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Abstract

Following the work of Shin (1993) and Cain, Law and Peel (1997, 2001), several researchers have reported estimates of the fraction of money placed on sports betting by "insiders" with superior information to bookmakers. We show the method for estimating the fraction of insiders used in this research is only accurate under highly unrealistic conditions and that these estimates will tend to be positive in realistic cases where there are no insiders. We also argue that variations in these estimates are unlikely to be related to variations in the amount of inside information but rather are more likely due to other factors such as variations in bookmakers' costs or the extent of competition in betting markets.

Keywords: Sports Betting, Inside Information, Shin's z

JEL Classification: G14, L83, Z20

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1. Introduction

Like financial markets, sports betting markets sell state-contingent securities and the prices of these securities—as implied by betting odds—provide information about the future. Specifically, betting odds can be used to estimate the probabilities of the various possible outcomes (e.g. Berkowitz, Depken and Gandar, 2018). However, also like some financial markets, sports betting markets may include participants who have inside information, in this case about the likely outcomes of future sporting events. In a series of papers, Hyun-Song Shin (1991, 1992, 1993) described how the presence of such insiders could affect betting markets and several researchers have since employed the model in his 1992 and 1993 papers to use odds set by bookmakers to estimate the fraction of money placed by bettors with superior information to bookmakers about the potential outcomes of events.

Shin (1992) presented a theoretical model with a monopolist bookmaker who was aware that a fraction z of the betting came from unidentifiable insiders who knew the result of the contest in advance. Shin (1993) implemented a regression-based method using odds to estimate the average value of z in a sample of sporting events.[1] Cain, Law and Peel (1997, 2001) subsequently showed it was possible to use the model to calculate z separately for each event based on its odds. This method has since been used in studies by Coleman (2007), Sung, Johnson and McDonald (2016) and others.

It is possible that some bettors have informational advantages that do not reflect inside knowledge but rather they use publicly available information better than bookmakers. However, it is well known that modern bookmakers use highly sophisticated statistical models, so it seems unlikely that many bettors are using superior modelling techniques and, for this reason, research using these measures has generally referred to them as estimates of insider trading.[2]

There are a couple of possible sources of inside information for bettors about sporting events. Shin's research cited the work of Crafts (1985) on horse racing which suggested some bettors have access to private information about the relative strengths of the participants in a contest but such information is likely to be hard to come by in the high-profile events that dominate volumes in modern betting markets. Another explanation, as discussed for example by Bag and Saha (2011, 2017), is corruption relating to cases where some bettors have bribed officials or players to influence the result. Corruption related to betting markets generally goes undetected but has sometimes been explicitly uncovered, from the infamous "Black Sox" scandal of the 1919 World Series to modern examples in Italian soccer (Boeri and Severgnini, 2011) and international cricket (Preston and Szymanski, 2003).

Concern with corruption as a potential explanation is perhaps increased by the fact that, if the results from using the Shin z measure are to be believed, then betting by those with an advantage over the bookmaker is common even for high-profile sporting events in which a private informational

[1] This regression method was also used in other studies such as Vaughan Williams and Paton (1997).

[2] Miller and Davidow (2023) is an excellent guide to the sophisticated way that modern bookmakers set odds and why it is so difficult to systematically beat them using publicly available information.

advantage is unlikely to be feasible. For example, we show below that applying this method to large datasets of odds on professional tennis and European soccer suggests that between 3% and 6% of money placed on these sports comes from people who pick the winner due to their informational advantage over bookmakers.

This paper argues, however, that empirical estimates of Shin's z are unlikely to provide an accurate measure of the importance of inside information in betting markets. We present theoretical models to illustrate that positive values of z will be reported in plausible cases when there are no insiders and also provide alternative interpretations for why the estimates of z tend to vary systematically across different types of events. We show that high values of z should be interpreted only as showing that the bookmaker's margin is high.

The paper is structured as follows. Section 2 describes the Shin (1992) model and its implied event-specific z measure. We argue that the model does not provide a good description of modern betting markets because the non-insiders in the model are sure that a specific competitor will win and thus the amounts placed on each contestant are not influenced by the odds offered by the bookmaker. But even within the restrictive structures of this model, we show that the z measure is only correct in the counter-factual case in which bookmakers earn zero average gross profits, meaning average payouts to bettors equal the average amount of money placed in bets. Allowing for a realistic level of profits for bookmakers, consistent with published accounting reports, we show that the model implies the z measure will falsely report positive amounts of insiders even when there are none.

We also show that within this model, the z estimates correlate closely with the margins charged by bookmakers. High margins should translate into high profits for bookmakers but because the z estimates are based on the assumption of zero profits, the calculation relies on the inference that a large fraction of insiders must exist to offset the effect of the high margins on profits.

Section 3 examines how the z measure would behave in a more realistic model of the betting market. Specifically, we use a generalised version of Shin's (1991) alternative model of a monopoly bookmaker. This model is more realistic than the Shin (1992) model because non-insiders have more reasonable beliefs—rather than being sure about the outcome, they disagree with each other about the underlying probabilities—and thus betting volumes depend on the odds. Again, we show that the odds generated by this model would imply positive estimates of z even if there were no insiders and that the factors that lead to higher bookmaker margins produce higher estimates of z.

Section 4 uses data from betting on soccer and tennis to provide empirical illustrations of how the z measure is highly correlated with the bookmakers' gross profit margins, as predicted by the theoretical models. We also show how both profit margins and z estimates are lower for higher-profile events. We propose alternative explanations to the presence of insiders for these findings. Section 5 provides a more general discussion of why inside information is unlikely to play an important role for the kinds of high-profile sporting events that dominate modern sports betting.

2. Estimating Insider Trading Using the Shin (1992) Model

Here we describe the theoretical model presented by Shin (1992) and the method developed by Cain, Law and Peel (1997, 2001) to produce event-specific estimates of the share of insider activity.

2.1. The Shin (1992) model

This model assumes there are N competitors in a sporting event in which only one can win. Competitor i has a probability p_i of winning. There is a continuum of bettors of size 1, each making equally sised bets, also normalised to 1. A fraction z of bettors are insiders who know which competitor is going to win. The remaining bettors are each certain that one of the competitors will win, with the fraction of these bettors believing competitor i will win equaling the actual probability p_i that it will win. The certainty of bettors means they do not consider the odds offered by the bookmaker other than not being wiling to lose money when their bet wins.

