Returns on Complex Bets: Evidence From Asian Handicap Betting on Soccer

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Abstract

The Asian Handicap is a way to bet on soccer matches where payouts depend on an adjustment to the score that favors the weaker team. These bets can can feature the possibility of all or half the bet being refunded and this makes the calculation of their expected return more complex than for traditional betting on a home win, away win or draw. We show that bettors systematically lose more money on Asian Handicap bets where refunds are not possible than when it is possible to obtain a half refund. We also show that bets with the possibility of a full refund have the lowest loss rates. We demonstrate that this pattern of differences in loss rates across bets is predictable based on the odds quoted. This pattern could represent preferences, with gamblers disliking bets featuring potential refunds, but we argue the evidence points more towards gamblers incorrectly calculating expected loss rates.

Keywords: Betting Markets, Asian Handicap, Pricing Complexity

JEL Classification: G13, G41, L83

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1. Introduction

Sports betting markets offer a convenient example for considering how markets price assets with state-contingent payoffs. The amounts of money at stake are often large, the number of potential outcomes for bets is limited and data on both pre-event odds and the subsequent payoffs are easily available. As with the literature on pricing financial assets, various studies have found examples of where the pricing of bets is inconsistent with their apparent fundamental value. For example, the well-known pattern of favorite-longshot bias—meaning bets on favorites lose less than bets on longshots—has been noted in various studies ever since Griffith (1949).[1] But other biases have been detected. For example, Cashmore et al (2022) report that betting odds on horse racing systematically understate the probability of success of female jockeys.

In this paper, we report an interesting pattern from a sports betting market that has emerged in recent years—the Asian Handicap market for betting on soccer.[2] Originally popular in Asia, this type of betting has become more prominent around the world over the past 20 years. Unlike traditional soccer betting where bets are made on whether a team will win, lose or draw, the payouts from Asian Handicap bets depend on an adjustment of the match result that applies a deduction (known as a handicap) to the goals total of the team considered more likely to win. For example, if Manchester City play Everton at home and the Asian Handicap is quoted at -2 (meaning a two goal deduction is applied to City's score) then a bet on Everton would pay out even if they lost the game by one goal. If the result precisely matches the handicap (in the above example, City beat Everton by two goals) then all bets are refunded. If the handicap is -1.5, then one or other of the bets wins and refunds do not occur. The market also offers bets where money is split equally between bets with possible refunds and bets without, so a refund of half the money is possible. One reason this type of betting is popular is that it generally takes away the option of betting on a draw, which tends to be unpopular in normal betting markets, perhaps because some people prefer the idea of backing one of the teams instead of hoping neither team wins.[3]

There are a number of reasons why it is interesting to examine the pricing of Asian Handicap bets. Most of the volume in this market is placed with specialist online bookmakers who have low profit margins per bet and offset this by taking high betting volumes. This market's low margins have made it particularly attractive for professional gamblers and betting syndicates. These so-called "sharp" bookmakers are generally happy to take bets from well-informed bettors and use these bets to adjust their odds. In contrast, traditional "high street" bookmakers tend to discourage (and even

[1] Snowberg and Wolfers (2008) survey the literature recording this bias in pari-mutuel racetrack betting. Forrest and McHale document the same effect for betting on tennis.

[2] The term Asian handicap was coined by journalist Joseph Saumarez Smith in the early 2000s when he was asked to give an English translation to describe a new type of betting he had encountered while visiting Indonesia.

[3] For example, Ötting et al (2023) show that, for in-match betting, even when draws are the most likely outcome they still attract only a minority of bets.

ban) informed bettors who they think may be able to make profits.[4]

A market in which money is wagered by well-informed gamblers seems more likely to set odds that fully reflect the value of bets. However, Asian Handicap bets are more complex than traditional bets on soccer for a number of reasons. They have three possible outcomes (win, lose or refund) whereas traditional bets have two. Also, they require bettors to assess the likely goal difference in the match rather than just the probabilities of a home win, away win or draw. We illustrate this greater complexity by showing that calculating the expected return from betting on a match is more complex for Asian handicap bets involving refunds than for traditional win/lose bets. There is theoretical and empirical research that points to the difficulties that people have making good decisions when faced with complexity in the pricing of products.[5] This provides a possible counter-argument for Asian Handicap bets being efficiently priced.

There has been limited empirical research on Asian Handicap betting but two previous studies have suggested potential inefficiencies in this market. Grant et al (2018) noted that there appeared to be arbitrage opportunities from taking simultaneous positions in Asian Handicap betting and in bets on Home/Away/Draw outcomes offered by traditional bookmakers. Constantinou (2022) provided an example of a betting strategy driven by a Bayesian network model of team strength could generate profitable returns on Asian Handicap bets.

Our paper documents a simpler and perhaps starker potential inefficiency: Using two large datasets of betting odds and outcomes for European soccer matches, we document that average loss rates differ systematically across the four different types of Asian Handicap bets (with handicaps that are an integer, or include a quarter goal, half goal, three-quarters goal). Bettors systematically lose more money on the type of Asian Handicap bets with no refunds than they do when they can obtain a half refund and bets with the option of a full refund have the lowest loss rates. While we do not report any violations of what Thaler and Ziemba (1988) termed "strong market efficiency" (meaning it is impossible to earn profits), our finding does contradict their definition of "weak market efficiency" which requires the expected returns on all available options in a contest to be equal.

We demonstrate our finding using two large datasets. The first dataset contains information on average Asian Handicap odds across bookmakers for one specific value of the handicap for each match while the second dataset contains multiple simultaneous handicaps and odds for each match from the same bookmaker. We present a method for estimating the ex ante expected loss on bets and show that these measures accurately predict the realized disparity in loss rates across the bet types. In other words, the variation in loss rates across bet types is predictable based on information available before matches are played.

[4]Davies (2022) documents the practices of customer profiling and stake restrictions by retail European bookmakers.

[5]See Carlin (2009) for a theoretical argument. Kalayci (2015) provides experimental evidence. Papers on difficulties that people face making in valuing products due to pricing complexity include Agarwal, Ben-David and Yao (2015) on mortgages, McElvaney, Lunn and McGowan (2018) on car finance and Lunn and Bohacek (2017) on electricity pricing.

The difference in loss rates stems from the average odds being the same across different types of bets, whether they offer the possibility of a refund or not. Because refunds don't involve losses, equating expected returns across bet types would involve offering lower winning odds for bets with potential refunds. However, we show that bookmakers do not do this. So why haven't bettors reacted to the differences in loss rates across handicap types by refusing to wager on bet types with higher loss rates until their odds are improved? One possible explanation is that bettors have a preference for a definite outcome and thus need less incentive to place bets without a refund. By this mechanism, the odds set by bookmakers reflect the preferences of bettors. Alternatively, bettors may be incorrectly using the traditional calculation of the expected loss rate on a bet, based on the "overround" or "vig"—the sum of the inverses of the potential payout odds—to calculate the expected loss for bets involving refunds. This approach would over-state the expected loss rates for bets featuring potential refunds. We argue that this second explanation is the more likely one.

