0.488	-1.300	
Sinkey and Logan (2014)	College football 1985-2008	bet on underdogs that failed to beat the spread last two games	0.483	-1.604	
Sinkey and Logan (2014)	College football 1985-2008	bet on home favorites that failed to beat the spread last two games	0.477	-1.753	
Sinkey and Logan (2014)	College football 1985-2008	bet on home underdogs that failed to beat the spread last two games	0.507	0.446	

Kochman et al. (2017)	College football 2015-2016	bet against teams that won at least 4 of the first five games against the spread	0.525	0.632	
Kochman et al. (2017)	College football 2015-2016	bet on teams that lost at least 4 of the first five games against the spread	0.533	0.851	
Shank (2018)	NFL 2009-2017	bet on the home team if it covered the spread last two games	0.481	-0.799	
Shank (2018)	NFL 2009-2017	bet on the home team if it failed to cover the spread last two games	0.530	1.342	
Shank (2018)	NFL 2009-2017	bet on the away team if it covered the spread last two games	0.495	-0.190	
Shank (2018)	NFL 2009-2017	bet on the away team if it failed to cover the spread last two games	0.460	-1.785	
Bennett (2020)	College football 2006-2018	for BCS/Power 5 teams, bet on teams that that exceeded the point spread by 20 points or more and betting against teams that fell short by 20 points or more in the previous game	0.501	0.052	
Bennett (2020)	College football 2006-2018	for non BCS/Power 5 teams, bet on teams that that exceeded the point spread by 20 points or more and betting against teams that fell short by 20 points or more in the previous game	0.534	**2.416**	0.702
Bennett (2020)	College football 2006-2018	for BCS/Power 5 teams and non-BCS/Power 5 teams that played a BCS/Power 5 team, bet on teams that that exceeded the point spread by 20 points or more and betting against teams that fell short by 20 points or more in the previous game	0.500	-0.024	
Bennett (2020)	College football 2006-2018	for non-BCS/Power 5 teams that played another non BCS/Power 5 team, bet on teams that that exceeded the point spread by 20 points or more and betting against teams that fell short by 20 points or more in the previous game	0.542	**2.759**	1.207

Bennett (2020) implements strategies that condition on last game performance of both teams. The rule is to bet on teams that did well against the spread in the previous game and to bet against teams that performed poorly against the spread when they play teams whose results were closer to the spread last game. The strategy is tested for different parameter values and shown in table K. The rows condition on the difference between the spread and the actual outcome of a team in its prior game. The columns indicate the result against the spread of its opponent in its own previous game. For example, in the cell with row header **≥35** and column header **<35**, the betting rule is implemented on teams where the difference between the outcome and point spread in the previous game was 35 points or more, while the difference for the opponent was smaller than 35 in its previous game. In only 1 of 22 tests, the null of randomness is rejected at the single test benchmark.

Table K: Bennett (2020) in college football games between 2006-2018. Strategy implemented is "bet on teams that did well against the spread in the previous game and bet against teams that performed poorly against the spread when they play teams whose results were closer to the spread in their previous game" strategy. The rows condition on the difference between the spread and the actual outcome of a team in its prior game. The columns indicate the results against the spread of its opponent in their previous game.

	<35	**<30**	**<25**	**<20**	**<15**	**<10**	**<5**
≥35	$\hat{\pi}$: 0.511 Z_1: 0.465	$\hat{\pi}$: 0.509 Z_1: 0.381	$\hat{\pi}$: 0.508 Z_1: 0.340	$\hat{\pi}$: 0.507 Z_1: 0.258	$\hat{\pi}$: 0.505 Z_1: 0.172	$\hat{\pi}$: 0.514 Z_1: 0.412	$\hat{\pi}$: 0.539 Z_1: 0.839
≥30	/	$\hat{\pi}$: 0.497 Z_1: -0.166	$\hat{\pi}$: 0.501 Z_1: 0.068	$\hat{\pi}$: 0.502 Z_1: 0.109	$\hat{\pi}$: 0.498 Z_1: -0.119	$\hat{\pi}$: 0.516 Z_1: 0.697	$\hat{\pi}$: 0.521 Z_1: 0.686
≥25	/	/	$\hat{\pi}$: 0.515 Z_1: 1.202	$\hat{\pi}$: 0.516 Z_1: 1.244	$\hat{\pi}$: 0.512 Z_1: 0.850	$\hat{\pi}$: 0.523 Z_1: 1.422	$\hat{\pi}$: 0.518 Z_1: 0.828
≥20	/	/	/	$\hat{\pi}$: 0.516 Z_1: 1.693	$\hat{\pi}$: 0.515 Z_1: 1.489	$\hat{\pi}$: 0.524 Z_1: **2.012** Z_2: 0.049	$\hat{\pi}$: 0.528 Z_1: 1.774