The bookmaker is a risk-neutral monopolist who incurs no costs other than paying out on bets. They know the probabilities p_i, so their expected profit is

$$E(\Pi) = 1 - \sum_{i=1}^{N} \left[z p_i O_i + (1-z) p_i^2 O_i \right] \tag{1}$$

where O_i is the decimal odds on the ith competitor, meaning someone who bets \$1 on competitor i receives back \$$O_i$ (inclusive of the original stake) if i wins. With all bettors willing to bet for any odds better greater than or equal to 1, the unconstrained profit maximizing odds would be $O_i = 1$ for all i. However, the model features a limit on the sum of the inverses of the odds, a value known in bookmaking circles as the "overround."

$$\sum_{i=1}^{N} \frac{1}{O_i} \leq \beta \tag{2}$$

This constraint could be interpreted in different ways. Shin (1992) describes it as a process by which potential bookmakers bid for a monopoly license and the body awarding the license (presumably some arm of government) gives it to the the bookmaker that submits the lowest value of β, thus providing the best value for bettors. An alternative interpretation is that the bookmaker is not a monopolist, competitive pressures set the value of β and once this value is set, each bookmaker obtains the same fraction of bets on each competitor.

Given the constraint, the bookmaker sets odds by optimizing the Lagrangian

$$L = 1 - \sum_{i=1}^{N} \left[z p_i O_i + (1-z) p_i^2 O_i \right] + \lambda \left(\beta - \sum_{i=1}^{n} \frac{1}{O_i} \right) \tag{3}$$

The first-order conditions are

$$\frac{\partial L}{\partial O_i} = -zp_i - (1-z)\,p_i^2 + \frac{\lambda}{O_i^2} = 0 \tag{4}$$

and that the constraint in equation 2 is binding. Optimal odds are

$$O_i = \sqrt{\frac{\lambda}{zp_i + (1-z)\,p_i^2}} \tag{5}$$

and the overround constraint means

$$\sum_{i=1}^{N} \frac{1}{O_i} = \sum_{i=1}^{N} \sqrt{\frac{zp_i + (1-z)\,p_i^2}{\lambda}} = \beta \tag{6}$$

This means we can solve for the square root of λ as

$$\sqrt{\lambda} = \frac{1}{\beta}\left(\sum_{i=1}^{N} \sqrt{zp_i + (1-z)\,p_i^2}\right) \tag{7}$$

and thus the optimal odds are given by

$$O_i = \frac{1}{\beta}\frac{\sum_{i=1}^{N} \sqrt{zp_i + (1-z)\,p_i^2}}{\sqrt{zp_i + (1-z)\,p_i^2}} \tag{8}$$

One can easily show that this formula implies a favourite-longshot bias. Average losses on longshots will be larger than for favourites and this bias will strengthen as z increases. This bias has been found for a wide range of different fixed-odds betting markets. For example, it has been reported for UK horse racing (Gabriel and Mardsen, 1990, Snowberg and Wolfers, 2010), US football and basketball (Berkowitz, Depken and Gandar, 2017, Moscowitz and Vasudevan, 2022), European soccer (Buhagiar, Cortis and Newell, 2018, Angelini and de Angelis, 2019, Hegarty and Whelan, 2023a) and tennis (Forrest and McHale, 2007, Lahvička, 2014).

So the model matches an aspect of the real-world data that has been documented for many types of fixed-odds betting. But does it provide an adequate description of the modern online sports betting industry? There are several ways in which it clearly does not.

Most importantly, the lack of any influence of the odds on the behavior of bettors means the model lacks a crucial feature that bookmakers need to consider when setting odds. That potential bettors are highly sensitive to odds can be seen in the popularity of special odds-boosting offers that bookmakers make in order to attract more business. Natural experiments such as the reform of betting tax in the UK in 2001 have also shown that the quantity of betting is closely linked to bettors' perceptions of the potential financial return. As described by Paton, Siegel and Vaughan Williams (2002, 2004), the UK's decision to abolish a "general betting duty" levied on all bettors as they placed their bets and replace it with a profit tax for bookmakers reduced the net loss rate from betting and led to a doubling in off-site betting activity over the next year.

Other devices in the model such as the externally-imposed overround condition and the devine coincidence of the fraction of people who believe competitor i is going to win exactly matching the probability that this competitor will win, are also questionable. The latter assumption could be justified as a form of "wisdom of crowds" assumption but, as we discuss below, this idea is perhaps best formulated in terms of the public understanding each contestant has a probability of winning and being relatively good on average at estimating this probability. Overall, this model seems unlikely to provide a useful description of how modern bookmakers set odds.

2.2. z estimates when profits are not zero

Empirical estimates of z have relied on an additional step beyond what we have just presented. Specifically, after the steps just outlined, Shin (1992) also assumed that bookmakers earned zero expected profits. Since the model assumed no non-payout costs, this meant that, on average, every dollar bookmakers take in from bettors is paid back in winnings. Inserting the odds in equation 8 into the profit function in equation 1 and setting profits equal to zero tells us that the overround constraint β in this case must equal

$$\beta = \left(\sum_{i=1}^{N} \sqrt{z p_i + (1-z) p_i^2} \right)^2 \tag{9}$$

so the odds become

$$O_i = \frac{1}{\sum_{i=1}^{N} \sqrt{z p_i + (1-z) p_i^2}} \frac{1}{\sqrt{z p_i + (1-z) p_i^2}} \tag{10}$$

Shin (1993) used Taylor series approximations of this odds formula to develop and implement a regression-based method for estimating the average value of z in a sample of sporting events.[3] However, Cain, Law and Peel (1997, 2001) showed that, under these assumptions, it is possible to calculate z separately for each event based solely on the odds. Their method works as follows.

With the additional assumption of zero profits, the Lagrangian multiplier becomes

$$\lambda = \frac{1}{\beta^2} \left(\sum_{i=1}^{N} \sqrt{z p_i + (1-z) p_i^2} \right)^2 = \frac{1}{\beta^2} \left(\frac{1}{\sum_{i=1}^{N} \frac{1}{O_i}} \right) = \frac{1}{\beta} \tag{11}$$

and β can be identified under the assumption that the overround constraint is binding. The first-

[3]This regression method was also used in other studies such as Vaughan Williams and Paton (1997).

order conditions for odds can now be written as a set of quadratic equations in p_i of the form

$$(1-z)\,p_i^2 + zp_i - \frac{1}{\beta O_i^2} = 0 \tag{12}$$

For each value of z, these equations have one positive solution for p_i and one negative solution, with the positive one being the relevant figure. The method guesses an initial value of z, then calculates the probabilities p_i from the positive solutions to the set of N quadratic equations described by 12. The N equations can then be summed and (using $\sum_{i=1}^{N} p_i = 1$) re-arranged to give

$$z = \frac{\frac{1}{\beta}\sum_{i=1}^{N}\frac{1}{O_i^2} - \sum_{i=1}^{N} p_i^2}{1 - \sum_{i=1}^{N} p_i^2} \tag{13}$$

This provides a new guess for z. The process is then repeated until the estimated z and p_i values have converged.[4]

A crucial aspect of these calculations is that the estimates of z they produce are dependent on the assumption of zero expected profits, meaning the average amounts taken in bets equals the average amount paid out to winners. However, the financial statements of real-world bookmakers show that this assumption is strongly counter-factual. For example, Flutter, the owner of well-known European bookmaker, Paddy Power, reported that the profit margin on bets (the fraction by which amounts paid out on winning bets was lower than the amount of bets taken in) for its "sportsbook" business in the UK and Ireland was 10.7% in 2022 and 11.8% in 2023.[5]

The assumption of zero profits may have been inspired by the idea that bookmaking is a competitive market but even with competition, there will be a need for bookmakers to make a profit even if it only provides them with a normal economic rate of return on their activities. Competition among bookmakers also often takes the form of heavy spending on advertising, as anyone who watches sports on TV these days will realize. Even just to cover these expenses and break even on net, bookmakers need to earn positive gross profits on the bets they take, invalidating the assumption that the average payouts will equal average amounts of bets placed.