The paper is structured as follows. Section 2 describes how Asian Handicap betting works. Sections 3 and 4 present our findings for the two different data sets. Section 5 shows the variation in loss rates across bet types is predictable based on the betting odds offered. Section 6 discusses explanations for our findings. Section 7 shows that, once bookmakers' profit margins are taken as given, Asian Handicap odds are efficient and do not exhibit the favorite-longshot bias that is evident for bets on whether a soccer match ends with a home win, away win or draw. Section 8 concludes.

2. How Asian Handicap Betting Works

The Asian Handicap market features bets with handicaps that change in increments of 0.25 goals. Obviously, teams can't score a quarter of a goal, so bets at quarter-goal handicaps are actually "hybrids" in which money is split between bets at other handicaps. We will explain how this type of betting works by illustrating the case in which a stronger team has four different possible handicaps applied to it—0.75, 1, 1.25 and 1.5. The market quotes decimal odds, so odds of O_S on the strong team mean this is the full payout on a successful bet inclusive of the original $1 stake. We denote odds on the bet on the weak team as O_W.

Consider first the case in which the Asian handicap is 1.5. In this case, there are only two possible outcomes:

- The stronger team wins by 2 or more. In this case, the bet on the stronger team pays out O_S and the bet on weaker team loses in full.
- The stronger fails to win by 2 or more. In this case, the bet on the weaker team pays out O_W and the bet on stronger team loses in full.

For the case in which the Asian handicap is 1, there are three possible outcomes

- The stronger team wins by 2 or more. In this case, the bet on the stronger team pays out O_S and the bet on weaker team loses in full.
- The stronger team wins by 1. In this case, bets on both teams are refunded.
- The stronger team fails to win. In this case, the bet on the weaker team pays out O_W and the bet on stronger team loses in full.

Bets with an Asian handicap of 1.25 place half the money on a bet with a handicap of 1 and the other half on a bet with a handicap of 1.5. Here, there are three possible outcomes:

- The stronger team wins by 2 or more. In this case, both halves of the bet on the stronger team are successful and there is a pay out O_S while the bet in the weaker team loses in full.
- The stronger team wins by 1. In this case, the half-bet on the stronger team with the handicap of 1.5 loses and the half-bet on the weaker team wins $\frac{O_W}{2}$. The half bets on both teams with the handicap of one are refunded.
- The stronger team fails to win. In this case the bet on the stronger team is lost and the bet on the weaker team pays out O_W.

The final example is an Asian handicap is 0.75. This puts half the money on a bet with a handicap of 1 and the other half on a bet with a handicap of 0.5. There are again three possible outcomes

- The stronger team wins by 2 or more. In this case, both halves of the bet on the stronger team are successful and there is a full pay out O_S while the bet on the weaker team loses in full.
- The stronger team wins by 1. In this case, the half-bet on the stronger team with the handicap of 1 gives a refund and the half-bet on the stronger team at 0.5 pays out $\frac{O_S}{2}$. The half bets on weaker team at 1 gives a refund and the half bet on the stronger team at 0.5 loses.
- The stronger team fails to win. In this case, the bet on the stronger team is lost and the bet on the weaker team pays out O_W.

All bets in the Asian Handicap market work in a similar fashion to these four cases, with handicaps that are either integers or else numbers ending in .25, .5 or .75.

It is worth emphasizing that, despite some obvious similarities, the Asian Handicap market differs from spread betting markets on US sports along a couple of dimensions that are important for the question we are examining. First, refunds (or "pushes" as they are sometimes called in US sports betting) rarely occur for bets on high scoring US sports such as basketball and American football because the chance of any specific numeric score difference being the outcome is low. In contrast, because soccer is a low-scoring sport, refunds are common in Asian Handicap betting. In our datasets, refunds occur about 28 percent of the time for those bets where refunds are possible.

Second, spread bets offered on high scoring sports are generally set to equate the odds for each side of the bet. This is not the case with Asian Handicap bets, for several reasons. Handicaps are only set in quarter-goal increments and these will rarely correspond precisely to the market's expected goal difference. This means bettors will generally think a bet on one of the teams in a match is more likely to win than the other, which will be reflected in differing odds. The mechanism of odds adjustment also tends to differ between these markets. With US spread bets, bookmakers normally react to new information by adjusting the handicap while leaving the odds fixed. However, because soccer is low scoring and the Asian Handicap is set to the nearest quarter of a goal, Asian Handicap bookmakers normally adjust the odds and leave the handicap fixed.

Finally, the hybrid quarter-point handicap bets have the feature that one side of the bet earns a profit in two of the three possible outcomes while the other side only makes a profit in one of the three outcomes. For both sides of such bets to be equally attractive, the expected payouts must be the same. This compensation can occur via bets that only make a profit in one outcome tending to have a higher probability of a full payout and so this also contributes to opposing sides of bets having different chances of success.

3. The Football-Data Dataset

Our first dataset comes from www.football-data.co.uk, a website maintained by gambling expert and author, Joseph Buchdahl. The dataset has information on outcomes and odds for Asian Handicap betting markets for 84,230 matches spanning the 2011/12 to 2021/22 seasons for 22 prominent leagues of European soccer across 11 different nations as described in Table 1. Our data on betting odds are the average closing odds (posted just before kickoff) across the various online bookmakers surveyed by Buchdahl.[6] For Asian Handicap betting, it is possible to find different handicaps quoted for the same match but this source lists only one handicap, generally the one that is offered by the most bookmakers, and it reports the average odds associated with that handicap.[7]

Table 2 presents our main finding. It reports the average realized loss rate that would be obtained from betting an equal amount on all bets offered, sorted by whether the handicap ends in an integer or with .25, or .5 or .75. The table shows average loss rates of 4.16% for bets with half goal handicaps, loss rates of 3.61% and 3.57% respectively for the hybrid bets with handicaps ending in .25 and .75

[6] From the 2019/2020 season onwards, the odds data come from the sample of providers available at www.oddsportal.com. For previous seasons, the sample was made up of those providers listed on www.betbrain.com.

[7] In personal communication, the compiler of the data set, Joseph Buchdahl informed us "The one I select is a combination of two methods ... closest to 50-50 and with the most contributing bookmakers. Usually both criteria apply together, but sometimes if the line with the most bookmakers is far from 50-50, I will choose the one closest to 50-50."

and a lower average loss rate of 3.24% for bets with integer handicaps. These losses reflect variations in bookmakers' margins (also called commission or "vig") but we note that the numbers here represent realized ex post loss rates, whereas margins or "vig" are typically calculated using the ex ante odds (we will return to ex ante expected loss calculations in Section 5).

The second row of the table reports the average decimal odds offered for each type of bet. These are all just over 1.92. The similarity of the average odds accounts for the differences in loss rates. Odds of 1.92 mean when both sides of the bet gamble $1 and one of them wins, the bookmakers pays out $1.92 of the $2 dollars that have been staked, implying an average loss rate of 4%. This explains the average loss rate for bets with half goal handicaps because they have no refunds. For bets with integer handicaps, there is the possibility of earning a full refunds, which reduces the average loss rate. For the hybrid bets with handicaps ending in .25 and .75, obtaining half-refunds reduce loss rates but not as much.