Performance not against the spread

Table L contains additional strategies based on performance not against the spread. Many of the strategies are similar to those discussed above, but the past information is now measured by the game outcome itself and not against the spread. The null of randomness is never rejected at the multiple test benchmark.

Table L: Overview of papers implementing "bet conditional on performance not against the spread characteristics" strategies.

Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Lacey (1990)	NFL 1984-1986	bet on teams that qualified for post season play last season when facing a team that did not	0.550	1.825	
Vergin (1998)	NFL 1984-1995	bet on teams that qualified for post season play last season when facing a team that did not	0.486	-0.901	
Vergin (2001)	NFL 1981-1995	bet on teams that qualified for post season play last season when facing a team that did not	0.503	0.256	
Fodor et al. (2013)	NFL 2004-2012	bet on teams that qualified for post season play last season when facing a team that did not	0.496	-0.276	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that won last game	0.520	1.583	

Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that won at least 2 consecutive games	0.532	1.874	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that won at least 3 consecutive games	0.510	0.456	
Woodland and Woodland (2000)	NFL 1985-1997	bet against favorite teams that won at least 4 consecutive games	0.515	0.492	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that lost or tied last game	0.526	**2.039**	0.170
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that lost or tied at least 2 consecutive games	0.523	1.350	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that lost or tied at least 3 consecutive games	0.525	1.147	
Woodland and Woodland (2000)	NFL 1985-1997	bet on underdog teams that lost or tied at least 4 consecutive games	0.536	1.254	
Vergin (2001)	NFL 1981-1995	bet on teams that lost their previous game by 10 points or more	0.498	-0.155	
Vergin (2001)	NFL 1981-1995	bet on teams that lost their previous game by 15 points or more	0.511	0.693	
Vergin (2001)	NFL 1981-1995	bet on teams that lost their previous game by 20 points or more	0.522	1.065	
Vergin (2001)	NFL 1981-1995	each week, bet on the team has been outscored by its opponents by the largest average amount last week	0.500	0.000	
Vergin (2001)	NFL 1981-1995	each week, bet on the team has been outscored by its opponents by the largest average amount last 2 weeks	0.471	-0.840	
Vergin (2001)	NFL 1981-1995	each week, bet on the team has been outscored by its opponents by the largest average amount last 3 weeks	0.479	-0.583	
Vergin (2001)	NFL 1981-1995	each week, bet on the team has been outscored by its opponents by the largest average amount last 4 weeks	0.503	0.076	
Vergin (2001)	NFL 1981-1995	each week, bet on the team has been outscored by its opponents by the largest average amount last 5 weeks	0.490	-0.239	
Paul et al. (2011)	NBA 2003-2009	bet on teams on a 2-game win streak	0.498	-0.262	
Paul et al. (2011)	NBA 2003-2009	bet on teams on a 4-game win streak	0.496	-0.307	
Paul et al. (2011)	NBA 2003-2009	bet against teams on a 2-game loss streak	0.504	0.503	
Paul et al. (2011)	NBA 2003-2009	bet against teams on a 4-game loss streak	0.502	0.150	
The rows below show the strategy “bet against teams that qualified for the playoffs last season when they face a team that did not qualify in game k of the next season”					
Authors	**Data set**	**Conditioning**	$\hat{\pi}$	Z_1	Z_2
Fodor et al. (2013)	NFL 2004-2012	k = 7	0.516	0.254	
		k = 8	0.404	-1.457	
		k = 9	0.473	-0.405	
		k = 10	0.475	-0.384	
		k = 11	0.469	-0.500	
		k = 12	0.492	-0.126	
		k = 13	0.564	0.944	
		k = 14	0.507	0.119	

		k = 15	0.508	0.128	
		k = 16	0.444	-0.882	
		k = 17	0.620	**2.018**	1.618

Table M: Overview of papers implementing "bet on teams in top of AP poll in first game of next season when playing against a team not in the top 25" strategy. The strategy is further conditioned on the team being the favorite (F) (which is of course often the case for last season top 25 teams) and playing against a power 5 team (P) or not (N).