To illustrate the role the counter-factual assumption of zero profits plays in affecting estimates of z, consider the case where this model applies but rather than there being zero profits, the overround

[4] In the special case of $N=2$, there is an analytical formula for z

$$z = \frac{\left(\frac{1}{O_1}+\frac{1}{O_2}-1\right)\left(\left(\frac{1}{O_1}+\frac{1}{O_2}\right)^2 - \frac{1}{O_1} - \frac{1}{O_2}\right)}{\left(\frac{1}{O_1}+\frac{1}{O_2}\right)\Bigg(\Bigg(\left(\frac{1}{O_1}-\frac{1}{O_2}\right)^2 - 1\Bigg)}$$

See Strumblej (2014).

[5] See page 95. https://www.flutter.com/media/a0rj0ng5/flutter-entertainment-plc-annual-report-and-accounts-2023-10-k_updated.pdf

constraint takes the form of competitive pressures placing a specific upper limit on the value of β. We applied the model to an event with two teams where the probability that the favourite wins ranges from 0.5 to 0.9, the true fraction of insiders varies from $z = 0$ to $z = 0.1$ and we used three different values of the overround constraint parameter, $\beta = 1.05$, $\beta = 1.07$ and $\beta = 1.09$.

Figure 1 shows the estimates of z that would be obtained from these cases using Cain, Law and Peel's method when the odds are set according to equation 8. The upper panel shows the values of z estimated when the constraint on the overround is $\beta = 1.05$, while the middle panel shows $\beta = 1.07$ and the bottom panel shows $\beta = 1.09$. These are realistic ranges for the overround in real-world fixed-odds betting given the evidence above from Flutter and the figures presented below for betting on soccer and tennis.

The blue lines show the estimates of z from the model when the true fraction of insiders equals zero. We see that for 50/50 tossup events, the estimate of the number of insiders precisely equals the overround constraint minus one (e.g. when $\beta = 1.05$, the z estimate is 0.05). Using the notation used in the previous section, this means $N = 2$, $p_1 = p_2 = 0.5$ and $O_1 = O_2 = \frac{2}{\beta}$. Inserting these into equation 13 gives $z = \beta - 1$.

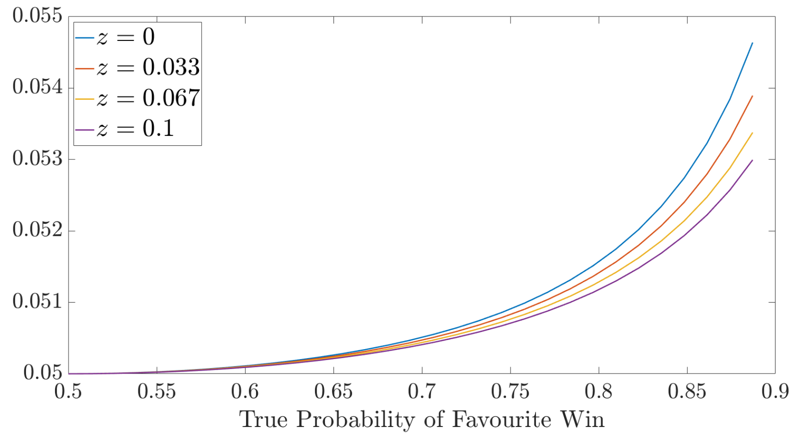
The rising blue lines then show the z estimates increase as the favourite becomes more likely to win the event. Perhaps surprisingly, the other colored lines in the charts show that the estimates of z will be slightly lower than when $z = 0$ even as the actual fraction of insiders rise. The estimated fraction of insiders may be higher or lower than the true figure depending on the overround constraint and the probability of the favourite winning but a robust pattern is that the higher the value of β is, the higher the estimate of z is.

This link between the size of the overround and the estimate of z is easily explained. If the overround is high, then the odds offered to normal bettors are relatively low. In the absence of insiders, these low odds would imply high profits for bookmakers. However, the calculation assumes the bookmaker earns zero profits so the model thus implies there is a lot of money placed by insiders that offsets the profits earned from non-insiders due to these low odds.

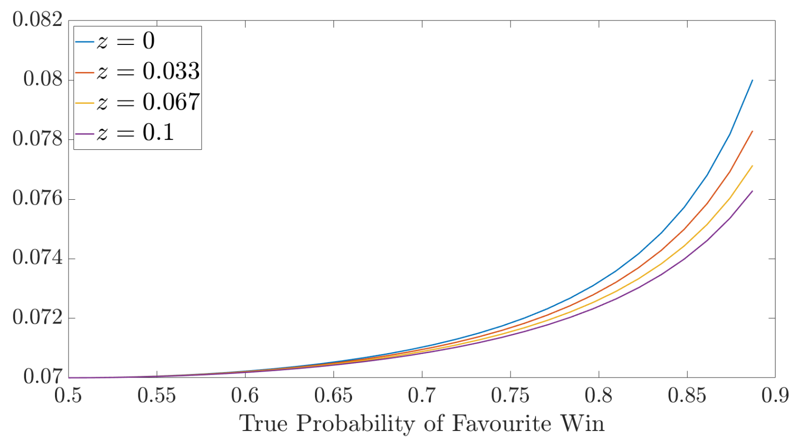
The key results here are that, even under the assumption that the Shin (1992) model is correct, loosening the zero profit assumption implies that Cain, Law and Peel's procedure will produce positive (and in some cases large) estimates of the fraction of insiders even when there are actually no insiders and that the higher the overround implied by the odds, the higher the estimated fraction of insiders will be. More generally, without the zero profit assumption, there is no clear relationship between the estimates generated by this procedure and the true fraction of insiders.