Unsurprisingly, given the large sample sizes, these differences are statistically significant. Table 3 reports t tests for equality of means and shows that the differences in average loss rates across handicap type are highly statistically significant while Table 4 reports the results from a regression of the average realized loss for each match on dummies for handicap type. Specifically, we estimated the following specification

$$R_{i,j,k,q} = \alpha_1 + \sum_{i=2}^{22} \alpha_j L_j + \sum_{k=2}^{11} \alpha_k S_k + \sum_{q=2}^{4} \delta_q H_q + u_{i,j,k,q} \quad (1)$$

where $R_{i,j,k,q}$ represents the average loss rate from betting the same amount on each team in game i from league j during season k with handicap type q. The base case corresponding to the intercept is a bet on an integer handicap in the Belgium Pro league in the 2011/2012 season.[8] The significant coefficients on the handicap type show that the results for means reported in Table 2 are not driven by composition bias relating to variations in loss rates across leagues or seasons.

Table 5 shows that the pattern reported here has been stable over time. For each season, the integer handicap bets have had the lowest loss rates and bets with half goal handicaps have had the highest loss rate. In Appendix A, we also show that these results are widely replicated at the individual league level. Table A.1 shows the finding of highest loss rates being for the .5 handicap holds for 20 of the 22 leagues in the dataset. Of the two that do not show the .5 handicap as the highest loss rate (Netherlands and Scotland) there is no clear alternative pattern of loss rate rankings. The finding of the integer handicap bet having the lowest loss rate is not quite as frequently reported but this is still the lowest loss rate in 14 of the 22 leagues. Table A.2 shows that differences in average odds across handicap types are also very small at the league level.

[8] Often in the empirical literature on sports betting, regressions of this form include multiple bets for each match and the correlations between errors in the same match require clustering at the match level. In this case, however, each match

Table 1: Description of the 22 football leagues included in the "Football-Data" dataset

Nation	Number of Divisions	Division(s)
England	5	Premier League, Championship, League 1 & 2, Conference
Scotland	4	Premier League, Championship, League 1 & 2
Germany	2	Bundesliga 1 & 2
Spain	2	La Liga 1 & 2
Italy	2	Serie A & B
France	2	Ligue 1 & 2
Belgium	1	First Division A
Greece	1	Super League Greece 1
Netherlands	1	Eredivisie
Portugal	1	Primeira Liga
Turkey	1	Super Lig

Table 2: Average loss rates from placing an equal amount on all bets, by Asian Handicap type

	Handicap Type			
	Integer	Ending .25	Ending .5	Ending .75
	Mean	Mean	Mean	Mean
Loss Rate	0.0324	0.0361	0.0416	0.0357
Odds	1.9240	1.9241	1.9226	1.9231
Matches	23,730	29,250	20,762	10,488

Table 3: t-tests for equality of average losses from placing an equal amount on all bets

Null Hypothesis	Mean Difference	Standard Error	p-value
Difference in mean loss between Integer hcp and .25 hcp equals zero	-0.0037	(0.0005)	0.0000
Difference in mean loss between Integer hcp and .5 hcp equals zero	-0.0093	(0.0006)	0.0000
Difference in mean loss between Integer hcp and .75 hcp equals zero	-0.0033	(0.0007)	0.0000
Difference in mean loss between .25 hcp and .5 hcp equals zero	-0.0056	(0.0005)	0.0000
Difference in mean loss between .25 hcp and .75 hcp equals zero	0.0004	(0.0006)	0.5170
Difference in mean loss between .5 hcp and .75 hcp equals zero	0.0059	(0.0007)	0.0000

Table 4: Regression of average loss rates from placing an equal amount on all bets on dummies for Asian Handicap bet type (robust standard errors)

	(1) Ex Post Loss	
Ending .25	0.00327***	(0.000538)
Ending .5	0.00899***	(0.000608)
Ending .75	0.00307***	(0.000638)
N	84,230	
R^2	0.009	

Standard errors in parentheses. League and season dummies included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Base case is a bet on an integer handicap in the Belgium Pro league in the 2011/2012 season.

Table 5: Average losses from placing an equal amount on all bets, by season and Asian Handicap type

	Handicap Type			
Season	Integer Mean	Ending .25 Mean	Ending.5 Mean	Ending .75 Mean
2011	0.0349	0.0330	0.0427	0.0356
2012	0.0315	0.0318	0.0344	0.0315
2013	0.0329	0.0353	0.0405	0.0376
2014	0.0347	0.0367	0.0433	0.0366
2015	0.0338	0.0411	0.0460	0.0398
2016	0.0347	0.0367	0.0433	0.0366
2017	0.0294	0.0380	0.0405	0.0355
2018	0.0342	0.0403	0.0430	0.0368
2019	0.0286	0.0343	0.0419	0.0352
2020	0.0296	0.0343	0.0381	0.0363
2021	0.0291	0.0344	0.0410	0.0353
Matches	23,730	29,250	20,762	10,488

Seasons are denoted by the start year.

For example, the 2011/2012 season is denoted by 2011.

4. Pinnacle Dataset

Our first dataset reports only one value of the handicap and its accompanying set of average odds for each match. One possible weakness of this approach is that there could be some other factor underlying the correlation between average loss rates and bet type. For example, what if bookmakers tended to offer integer handicaps on games that would have lower average loss rates anyway? For example, margins tend to be lower for matches that generate higher volumes. The English Premier League dummy in the regression reported in Table 4 is negative because bookmakers set lower margins for this league, being willing to trade off a lower average profit per bet for a higher total profit. What if bookmakers tended to set integer handicaps—which are probably easier to understand—for games in which there was greater interest among bettors? This could possibly explain our previous findings.

To address this issue, we obtained a large dataset of match results and Asian Handicap odds offered by Pinnacle, a leading "sharp" bookmaker that offers low margins on a wide range of Asian Handicap bets.[9] This dataset allows us to observe the odds set by Pinnacle for a range of different values of the handicap that are offered simultaneously on the same matches. For example, we could take a specific match, say Bayern Munich versus Borussia Dortmund, and see four different possible handicaps with a different set of odds for each handicap. Any differences that we see across handicap types in this case could not be explained by differences in the characteristics of the match being betted on. This dataset spans the period 31st August 2016 to 25th April 2022 and covers matches in all European professional soccer leagues.

To examine how Pinnacle priced bets with different handicaps, we constructed two sub-samples. The first sub-sample, consists of 43,235 matches for which Pinnacle simultaneously offered handicaps of 0.25, 0, -0.25 and -0.5, so that the first three of these handicaps featured refunds if the match ended in a draw. The second sub-sample consists of 24,138 matches for which Pinnacle simultaneously offered handicaps of size 0.75, 1, 1.25 and 1.5, so that the first three of these handicaps featured refunds if the match ended with the stronger team winning by one. Of these matches, 17,288 had handicaps that subtracted from the home team's score and 6,850 had handicaps that subtracted from the away team's score.

Table 6 confirms the main finding from our previous dataset. Across the same set of matches, bets placed with Pinnacle on integer handicaps have the lowest loss rates and bets on the half goal handicaps have the highest loss rates. For both sub-samples, the difference in loss rates between half goal handicap bets and the integer handicap were about 1.8% or 1.9%. Rather than effect we documented previously going away once we focus on an individual bookmaker, we actually find larger differences in average returns than recorded for our previous dataset. The results for the hybrid handicap

only appears once in the regression.