Authors	Data set	Top 25 P	Top 25 F P	Top 25 N	Top 25 F N	Top 10 P	Top 10 F P
Bennett (2019)	College football 2008-2016	$\hat{\pi}$: 0.458 Z_1: -0.577	$\hat{\pi}$: 0.500 Z_1: 0.000	$\hat{\pi}$: 0.413 Z_1: -1.960 Z_2: -1.427	$\hat{\pi}$: 0.416 Z_1: -1.878	$\hat{\pi}$: 0.500 Z_1: 0.000	$\hat{\pi}$: 0.520 Z_1: 0.200
		Top 10 N	**Top 10 N F**	**Top 11-25 P**	**Top 11-25 F P**	**Top 11-25 N**	**Top 11-25 N F**
		$\hat{\pi}$: 0.309 Z_1: **-2.832** Z_2: **-2.481**	$\hat{\pi}$: 0.321 Z_1: **-2.610** Z_2: **-2.266**	$\hat{\pi}$: 0.448 Z_1: -0.557	$\hat{\pi}$: 0.500 Z_1: 0.000	$\hat{\pi}$: 0.480 Z_1: -0.346	$\hat{\pi}$: 0.480 Z_1: -0.346

Spread movements

Table N supplements the strategy discussed in table 11 of the main text. The null of randomness is never rejected. Baryla Jr, Borghesi, Dare, and Dennis (2007) zoom in on the efficiency of the betting market during the first four games of a season. They compare early season price formation with that of the IPO process banks face when pricing a new security. At the start of a season, the betting market has some indications about the strength of a team, but true values are only revealed gradually as the season progresses. More concretely, they test whether movements in the point spread between the opening line and closing line contain useful information in the first four games of a season. As shown in table N, the null of randomness is never rejected.

Table N: Overview of papers implementing "bet conditional on spread movements" strategies

	Authors	Data set	Conditioning	$\hat{\pi}$	Z_1	Z_2
Rows 1-8 show the strategy "bet on home team when the spread for the home team moves by k points".						
1	Gandar et al. (1998)	NBA 1985-1994	k = -3.5	0.433	-0.730	
2			k = -2.5	0.536	0.805	
3			k = -1.5	0.490	-0.469	
4			k = -0.5	0.500	0.000	

5			k = 0.5	0.490	-0.819	
6			k = 1.5	0.520	0.986	
7			k = 2.5	0.563	1.463	
8			k = 3.5	0.467	-0.365	
Rows 9-25 show the strategy “bet on home team when the spread moved by k points from the opening line to the closing line in the first four home games of a season”.						
9	Baryla Jr et al. (2007)	NBA 1985-2005	k ≤ -4	0.488	-0.152	
10			k ≤ -3.5	0.423	-0.784	
11			k ≤ -3	0.375	-1.414	
12			k ≤ -2.5	0.520	0.283	
13			k ≤ -2	0.440	-1.153	
14			k ≤ -1.5	0.422	-1.584	
15			k ≤ -1	0.510	0.280	
16			k ≤ -0.5	0.504	0.124	
17			k ≤ 0	0.544	1.677	
18			k ≤ 0.5	0.506	0.197	
19			k ≤ 1	0.448	-1.405	
20			k ≤ 1.5	0.571	1.604	
21			k ≤ 2	0.456	-0.887	
22			k ≤ 2.5	0.424	-1.172	
23			k ≤ 3	0.589	1.336	
24			k ≤ 3.5	0.458	-0.577	
25			k ≤ 4	0.500	0.000	
26	Gandar et al. (1988)	NFL 1980-1985	bet on the team that becomes less favored (more of an underdog) over the course of the week’s betting for games in weeks following “winning” weeks for the public. “Winning” weeks were those for which at least 50% of line changes from the opening to the closing line moved the betting line closer to the eventual game outcome	0.570	**2.669**	**1.762**

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