Figure 1: z calculated from the Shin (1992) model (using the Cain, Law and Peel method) with no insiders for a two-contestant event for various values of β and the probability of the favourite winning

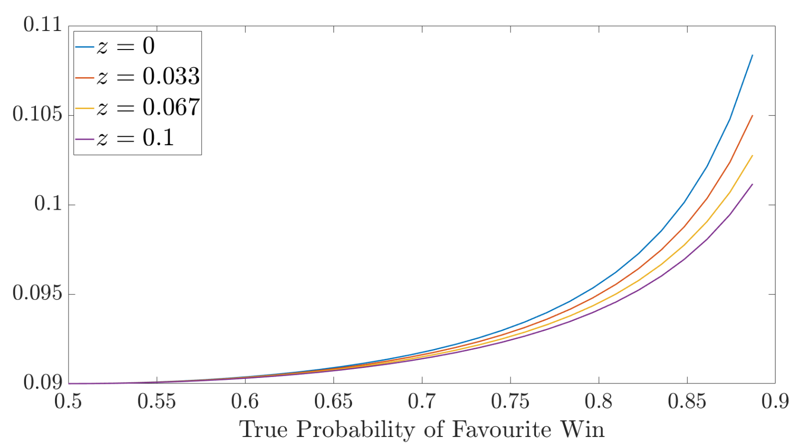
(a) $\beta = 1.05$



(b) $\beta = 1.07$



(c) $\beta = 1.09$



3. A More Realistic Model

A clear weakness of the model in the previous section is that potential bettors do not take into account the generosity of odds when considering whether to place a bet. They are certain their pick is going to win so they place this bet as long as the odds don't see them losing money. In reality, bookmakers are aware that offering higher odds on a bet will result in more people taking it up.

Here we present a model which is a generalization of the model in Shin (1991) which also features a monopoly bookmaker but in this case the bookmaker sets odds to maximise profits given their understanding of the demand for bets as a function of odds. This profit-maximising assumption runs counter to claims that are sometimes made that bookmakers set odds, not to maximise profits, but to lock in a guaranteed profit by making odds inversely proportional to volumes, thus ensuring the payout is identical no matter which competitor wins. However, the balance of evidence points against this book-balancing model.

To give some examples, Levitt (2004) presented evidence from a spread-betting competition for NFL games which was consistent with the bookmaker setting spreads to maximise profits rather than to guarantee a certain return. Strumpf (2003) analysed data on the operations of illegal New York bookmakers from documents made available in court proceedings to show the bookmakers were taking substantial positions on individual events and were operating to maximise profits. More recently, Flepp, Nüesch and Frank (2016) show that betting volumes for markets on under or over 2.5 goals to be scored in a soccer match were overwhelmingly placed on the over side, with bookmakers taking the risk that this entails.[6]

3.1. The Model

The model is as follows. There is an event with two teams where one of them will win. One of the teams is the favourite and has a probability $p \geq 0.5$ of winning; the other team we will term the longshot. The bookmaker knows the value of p and incurs an administrative cost of μ per bet. Rather than being constrained by a regulator, the bookmaker is assumed to set decimal odds of O_F on the favourite and O_L on the longshot to maximize their expected profits.

The total amount of wealth available to be placed as bets is normalised to 1. A fraction z of the wealth is held by bettors who are insiders who know the outcome of the event and always win their bets. The remaining wealth is held by a continuum of non-insiders of size 1 who can chose to bet or not. When they do bet, they bet one unit. These bettors disagree with each other about what the

[6]Less formally, there is evidence from interviews with bookmakers that they do not adopt the book-balancing model. Jay Kornegay, perhaps the most famous bookmaker in Las Vegas, is quoted in Miech (2019) as saying "*I think there's a little urban legend that's out there, that we just want to balance every game. In a perfect world, yeah. But in a perfect world, it just doesn't happen. You go through every single game today and probably none of them ... are balanced on both sides. That scenario right there, it just doesn't happen. I don't want to sound corny but it is somewhat of an art form. You're dissecting the money, you're dissecting the market, you're dissecting the betting patterns that we're seeing between the sharps and the general public. What we're trying to do is put ourselves in the best possible position to win, not necessarily balancing both sides.*"

probability p is, having subjective beliefs $\tilde{p}$ about p that are drawn independently from a uniform distribution on $[A, B]$. Shin (1991) assumed $A = 0$ and $B = 1$. Non-insiders are risk-neutral and only bet if they perceive the expected profit to be at least zero.

The condition for non-insiders to be willing to bet on the favourite is that their subjective expected payout on a one unit bet exceeds one

$$\tilde{p}O_F \geq 1 \Longrightarrow \tilde{p} \geq \frac{1}{O_F} \tag{14}$$

This generates a demand function for bets on the favourite from non-insiders of the form

$$D\left(O_F\right) = \begin{cases} 0 & \text{if } O_F < \frac{1}{B} \\ 1 - \frac{1}{B-A}\left[\frac{1}{O_F} - A\right] & \text{if } \frac{1}{B} \leq O_F \leq \frac{1}{A} \\ 1 & \text{if } O_F > \frac{1}{A} \end{cases} \tag{15}$$

Bets are placed after the bookmaker has set the odds, so the bookmaker is unable to use the information in betting volumes to adjust odds. However, the bookmaker is aware that a fraction z of wealth will be placed on the winner by insiders. Given these assumptions, the bookmaker's expected profit from taking bets on the favourite is

$$E\left(\Pi_F\right) = pz\left(1 - \mu - O_F\right) + (1 - z)\left[(1 - \mu) D\left(O_F\right) - pO_F\left(D\left(O_F\right)\right)\right] \tag{16}$$

The bookmaker sets odds to maximize the expected profit on each type of bet. Combining the demand for bets on the favourite with the expected profit equation (and assuming odds that generate non-insider demands between zero and one) the first-order condition for expected profit maximization is

$$\frac{\partial E\left(\Pi\right)}{\partial O_F} = -zp + (1 - z)(1 - \mu)\left(\frac{1}{B - A}\right)\frac{1}{O_F^2} - \frac{(1 - z)\,p}{B - A} = 0 \tag{17}$$

which solves to give

$$O_F = \sqrt{\frac{1 - \mu}{p\left(\frac{z(B-A)}{1-z} + B\right)}} \tag{18}$$

The bookmaker's problem for setting odds on the longshot is the same apart from the true probability being $1 - p$ instead of p and beliefs are drawn from a uniform distribution on $[1 - B, 1 - A]$ instead of $[A, B]$. The odds on the longshot are thus

$$O_L = \sqrt{\frac{1 - \mu}{(1 - p)\left(\frac{z(B-A)}{1-z} + 1 - A\right)}} \tag{19}$$

As discussed by Montone (2021) and Hegarty and Whelan (2023b), the economics of a monopoly bookmaker are similar to the standard economic theory of monopoly. The optimal odds for any bet equal the zero-profit odds that would be set in a perfectly competitive market multiplied by a "mark down" that depends negatively on the elasticity of demand for bets. If demand for bets is inelastic, then the optimal strategy is to offer relatively low odds. In this case, the odds on both the favourite and the longshot depend negatively on z because insiders are not sensitive to odds and so a higher z lowers the elasticity of demand. The odds on the favourite depend negatively on B, the subjective probability belief about the favourite winning of the bettor that is most optimistic about the favourite. As bettors become more optimistic about their pick winning, they are willing to accept lower odds. Similarly, the odds on the longshot depend negatively on $1 - A$, the subjective probability belief about the longshot winning of the bettor that is most optimistic about the longshot. This shows that bookmakers will manipulate odds to take advantage of biases in bettor's beliefs.[7]

3.2. Estimates of z from this model

Once we specify A, B, μ and z, we can obtain the odds generated by the model and thus use the Cain, Law and Peel method to generate estimates of the fraction of insiders that would be implied by these odds. The upper panel of Figure 2 shows the estimates of z produced for different values of the true z and for different values of p using Shin's (1991) assumption of $A = 0$ and $B = 1$. A value of $\mu = 0.02$ is used. For all values of the true z, the Cain, Law and Peel method produces high estimated values of z, all of which are larger than the true value. This occurs because the inaccurate beliefs of the public in this case allow the monopolist to set very low odds. The resulting large overround is interpreted through the prism of the Shin (1992) model as implying there must be a large amount of insider activity.