[9] This dataset was provided by Christian Baier of https://bettingiscool.com.

bets also differ a bit from our previous dataset because the loss rates on these two bets differ by more than they did in the Football-Data dataset but they still, as predicted, fall between the loss rates for half-goal and full goal handicaps. Tables 7 and 8 confirms the significance of these differences using the the same regression specification as equation 1. The base category here is a bet on the zero handicap in the Albanian Superliga in 2016. Note that, unlike the previous regression, in which each match only appears once, this dataset has each match appearing as four separate observations. Given the clear correlation between errors for individual matches, we cluster the standard errors at the match level.

These findings provide clear evidence for the Asian Handicap market violating what Thaler and Ziemba called weak market efficiency. You can find different betting options on the same matches with average returns varying by as much as almost 2%. This effect may perhaps seem like a small effect that is perhaps not of much interest but this would underestimate how hard it is to make money on sports betting. Gaining an edge of 2% is incredibly difficult and losing 2% by picking the wrong betting option will likely make it impossible for even the smartest bettors to make money.

To give an example, the most famous gambler in the world, Tony Bloom, runs the secretive firm StarLizard which takes money from millionaires to bet on sports based on complex statistical algorithms. StarLizard is understood to bet actively in the Asian Handicap market. Reports suggest that StarLizard look to make average profit margins of 1% to 3% on their bets.[10] This shows that the size of the discrepancies documented here are of first-order importance when compared with the potential profit rates that professional gamblers seek.

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

Table 6: Average losses from placing an equal amount on all bets for various Pinnacle Asian Handicaps with different handicaps when all are offered simultaneously

	Average Loss	*N*
Matches with Handicaps		
Plus 0.25 to Minus 0.50		
Handicap Plus 0.25	0.0426	43,235
Handicap 0	0.0297	43,235
Handicap Minus 0.25	0.0353	43,235
Handicap Minus 0.50	0.0486	43,235
Matches with Handicaps		
From 0.75 to 1.5		
Handicap 0.75	0.0400	24,138
Handicap 1	0.0298	24,138
Handicap 1.25	0.0363	24,138
Handicap 1.5	0.0476	24,138

Table 7: Regression of average losses from placing an equal amount on all bets on Asian Handicap bet type dummies:
First Pinnacle sample (standard errors clustered at match level)

Loss rate		
Handicap plus 0.25	0.0056 ***	(0.0007)
Handicap minus 0.25	0.0129 ***	(0.0007)
Handicap minus 0.5	0.0189 ***	(0.0014)
Matches	43,235	
Observations	172,940	

Standard errors in parentheses are clustered at the match level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Specification also includes year and league dummies.

Base bet is on the 0 handicap in the Albanian Superliga 2016.

Table 8: Regression of average losses from placing an equal amount on all bets on Asian Handicap bet type dummies:
Second Pinnacle sample (standard errors clustered at match level)

Loss rate		
Handicap minus 0.75	0.0140***	(0.0009)
Handicap minus 1.25	0.0042***	(0.0010)
Handicap minus 1.5	0.0152***	(0.0020)
Matches	24,138	
Observations	96,552	

Standard errors in parentheses are clustered at the match level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Specification also includes year and league dummies.

Base bet is on the minus 1 handicap in the Albanian Superliga 2016.

5. Are Loss Rate Patterns Predictable?

Our results show that average loss rates vary across handicap types. Here, we show that this variation in losses is predictable from the information available to the bettor. We first describe the traditional method for assessing the expected loss rates that will be incurred by bettors and then present an approach developed in Hegarty and Whelan (2023a) for estimating the expected loss rate when refunds are possible. We show that these ex ante expected loss rates explain the patterns we have reported.

5.1. Calculating expected losses

Consider the case in which the Asian handicap is 1.5. In this case, either the bet on the stronger team wins O_S or the bet on the weaker team wins O_W. Refunds do not occur. With two odds and two outcomes, we can use the following standard method to estimate the probabilities of each team winning and the expected average loss rate for the bets. We calculate the expected loss from betting on a maatch by assuming that the expected return will be the same for bets placed on both teams. Bookmakers make profits on average and have to cover costs, so the expected payout on a \$1 bet must be equal to some value $\mu < 1$. In other words, our calculations of expected returns are based on the assumption

$$P_S O_S = P_W O_W = \mu \tag{2}$$

Two quick observations on this assumption. First, this assumption will not hold if bookmakers set odds so returns on one side of bets are systematically different from those on the other side. For example, favorite-longshot bias has been widely documented in the literature on fixed-odds betting and, as we describe below in Section 7, there a strong favorite-longshot bias pattern for bets on home, away or draw outcomes in the Football-Data dataset used here. However, we show that this bias does not apply to Asian Handicap betting: There is no statistically significant pattern of differences in returns for bets by odds. So, equation 2 appears to provide a good description of this dataset. Second, this this assumption about equal returns for both sides of bets does not make any assumptions about the quantities being taken by bookmakers, e.g. it does not assume "book balancing" or other strategies to manage risk.

Equation 2 can be combined with the condition that the probabilities sum to one to provide 3 linear equations for each sporting event that can be solved to obtain a unique set of 2 probabilities and an expected payout μ. Specifically, μ is estimated as

$$\mu = \frac{1}{\frac{1}{O_S} + \frac{1}{O_W}} \tag{3}$$

and the so-called "normalized" probabilities can then be calculated directly from equation 2. The expected payout is determined by the sum of the inverses of the odds. This sum, known in bookmaking as the "overround" or "vig", is commonly used by gamblers to estimate the gross profit margin being taken by bookmakers. Indeed, there are many "overround calculators" on the internet, designed for people to plug in odds and quickly calculate the bookmaker's margin on a match.

Now consider the case where the Asian handicap is 1. In this case, we want to calculate probabilities for three different outcomes

$$P_{S2} = \text{Probability the stronger team wins by 2 or more} \tag{4}$$
$$P_{S1} = \text{Probability the stronger team wins by 1} \tag{5}$$
$$P_W = \text{Probability of a draw or the weaker team winning} \tag{6}$$

Again assuming the expected payoff for all \$1 bets is μ, the following conditions hold.

$$P_{S2}O_S + P_{S1} = \mu \tag{7}$$
$$P_W O_W + P_{S1} = \mu \tag{8}$$
$$P_W + P_{S1} + P_{S2} = 1 \tag{9}$$

This is a system of three linear equations in four unknowns (the three probabilities and the expected payoff) so there is no unique solution.

In another paper that uses Asian Handicap odds, but which does not focus on the average loss rates across bet types that is the focus of this paper, Hegarty and Whelan (2023a) approach this problem by using the Football-Data dataset described here and setting P_{S1} equal to the sample average of the fraction of matches than end in a refund for each kind of handicap. They show that for each type of Asian handicap bets with a refund element, the fraction of bets that end in a refund is stable over time and does not depend on observable factors such as the betting odds quoted on the match. See Appendix B for details. Given this result, they use the average realized fraction of matches that end in a refund for each handicap type (full goal, quarter goal and three-quarter goal) involving potential refunds as the probability of a refund, P_{S1}. Conditional on this value, the other unknowns can be solved to give

$$P_{S2} = \frac{(1 - P_{S1})\, O_W}{O_S + O_W} \tag{10}$$
$$P_W = \frac{(1 - P_{S1})\, O_S}{O_S + O_W} \tag{11}$$
$$\mu = P_{S_1} + \frac{(1 - P_{S1})\, O_S O_W}{O_S + O_W} \tag{12}$$

Applying a similar method for the two hybrid bets, Hegarty and Whelan show the expected payoff for each is

$$\mu = \frac{P_{S_1}}{2} + \left(1 - \frac{P_{S1}}{2}\right)\frac{O_S O_W}{O_S + O_W} \tag{13}$$

As noted above, this calculation is more complex than the standard "overround" calculations

5.2. Evidence

Tables 9 and 10 use our two datasets to compare the realized average loss rates for each type of Asian Handicap with the estimated ex ante expected loss rates implied by our calculations just described. The ex ante expected losses are extremely close to the realized averages, with the maximum difference being 0.07%.[11] Indeed, Table 11 shows that, once the ex ante expected loss is controlled for, there is no further statistical evidence of handicap type influencing the realized loss rates. The ex ante expected loss fully explains our finding of different loss rates across bets.

Figure 1 shows the estimated ex ante loss rates in the Football-Data dataset for each of the four handicap types. The figure clearly illustrates that the distribution of expected losses for the integer handicap is to the left of the distribution for half goal handicaps, with the other two handicaps having distributions that are in between.

Figures 2 and 3 provide a more stark illustration of the predictability of greater losses for half goal handicap bets relative to integer handicaps. For both Pinnacle samples, these charts show histograms of the expected loss rate for bets with a half goal handicap minus the corresponding expected loss rate for bets on the same match that have integer handicaps. Almost all of the observations are greater than zero, meaning the expected loss on Pinnacle's half goal handicaps are systematically higher than for integer handicap bets offered on the same matches. We can be confident that each of the handicaps and odds quoted here by Pinnacle had a reasonably large amount of money placed on them—if they weren't attracting betting volume, Pinnacle would move the odds to make them more attractive. This means bettors are taking on bets with half goal handicaps when superior options are available to them.

[11] Calculating the probability of a refund was more complex for the Pinnacle dataset. We did this as follows. For each match, we chose the handicap that was most likely to be one chosen as the "main handicap" by Buchdahl for his dataset as the one which had the smallest absolute value for the difference between the odds. We then used the fraction of matches in the Football Data dataset that ended in a refund for this type of handicap.

Table 9: Mean expected ex ante loss and realized ex post loss rates for equal sized bets on all options, organized by Asian Handicap type (Football-Data dataset)

	Handicap Type			
	Integer	Ending .25	Ending.5	Ending .75
	Mean	Mean	Mean	Mean
Ex Ante Loss Rate	0.0317	0.0356	0.0421	0.0361
Realized Loss Rate	0.0324	0.0361	0.0416	0.0357
Odds	1.9240	1.9241	1.9226	1.9231
Matches	23,730	29,250	20,762	10,488

Table 10: Mean expected ex ante loss and realized ex post loss rates for equal sized bets on all options, organized by Asian Handicap type (Pinnacle samples)

	Handicap Type			
	Integer	Ending .25	Ending.5	Ending .75
	Mean	Mean	Mean	Mean
Ex Ante Loss Rate	0.0293	0.0396	0.0473	0.0399
Realized Loss Rate	0.0297	0.0384	0.0482	0.0400
Matches	67,373	67,373	67,373	24,138

Table 11: Regression of realized losses from placing an equal amount on all bets on ex ante predicted losses (Football-Data dataset)

	(1)	
	Ex Post Loss	
Ex Ante Loss	1.003***	(0.0549)
Ending .25	-0.00019	(0.0005)
Ending .5	-0.0012	(0.0008)
Ending .75	-0.0011	(0.0007)
N	84,230	
R^2	0.013	

Standard errors in parentheses

Specification also includes season and league dummies.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Estimated ex ante expected losses by Asian Handicap bet type (Football-Data dataset)

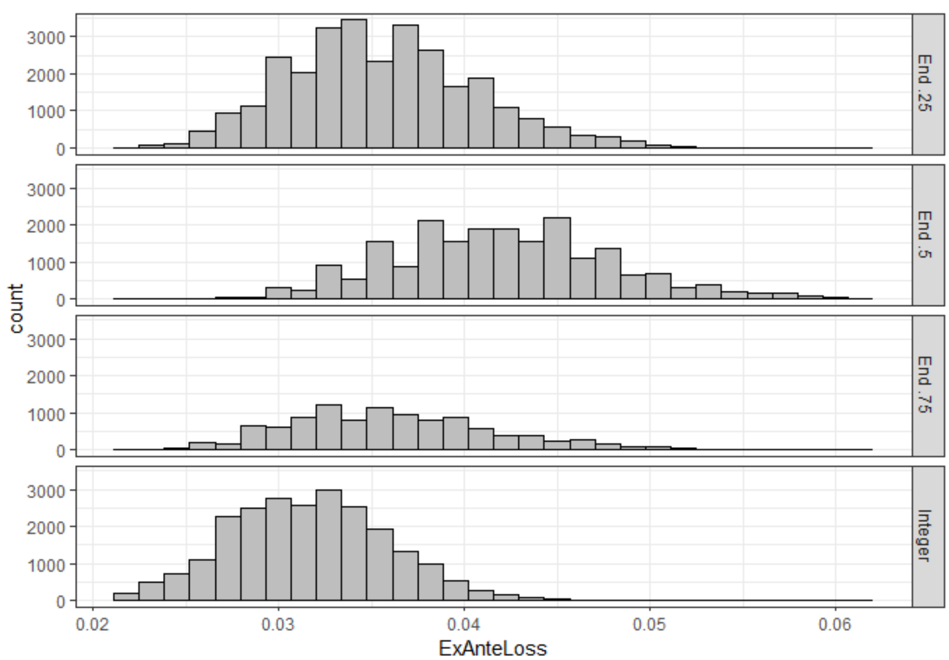


Figure 2: Histogram of differences in ex ante expected losses between 0 handicap and 0.5 handicap when both are offered (Pinnacle data)