Shin's assumption of $A = 0$ and $B = 1$ is not very realistic. It means that beliefs about which team will win are essentially randomly assigned and unrelated to team's actual probabilities of winning. An alternative approach is to assume that non-insider beliefs are uniform on $[p - \sigma, p + \sigma]$. This approach, previously used by Hegarty and Whelan (2023a) and Whelan (2024), is a more attractive formulation of the "wisdom of crowds" idea than the one discussed above. The public are, on average, correct in their assumptions about the probability of the favourite winning but they disagree with other, with some people being too optimistic about the favourite and some being too

[7] This is also a feature of the model of Goto and Hamada (2023), though their model differs in having a monopolistically competitive structure rather than a monopolistic one. It also differs in deriving the demand for bets from an ad hoc demand function where demand is a function of the bettors' perceived ratio of the probability of winning to the odds-implied probability. In contrast, in our model, the demand for odds is based on risk-neutral bettors maximising their expected return.

pessimistic. It is worth noting that the ratio of favourite odds to longshot odds in this case is

$$\frac{O_F}{O_L} = \sqrt{\frac{(1-p)\left(\frac{2\sigma z}{1-z} + 1 - p + \sigma\right)}{p\left(\frac{2\sigma z}{1-z} + p + \sigma\right)}} \tag{20}$$

Even if $z = 0$, these odds exhibit a favourite-longshot bias such that the expected return on the favourite pO_F is greater than the expected return on longshots $(1-p)\,O_L$ with the size of the bias increasing in σ, which measures the extent of disagreement among bettors. Hegarty and Whelan (2023a) describe how this result emerges from the demand for bets on longshots having a lower elasticity of demand than bets on favourites.

The finding that odds can be biased even when the public's beliefs are on average correct seems to run counter to Levitt's (2004) model in which the bookmaker only sets a biased spread when the public's beliefs are biased. However, this result is specific to spread bets where the odds on each team are the same. In our case, if a bet is such that $p = 0.5$, so each side of the bet is equally likely to win, then unbiased beliefs would rule out favourite-longshot bias. However, the fact that fixed-odds betting generally involves competitors that are not seen as equally likely to win means disagreement among bettors allows bookmakers to set biased odds, even if the public's beliefs are unbiased on average.

These results shows that favorite-longshot bias can derived from models that do not rely on the assumption of insiders, which provides an additional argument against this assumption since the idea that insider information explains such bias is sometimes invoked as an argument in favour of models with this feature.

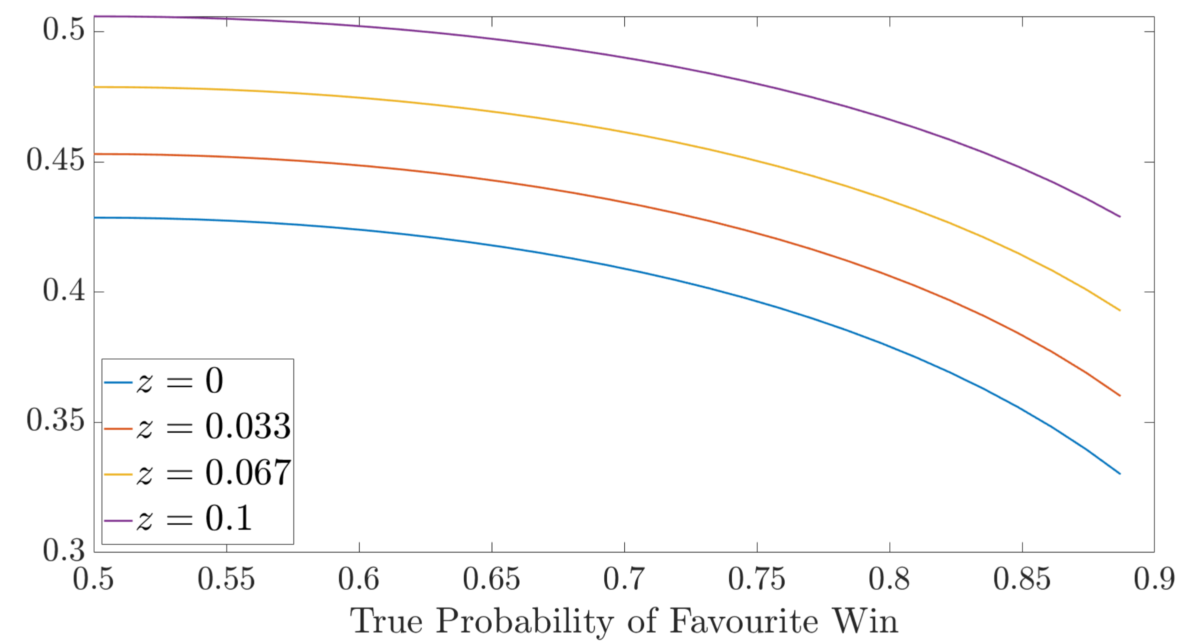
The lower panel in Figure 2 repeats the exercise of calculating the values of z implied by the odds generated by different values of the true z and for different values of p, this time with the assumption that non-insider beliefs are uniform on $[p-\sigma, p+\sigma]$ where $\sigma = 0.06$. One thing to note about this chart is that there are missing values. This is because we do not implement the estimation of z in the case where the optimal profits from maximizing equation 16 are negative. In this case, the optimal strategy for the bookmaker would be to choose not to enter the market. The amount of missing values rises with z because as the true fraction of insiders increases, it becomes less possible for the bookmaker to earn a profit and more likely that the market collapses. With this specification of beliefs, because non-insiders are much more sensitive to the odds offered, it becomes impossible to recoup the losses to insiders by setting bad odds for non-insiders once the fraction of insiders is sufficiently high.

Again, the odds generated by the model imply sizeable positive estimates of z, even when the true value is $z = 0$. In this case, the procedure reports higher values of z as the true fraction of insiders increases and, within the range shown here, it still over-states the true value of z.