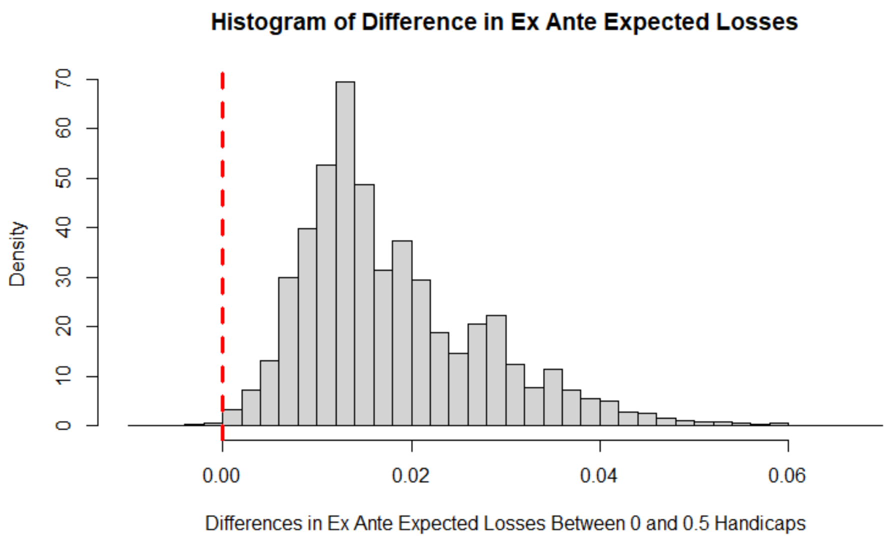
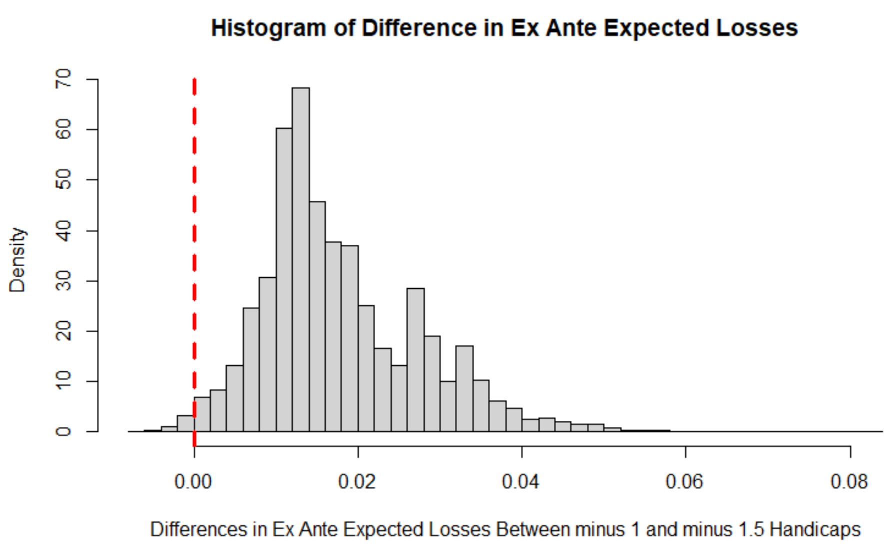


Figure 3: Histogram of differences in ex ante expected losses between minus 1 handicap and minus 1.5 handicap when both are offered (Pinnacle data)



6. Explanations

What explains our findings? As noted above, we can point to two possible explanations. The first is that the results reflect the preferences of bettors. They may simply prefer bets with a clear win/loss outcome to those involving potential refunds. Since Friedman and Savage (1948), one of the explanations for why people gamble is that, at least for sufficiently low stakes, gamblers enjoy the increased variance in expected utility associated with placing bets. Since refunds reduce this variance, perhaps bookmakers need to offer gamblers higher expected returns for bets that have the possibility of a refund. For this reason, even though the odds are set by bookmakers, one can possibly infer the preferences of gamblers from these odds.

For example, one could assume bettors are aware of how to calculate expected payouts on these gambles, as described in our previous section, and have expected utility preferences as a function of payouts of the form

$$E\left[U\right]=\begin{cases}\frac{O_S O_W}{O_S+O_W} & \text{if there is no potential refund}\\ P_{S1}+\frac{(1-P_{S1})(O_S O_W)}{O_S+O_W}-\epsilon_1 & \text{if there is potential for a full refund}\\ \frac{P_{S_1}}{2}+\left(1-\frac{P_{S1}}{2}\right)\frac{O_S O_W}{O_S+O_W}-\epsilon_2 & \text{if there is potential for a half refund}\end{cases} \tag{14}$$

where ϵ_1 and ϵ_2 are a pair of certainty-equivalent valuations of the utility loss from taking a bet with either a full or half refund as a possibility. The equilibrium odds at which bettors are indifferent between these bets would reflect compensating differentials from these utility losses. So, for example, letting m_1 and $m_{0.5}$ represent the overround-based estimate of the expected return on a bet without factoring in a refund (i.e. $\frac{O_S O_W}{O_S+O_W}$). Then we would have the following arbitrage equation

$$P_{S1}+(1-P_{S1})\,m_1-\epsilon_1=m_{0.5}\Longrightarrow m_1=\frac{m_{0.5}-P_{S1}+\epsilon_1}{1-P_{S1}} \tag{15}$$

where P_{S1} is the probability of a refund for the bet with an integer handicap. Similarly, denoting $m_{0.75}$ as the overround-based estimate of the expected return on a bet without factoring in a refund using the odds on a 0.75 goal handicap, we would have an arbitrage condition of the form

$$\frac{P_{S_1}}{2}+\left(1-\frac{P_{S1}}{2}\right)m_{0.75}-\epsilon_2=m_{0.75}\Longrightarrow m_{0.75}=\frac{m_{0.5}-\frac{P_{S1}}{2}+\epsilon_2}{1-\frac{P_{S1}}{2}} \tag{16}$$

where in this case, P_{S1} is the probability of a refund for the bet with a three-quarter goal handicap. This could provide a preference-based explanations for the different expected returns that we observe.

The second explanation is that the complexity of these bets mean that gamblers do not calculate expected returns correctly. This could occur if bettors do not factor in the possibility of a refund when calculating the expected value of a bet. As discussed above, there is a well-known simple calculation of the expected return when there is no refund but this calculation does not give the correct expected return when refunds are possible. The average decimal odds offered in this market are 1.92 and it may be that bettors believe the average loss rates across all of these bets is 4% based on using the standard overround or vig calculation. However, while this will be the average loss rate for bets with half-goal handicaps, average loss rates for bets that allow for possible refunds will be lower.

Clearly, both of these explanations could be contributing to the pattern we document but we think this second explanation is perhaps more compelling because the equality of average odds across all four kinds of bets is precisely what we would expect if bettors are using the overround to assess the return on bets. In contrast, the average overround being the same for each of the bet types means the compensating differential theory can only fit the data if

$$\epsilon_1 = P_{S1}\left(1 - m_{0.5}\right) \tag{17}$$

$$\epsilon_2 = 0.5P_{S1}\left(1 - m_{0.5}\right) \tag{18}$$

Clearly, we cannot rule out the compensating differentials explanation based on the evidence that we have. However, it is hard to think of any prior reasons why these specific values would be the potential disutility from taking bets with refunds. For example, does the disutility from potentially getting half your money refunded have to be half the disutility from potentially getting all your money refunded? And it seems an unlikely coincidence that bettors both have this preference against refunds and that the compensating differentials that make them indifferent across bet types are precisely equal to the amounts predicted by the alternative explanation of bettors judging the bets based on the overround calculation.