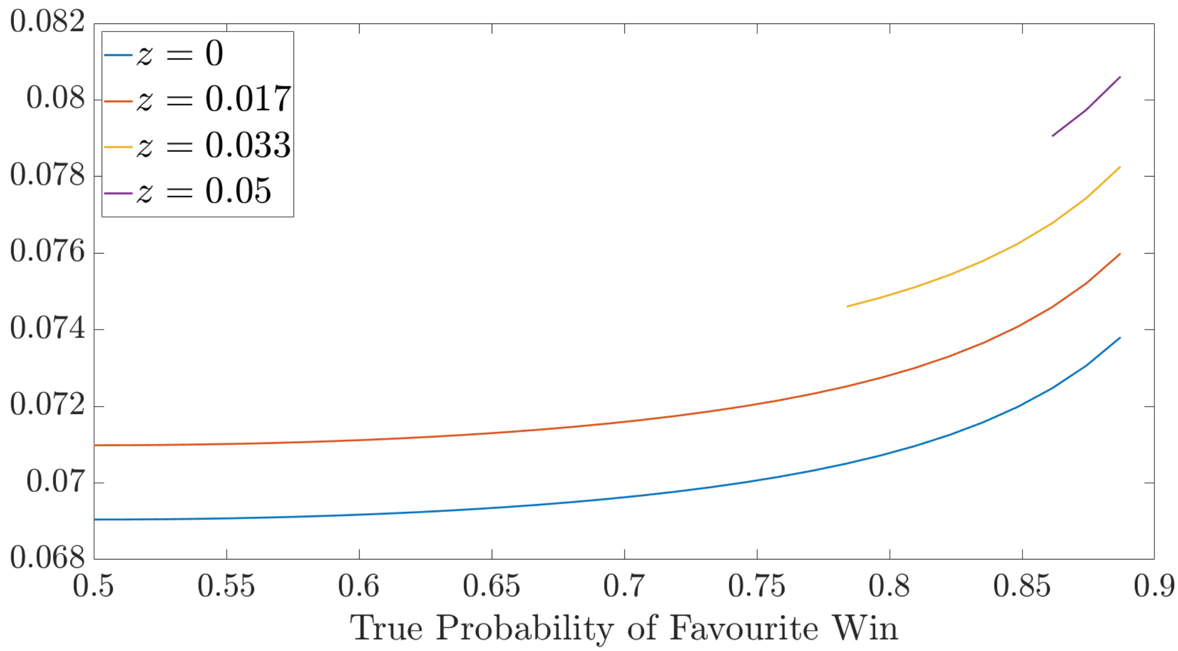
In this model, we again see that varying parameters in ways that raise the overround produces higher estimates of z. Overrounds rise with the cost parameter μ and with the parameter for the extent of disagreement among bettors σ. Higher values of σ raise the overround in this model by reducing the elasticity of demand. These calculations, based on arguably more realistic assumptions than the Shin (1992) model with a zero profit requirement, show that the z measure can conflate the presence of insiders with other factors driving bookmakers' margins.

Figure 2: Shin's z for various values of p and z as calculated for the Shin (1991) model with $\mu = 0.02$

(a) Non-insider beliefs are uniform on $(0, 1)$



(b) Non-insider beliefs are uniform on $(p - 0.06, p + 0.06)$



4. Empirical Evidence and Interpretation

Here we present empirical evidence on patterns for the event-specific z measure and argue that this evidence is best explained by other factors than the presence of insiders.

4.1. Evidence from tennis and soccer

The theoretical models just considered predict there is likely to be a strong correlation between empirical estimates of Shin's z and the overround. We check this prediction using two datasets made publicly available by gambling expert, Joseph Buchdahl. From www.football-data.co.uk, we have betting odds and outcomes on 84,230 European professional soccer matches, spanning the 2011/12 to 2021/22 seasons for 22 European soccer leagues across 11 different nations. The leagues covered are listed in an appendix. From www.tennis-data.co.uk, we have odds and outcomes for all 58,112 professional men's and women's matches played across the world on the ATP and WTA tours between 2011 and 2022. Our measure of betting odds is the average closing odds across the wide range of online bookmakers surveyed by Buchdahl.

For both datasets, we calculate match-by-match estimates of the overround and z (using the method outlined in Section 2.2). Figure 3 shows scatter plots for the z estimates and overrounds. The correlations are extremely strong: 0.99 for the soccer data and 0.97 for the tennis data.

This correlation between z estimates and overrounds is also visible in various other cross-sectional relationships. For example, Table 1 updates some results for overrounds previously presented for an earlier version of the tennis dataset by Lyócsaa and Fedorko (2014). It shows that overrounds are lower for Grand Slam tennis tournaments than for other tournaments and also that overrounds decline as a tournament progresses, with average overrounds of 5.55% for finals compared with 5.85% for first round matches. The table shows that these patterns are matched by variations in the estimated values of z.

Similar patterns can be seen for the soccer dataset. Table 2 reports average overrounds and z estimates for each of the 22 leagues in our dataset. Again, the variations in the average estimates of z match with variations in the overround. For the six countries with multiple leagues in the dataset, overrounds and z estimates consistently rise as you go down the "football pyramid" to lower leagues featuring weaker teams. Across countries, the English Premier League, the highest profile league in the world, has the lowest average overrounds and z estimates, followed by the top leagues in Spain, Germany, Italy and France, the other leagues that receive the most attention.

4.2. Alternative interpretations

The presence of insiders is one possible explanation for these patterns. It may be easier to source inside information for lower-profile events than for high-profile events where the stakes are high and in which the competitors are well known and receive a lot of press coverage. However, the z estimates here are consistently high enough that they would likely lead to the collapse of betting markets if non-insiders had realistic beliefs as in the model in Section 3.

There are also other reasonable explanations for the patterns in the observed overrounds (which lead to similar patterns for z estimates). In models with realistic bettor beliefs and no insiders, we have seen that overrounds can be driven by non-payout costs for bookmakers (modeled here via the μ parameter), by positive economic profit requirements and by bookmakers taking advantage of disagreement among bettors.

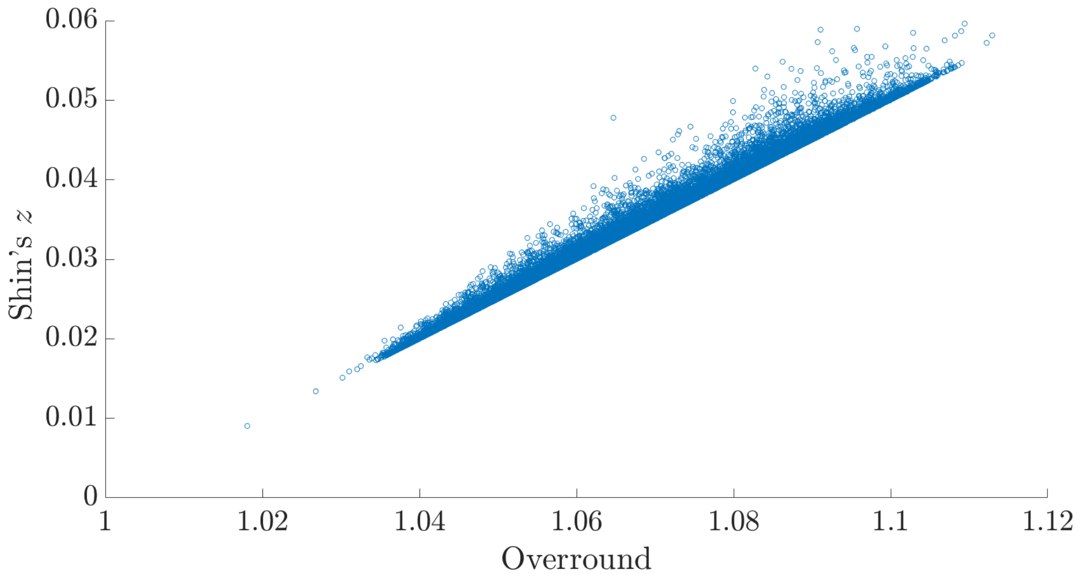
From this perspective, there are some obvious explanations, unrelated to inside information, for the lower overrounds for higher profile events. For example, research costs per dollar taken in bets placed are likely to be lower for high-profile matches. Modeling probabilities of potential outcomes from high-profile English Premier League soccer matches isn't necessarily more complex than doing the same for lower league matches but the quantity taken in bets will be much higher for the English Premier League match. This can be modeled as the cost-per-dollar-bet μ parameter being lower for high-profile events, implying lower overrounds. There may also be less disagreement among bettors about the relative merits of well-known competitors in high profile events, implying lower values of the σ parameter which again implies lower overrounds and lower estimates of z.

It also seems likely that competition between bookmakers will be more intense for high-volume matches than ones with more obscure participants and lower betting volumes: It may be worth trading off a small amount of the profit margin per bet for a larger slice of the betting on a high volume event. Also, if bookmakers are risk averse, they may have have less certainty about their modeling of lower-profile events where less information is available about the participants and may add a "risk premium" element to their pricing to protect themselves against their probability estimates being incorrect.

These factors all point to there being lower margins for high profile events, without needing to appeal to inside information as an explanation.

Figure 3: Shin's z estimates and overrounds for the soccer and tennis datasets

(a) Soccer



(b) Tennis

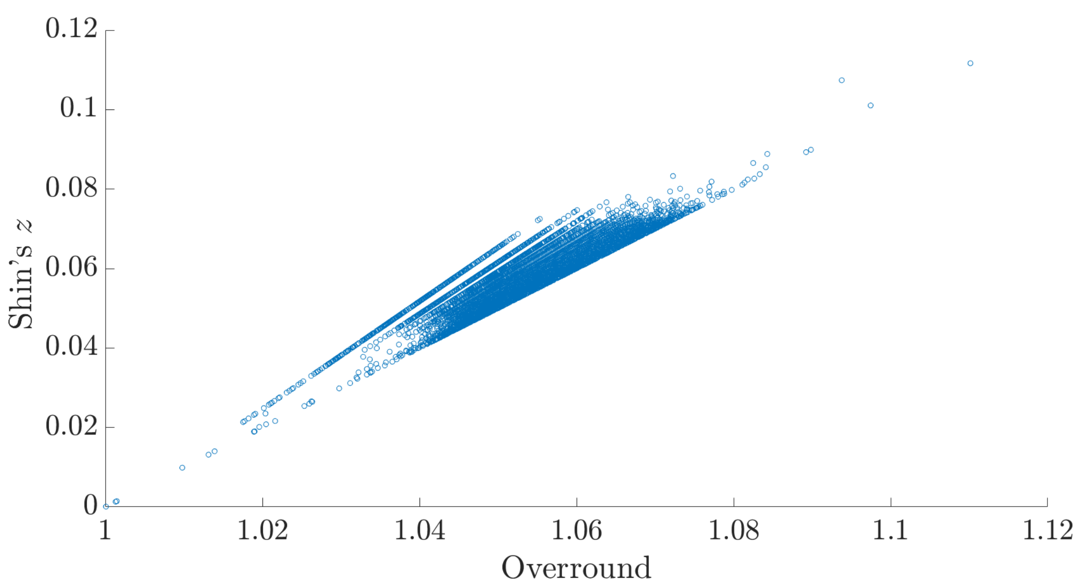


Table 1: Average overrounds and Shin's z for Tennis Betting

	Overround	**Shin's z**	N
All Matches	1.0576	0.0589	55,988
By Event Type			
Grand Slam	1.0538	0.0563	6,207
Non Grand Slam	1.0581	0.0593	49,781
By Event Round			
First	1.0585	0.0597	25,731
Second	1.0579	0.0594	15,578
Third	1.0554	0.0571	3,901
Quarter-Final	1.0569	0.0580	5,311
Semi-Final	1.0559	0.0569	2,709
Final	1.0555	0.0563	1,350

Table 2: Average overrounds and Shin's z for European Soccer Leagues

	Overround	**Shin's z**	N
All Matches	0.0692	0.0349	84,230
By League			
Belgian First Division	1.0724	0.0366	2,754
German First Division	1.0531	0.0268	3,349
German Second Division	1.0701	0.0352	3,357
English Premier League	1.0481	0.0243	4,152
English Championship	1.0607	0.0304	6,060
English League 1	1.0695	0.0349	5,907
English League 2	1.0709	0.0355	5,946
English Conference	1.0840	0.0423	5,799
France Ligue 1	1.0582	0.0293	4,055
France Ligue 2	1.0748	0.0375	4,059
Greece Super League	1.0816	0.0416	2,733
Italy Serie A	1.0543	0.0274	4,170
Italy Serie B	1.0780	0.0391	4,708
Netherlands Eredivisie	1.0671	0.0341	3,625
Portugal Primeira Liga	1.0696	0.0354	3,157
Scotland Premier League	1.0689	0.0349	2,453
Scotland Championship	1.0860	0.0435	1,885
Scotland League 1	1.0916	0.0462	1,864
Scotland League 2	1.0931	0.0470	1,860
Spain La Liga	1.0531	0.0269	4,143
Spain La Liga 2	1.0773	0.0388	5,024
Turkey Super Lig	1.0719	0.0362	3,350

4.3. Rate of return for potential insiders

In assessing the potential role of insiders, it is also worth thinking about the returns they would earn. Someone who won every single bet in our soccer dataset would earn an average return of 176% on their bets which would be extraordinary. To give a concrete example, at this return, someone who placed an original bet of $1 and then re-invested the proceeds would have over $1.3 million dollars after 25 bets.

It is possible, however, to re-interpret the model with a less extreme version about the informational advantage of insiders. Fingleton and Waldron (1996) observed that observationally equivalent versions of Shin's models would have a fraction Mz of bets are placed by bettors who are randomly correct about the outcome one-Mth of the time and the rest of the time have the same randomly-distributed beliefs as non-insiders. In other words, the insiders may be people who guess the correct outcome more often than other bettors rather than people who always know the outcome. Under this interpretation, z represents the amount of money placed by the more informed bettors who are, in this case, correct in their assessment.