From the point of view of the bookmakers that offer these odds, it seems almost certain they are aware that they make more money on Asian Handicap bets that do not offer the possibility of a refund. It is well known that the "sharp" bookmakers that dominate this market are willing to offer very low margins and they are prepared to accept profit rates of about 3% on bets. For example, in another dataset that we have analyzed featuring matches from 2019 to 2022, we find that Pinnacle set an average margin of 3% on home/away/draw bets on European soccer. Montone (2021) shows that optimal odds setting for bookmakers involves setting odds as a "markdown" on zero-profit odds where the size of the markdown depends negatively on the elasticity of demand. If the gamblers in this market are not sufficiently sensitive to the true "price" of bets without refunds and are thus willing to take bets that imply profit rates for bookmakers of 4%, the bookmakers will have no incentive to improve their odds to equate expected returns across bet types.

7. Favorite-Longshot Bias?

Thaler and Ziemba's formulation of weak market efficiency in betting markets assumes the expected return on all bets are equal and so it is not possible to win or lose systematically more or less simply by adjusting your betting strategy. The patterns we have documented suggest the Asian Handicap is not a fully efficient market by this definition. This raise the question of whether Asian Handicap betting is simply an inefficient market in which there are possibly multiple ways in which the odds do not reflect the underlying probabilities. Given the potential inefficiencies mentioned earlier from the studies by Grant et al (2018) and Constantinou (2022), perhaps this is just a systematically inefficient market.

An important counter-example, however, is that along one important dimension that has received a lot of attention in the literature on betting market—the pricing of favourites relative to longshot—the Asian Handicap market appears to be an efficient one. Hegarty and Whelan (2023a) show that Asian Handicap bets do not exhibit favorite-longshot bias: See Figure 4 for illustration. This figure shows the average payouts for $1 bets sorted by the estimated probability of the bet winning a full payout, calculated using the methodology described in the previous section. There is no clear pattern of bias across the estimated probability ranges.

In contrast, for the same Football-Data dataset used here, Hegarty and Whelan (2023a) show that bets on whether the home team or the away team will win, or whether there will be a draw show a highly significant pattern of favorite-longshot bias, a pattern already reported for in a smaller sample of matches from similar data sets by Buhagiar, Cortis and Newall (2018) and Angelini and De Angelis (2019). Figure 5 shows the average payouts for $1 bets on Home/Away/Draw outcomes sorted by the estimated probability of the bet winning.

We have also shown here how realized loss rates for Asian Handicap bets are very close to those predicted by the odds, once one factors in the probability of refunds occurring. However, Hegarty and Whelan (2023a, 2023b) show that this is not the case for Home/Away/Draw betting and this discrepancy between ex ante and ex post loss rates is a function of the odds exhibiting a favorite-longshot bias. So, despite the inefficiency we have documented here, along other dimensions, the Asian Handicap's odds appear to be quite efficient, as we might expect from a market featuring substantial participation by professional gamblers and syndicates.

Figure 4: Average payouts by probability deciles for Asian Handicap bets, Football-Data dataset

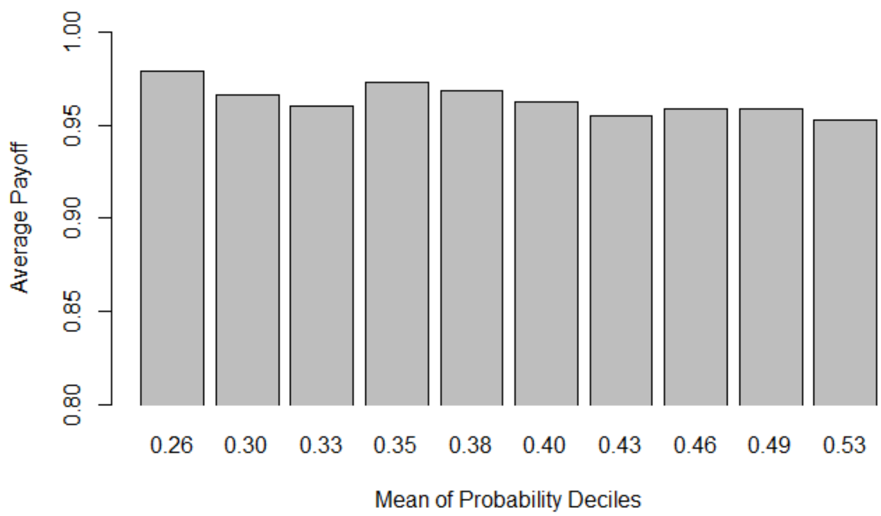
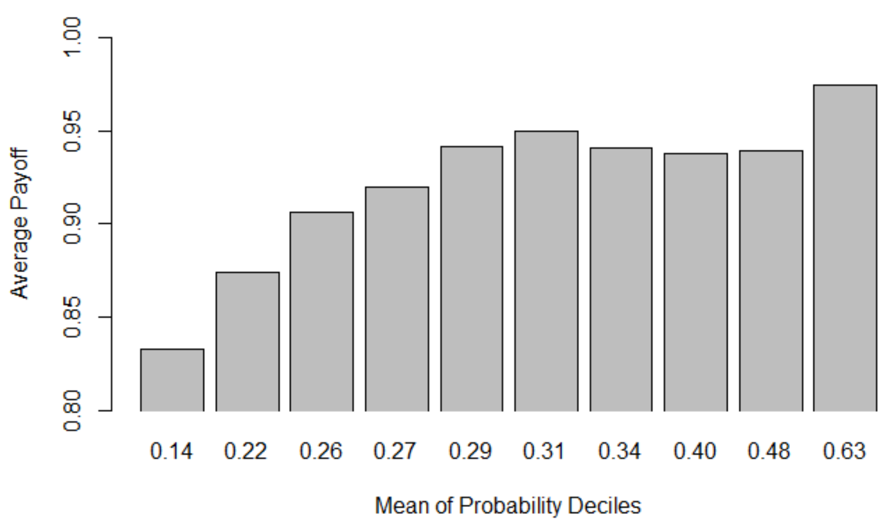


Figure 5: Average payouts for the probability deciles of Home/Away/Draw bets, Football-Data dataset



8. Conclusions

We have shown that in a large online betting market, known to attract betting syndicates and professional gamblers, there are systematic differences in loss rates across the types of bets based on whether the handicap applied to the stronger team is an integer or not. The largest average loss rates are for those bets where the handicap ends in .5, meaning there are no refunds.

We have discussed two possible explanations for these results. The first explanation is that the return differentials reflect preferences such that bettors have a preference for bets without the possibility of refunds: Bookmakers know that bettors dislike bets that feature potential refunds and thus have to offer slightly better odds on these bets to get bettors to take them up. The second explanation is that bettors evaluate the attractiveness of bets using the traditional "overround" or "vig" calculation method, even though this calculation is incorrect when bets feature potential refunds and thus the payoff structure is more complex.

We think the evidence for the second explanation is stronger because this theory predicts that the average odds offered for a full win on each of the bets should be the same and this is indeed what is observed in the data. The preference-based explanation predicts the ranking of returns that we observe but it seems an unlikely coincidence that the compensating differentials for odds implied by this theory precisely equal the differential predicted by the explanation that bettors are assessing bets with refunds using the traditional overround method.

In light of the large amounts of money placed in the Asian Handicap market and the generally well-informed nature of those who participate in it, we think it will be interesting to see if this anomaly persists now that it has been publicly documented or whether it follows the pattern of other financial anomalies in tending to disappear once it has been publicised (see Zaremba, Umutlub and Maydybura, 2020 and Shanaev and Ghimire, 2021). If the pattern we have documented reflects preferences, it seems likely to persist but if it represents mis-calculations, which is our preferred explanation, then it may cease to hold once publicised.