How would bettors with this weaker informational advantage perform? The average return across all bets in the soccer dataset is -7.8%. In contrast, someone who randomly won one-fifth of their bets and then picked their bets randomly the other four-fifths of the time would have earned an average return per bet of about 30%. Even a gambler who won one-tenth of their bets and picked the other bets at random would have earned an average return per bet of about 11%, which would be sufficient to generate huge cumulative returns over a relatively short space of time. And with an average estimated z for the soccer dataset of 0.035, would imply that 35% of the money being placed is from bettors with this kind of advantage.

In reality, there is no evidence that even the most successful professional bettors make anything like these high average returns. The most famous gambler in the world, Tony "The Lizard" Bloom, runs the secretive firm StarLizard which takes money from millionaires to bet on sports based on complex statistical algorithms. Reports suggest that StarLizard bet heavily on soccer and look to make average profit margins of 1% to 3% on their bets.[8] If insider information was widely available, one might imagine Bloom's firm would have resources to obtain it and use it to earn higher returns.[9]

A final possible interpretation of an average estimate of $z = 0.035$, could be that for each event 3.5% of all bettors are randomly selected to be given a sure-fire tip. However, in this case, the average return across all bettors in the soccer data would be -1.4%. This value is inconsistent with the large gross margins reported in the accounting statements of real world bookmakers, such as those reported by Flutter mentioned earlier.

[8] See this story by Business Insider https://www.thejournal.ie/tony-bloom-starlizard-2597458-Feb2016/

[9] Like most professional bettors, Bloom's company bets on soccer in the Asian Handicap market, which has lower margins than the home/away/draw betting market that we have used here. This mean his firm's win rates would be lower than what is needed to make the corresponding returns on the markets we have examined.

5. Some Additional Skepticism About Insiders

Going beyond the theoretical frameworks presented so far, there are a number of additional reasons to be skeptical about the idea of inside information playing an important role in betting on most modern sporting events. Shin's research on this topic was published at a time when horse racing dominated betting in the UK and he noted that his models were partly inspired by Crafts's (1985) description of inside information in horse racing. Crafts described how many of the staff involved in training horses were poorly paid and used gambling as a way to top up their salary, with inside information about horses that had never competed before or were returning from injury providing particularly good opportunities for these staff to have useful information.

While some of these elements may still apply to horse racing, this sport no longer dominates fixed-odds betting around the world. UK data show that betting on horses has accounted for only 35% of online betting in recent years and horse racing plays only a small role in the emerging US online fixed-odds betting market.[10] Instead, the vast majority of money in modern online betting markets is being placed on events where the form of the competitors can be well evaluated using publicly-available information.

As noted above, another source of inside information is corruption. This may take the form of competitors taking money from gamblers, bookmakers or opponents to deliberately lose or match officials being bribed to favor one of the teams. Corruption of this kind has been sometimes been explicitly uncovered, with two modern examples in Italian soccer being the *Calciopoli* scandal involving referees and the *Scommessopoli* scandal involving players (see Boeri and Severgnini, 2011). However, the stakes for competitors in the high-profile events that attract most of the volume in modern betting are extremely high and the career consequences associated with being caught taking bribes from gamblers are severe. This makes it unlikely that this kind of corruption is commonplace in today's high-profile sports. Even if this kind of corrupt activity takes place occasionally, bookmakers are unlikely to be factoring in a reasonable chance of this possibility into their odds on every event in these major sports.

There have also been various studies that document corruption in sports indirectly by spotting patterns indicative of one of the competitors not trying to win, e.g. Duggan and Levitt's (2002) study of sumo wrestling and Elaad, Krumer and Kantor's (2018) evidence that these patterns are more likely for soccer games in countries with poor reputations for corruption. However, if these patterns are systematic, then one may not need inside information to predict them.

The models presented here also probably over-state the threat to bookmakers from inside information. They assume that odds are set prior to bets being placed and so bookmakers cannot adjust their odds in response to betting patterns. In practice, bookmakers are aware their models may not be perfect and that some people have better knowledge than them. For this reason, bookmakers use

[10] https://www.gamblingcommission.gov.k/statistics-and-research/publication/industry-statistics-july-2022-revision

betting patterns to revise their odds. Ed Miller and Matthew Davidow's (2023) book *Interception: The Secrets of Modern Sports Betting*, describes how bookmakers place restrictions on betting volumes during the early "price discovery" stage of setting odds, thus restricting potential losses due to posting odds based on inaccurate probabilities and using the information from bets accepted to adjust odds.

Modern online bookmakers also profile their customers in ways that limit damage from those with superior information. Most online bookmakers discourage those who are consistently successful in their betting, placing stake limits on them or banning them altogether.[11] This makes it difficult for bettors with superior judgment or information to benefit by placing bets. In contrast, the so-called "sharp" bookmakers such as Pinnacle do not discourage successful bettors but they also profile customers and bets placed by those who have a record of being successful are more likely to move odds than those from regular bettors. These practices substantially reduce the risk to bookmakers due to bettors having superior knowledge. Of course, those who have superior knowledge can attempt to beat these profiling practices by funneling their bets through new accounts but the reality for anyone with superior information is that making money from bookmakers is far more complex than the models discussed here imply.

Another modern development that has likely diminished the importance of insider information in fixed odds bookmaking markets is the rise of betting exchanges, such as BetFair, where people agree bilateral bets without having a bookmaker set odds. For those with superior information, exchanges are likely to provide a more practical option than placing bets with bookmakers who carefully monitor performance to exclude serial winners. Exchanges will also allow informed bettors to explicitly "short" a competitor which cannot be done with fixed-odds bookmakers. Papers such as Smith, Paton, and Vaughan Williams (2009) and Franck, Verbeek, and Nüesch (2010, 2013) show that odds in betting exchange markets are more informative in predicting game outcomes than bookmakers' odds. This may reflect the greater presence of informed bettors in these markets.

6. Conclusions

Several studies have concluded that insiders played an important role in sports betting markets because they used a measure of the presence of insiders suggested by the Shin (1992) model. However, this measure relies on the counterfactual assumption that bookmakers on average pay out all the money placed with them as bets. If the Shin (1992) model is correct but bookmakers make profits on their betting books, then this measure overstates the fraction of insiders. It can also mis-measure the fraction of insiders if the world is described by more realistic models where bettors are sensitive to betting odds, such as the generalised version of the Shin (1991) model presented here. In practice, this measure of the fraction of insiders varies very closely with the standard measure of the bookmaker's gross profit margin on an event. These margins can vary for lots of reasons that are unrelated

[11] See Davies (2022a, 2022b) for a description of how bookmakers profile and restrict bettors.

to the presence of insiders but the event-specific measures that have been used in this literature will attribute all of this variation to insiders.

None of these arguments imply that there aren't smart bettors who may, at certain times, have a better understanding of the probabilities than bookmakers. However, bookmakers are generally careful with how they set opening odds. They often place limits on the amounts that can be placed in early betting and use the information from betting patterns to adjust odds in line with the information gleaned from these patterns. There is at best weak theoretical or empirical justification for the idea that there are a group of people that have a systematically better understanding of event probabilities than bookmakers once closing odds have been posted.

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