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A League-Level Evidence

Table A.1: Average post loss rates by league and Asian Handicap type

League	Handicap Type: Integer Mean	Ending .25 Mean	Ending .5 Mean	Ending .75 Mean	Matches
Belgium First Div A	0.0311	0.0348	0.0388	0.0356	2,754
Germany Bundesliga	0.0309	0.0303	0.0369	0.0291	3,349
Germany Bundesliga 2	0.0330	0.0334	0.0437	0.0395	3,357
England Premier League	0.0248	0.0267	0.0367	0.0286	4,152
England Championship	0.0301	0.0320	0.0424	0.0332	6,060
England League 1	0.0369	0.0363	0.0416	0.0387	5,907
England League 2	0.0345	0.0389	0.0455	0.0353	5,946
England Conference	0.0340	0.0420	0.0450	0.0391	5,799
France Ligue 1	0.0316	0.0334	0.0411	0.0312	4,055
France Ligue 2	0.0335	0.0334	0.0425	0.0317	4,059
Greece Super League	0.0379	0.0428	0.0471	0.0381	2,733
Italy Serie A	0.0277	0.0323	0.0371	0.0315	4,170
Italy Serie B	0.0335	0.0364	0.0429	0.0379	4,708
Netherlands Erdivisie	0.0279	0.0357	0.0336	0.0334	3,265
Portugal Primeira Liga	0.0300	0.0366	0.0422	0.0354	3,157
Scotland Premier League	0.0356	0.0404	0.0444	0.0356	2,453
Scotland Championship	0.0440	0.0424	0.0518	0.0466	1,885
Scotland League 1	0.0374	0.0472	0.0522	0.0497	1,864
Scotland League 2	0.0406	0.0474	0.0430	0.0392	1,860
Spain La Liga 1	0.0279	0.0315	0.0358	0.0330	4,143
Spain La Liga 2	0.0325	0.0380	0.0429	0.0344	5,024
Turkey Super Lig	0.0337	0.0318	0.0397	0.0367	3,530
Matches	23,730	29,250	20,762	10,488	

Table A.2: Average decimal odds by league and Asian Handicap type

	Handicap Type				
League	Integer	Ending .25	Ending .5	Ending .75	
	Mean	Mean	Mean	Mean	Matches
Belgium First Div A	1.9187	1.9219	1.9196	1.9222	2,754
Germany Bundesliga	1.9375	1.9363	1.9340	1.9351	3,349
Germany Bundesliga 2	1.9212	1.9233	1.9210	1.9231	3,357
England Premier League	1.9404	1.9417	1.9378	1.9390	4,152
England Championship	1.9237	1.9286	1.9245	1.9271	6,060
England League 1	1.9175	1.9219	1.9204	1.9204	5,907
England League 2	1.9170	1.9208	1.9208	1.9199	5,946
England Conference	1.9153	1.9163	1.9150	1.9138	5,799
France Ligue 1	1.9304	1.9314	1.9275	1.9298	4,055
France Ligue 2	1.9228	1.9234	1.9201	1.9225	4,059
Greece Super League	1.9200	1.9166	1.9153	1.9155	2,733
Italy Serie A	1.9397	1.9359	1.9338	1.9344	4,170
Italy Serie B	1.9216	1.9210	1.9190	1.9213	4,708
Netherlands Erdivisie	1.9249	1.9252	1.9258	1.9253	3,265
Portugal Primeira Liga	1.9231	1.9245	1.9213	1.9234	3,157
Scotland Premier League	1.9164	1.9201	1.9157	1.9183	2,453
Scotland Championship	1.9130	1.9119	1.9130	1.9131	1,885
Scotland League 1	1.9092	1.9056	1.9053	1.9066	1,864
Scotland League 2	1.9129	1.9075	1.9072	1.9061	1,860
Spain La Liga 1	1.9386	1.9383	1.9352	1.9363	4,143
Spain La Liga 2	1.9203	1.9216	1.9171	1.9212	5,024
Turkey Super Lig	1.9188	1.9223	1.9202	1.9217	3,530
Matches	23,730	29,250	20,762	10,488	

B Evidence on Predictability of Refunds

Here we provide evidence to support our approach of setting the probability of refunds equal to a fixed number for each type of handicap. If the probability of a refund varied systematically across matches, then our approach could be flawed and a correct calculation of expected losses would require a match-by-match adjustment for the refund probability.

To test whether refunds were predictable, we estimated the following specification for all three types of bets where refunds are possible

$$R_{ijkq} = \sum_{j=1}^{22} \alpha_j L_j + \sum_{k=1}^{11} \beta_k S_k + \sum_{q=1}^{3} \delta_q H_q + \eta_1 O_{iH} + \eta_2 O_{iA} + u_{ijkq} \tag{B.19}$$

where R_{ijkq} equals 1 if a refund was issued for match i in league j and season k with handicap type q and equals zero otherwise and O_{iH} and O_{iA} are the Asian Handicap odds for the bets on the home and away teams. The H_q are dummies for the three handicap types featuring refunds.

Table B.1 reports the results from estimation of this regression via weighted least squares for the 63,468 matches that had the possibility of a refund occurring, where the estimated handicap-specific average rate of refund is used to construct match-specific variances for weighting purposes.[12] None of the year dummies are significant, implying the probability of refunds occurring has been stable across seasons. We also do not find any significant effect of either the home or away odds. We do find evidence that refunds are most likely for bets with handicaps ending in .25 and least likely for bets with handicaps ending in .75. For this reason, to generate our probability estimates, we estimate the probabilities of a refund separately for each of the three relevant handicap types as the sample average fractions of bets that end in refunds for each type. One concern with this procedure is that it uses data from the full sample, so information about future matches is being used to "forecast" matches occurring at a time when this information is not available. However, we obtain the same results if we only use estimates of the probability of a refund from seasons prior to when matches occurred.

We can summarize the evidence on refunds as follows: The fraction of refunds that occur for each type of handicap is stable and predictable over time but there is no information available in the betting odds that help predict which specific matches will generate refunds.

[12] Similar results are obtained from Probit estimation.

Table B.1: Weighted least squares regression predicting refunds

	Coefficients	Standard Errors
Home Odds	0.0316	(0.0539)
Away Odds	0.0235	(0.0546)
2012 Season	-0.00235	(0.00831)
2013 Season	-0.00360	(0.00866)
2014 Season	0.00493	(0.00855)
2015 Season	-0.00215	(0.00851)
2016 Season	0.00493	(0.00855)
2017 Season	-0.00449	(0.00836)
2018 Season	-0.00210	(0.00826)
2019 Season	0.00353	(0.00856)
2020 Season	0.000989	(0.00836)
2021 Season	0.00952	(0.00838)
Handicap Type ending .25	0.00884^{*}	(0.00400)
Handicap Type ending .75	-0.0260^{***}	(0.00521)
N	63,468	
R^2	0.003	

The baseline bet here relates to a match in 2011 with an integer handicap.

Specification also includes dummy variables for each league.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$