ECON30580 Economics of Betting Markets
11. Applications of the Monopoly Model: Draws, Advertising and Inside Information

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Part I

Application to Betting on European Soccer

Testing the Disagreement Model

- We have shown how the model featuring a monopoly bookmaker and bettors that disagree with each other can explain the favourite-longshot bias pattern observed in the fixed-odds betting data.
- But you could imagine other explanations that mirror those that have been used for pari-mutuel betting.
- For example, accepting that odds will depend on the elasticity of demand, maybe longshot bets have poor odds because people who like risk or enjoy the thrill of a longshot bet have low elasticies of demand.
- It would be hard to tell whether the data are generated by models like that or the disagreement-based model.
- Here, we apply the monopoly model to soccer.
- We show the model generates a set of very specific predictions and then check whether they hold in the data.

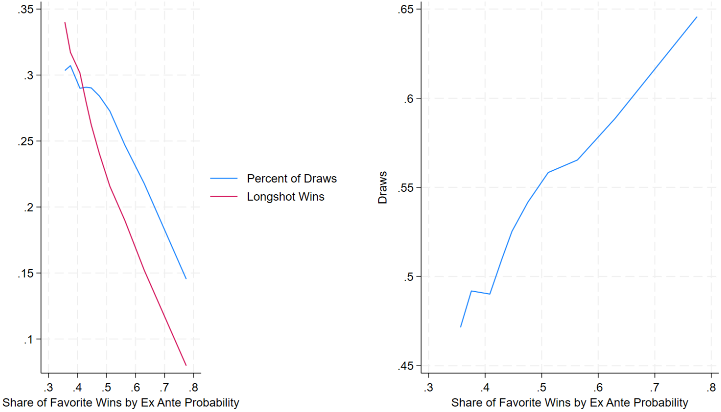
Modelling Beliefs about Soccer with 3 Outcomes

- In soccer there are three possible outcomes: Home win, away win or draw.
- With two outcomes, the disagreement about the probability of the favourite winning is the same as the disagreement about the probability of the longshot winning.
- The amount of disagreement about p is the same as the amount of disagreement about $1 - p$.
- But with three possible outcomes, it is more complicated. Two people could agree about the probability of the favourite winning but disagree about the probability of the match being a draw versus a longshot win.
- So we need a way to specify reasonable beliefs about each of the 3 possible outcomes while making sure their subjective probabilities still add up to 1.
- In my paper with Tadgh Hegarty "Disagreement and Market Structure in Online Betting Markets: Theory and Evidence from Soccer", we provide a simple way to model how people might think about these probabilities.

Predicting Draws and Longshot Wins

- We used a dataset of 151,683 matches from www.football-data.co.uk spanning the 2005/06 to 2024/25 seasons for 22 European soccer leagues across 11 different nations.
- For each match, we used the betting odds to figure out which team was the favourite, using normalised probabilities.
- We then sorted the matches in to 10 deciles, going from the matches with the weakest favourites up to the matches with the strongest favourite, and figured out what the average results were in each decile.
- Unsurprisingly, the stronger the favourite, the more likely it was that the outcome was a win for the favourite.
- But what about the other two outcomes, the longshot win and draw?
- We found that as the probability of the favourite winning goes up, the probability of a draw and a longshot win both decline.
- But the probability of the draw declines slower.
- In fact, the share of non-favourite win outcomes due to draws increases more or less in a straight line as the probability of the favourite winning rise.

Draws rise relative to longshot wins as the probability of the favorite winning rises



Left panel shows fraction of draws and longshot wins for each decile. Right panel shows the share of draws among non-favourite-win outcomes.

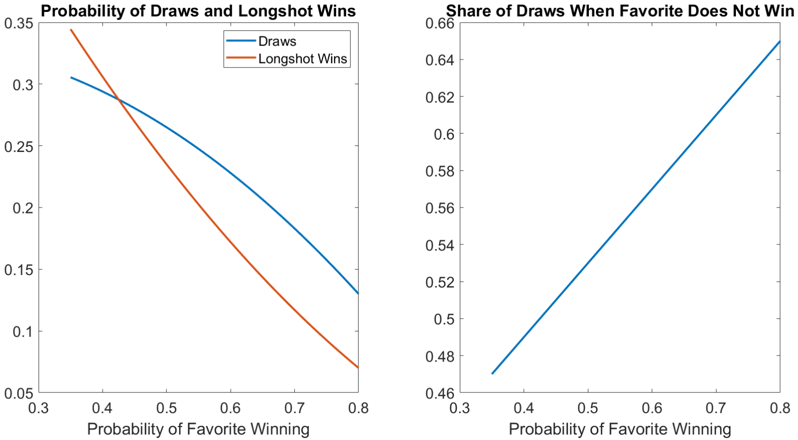
A Model of Beliefs about Soccer

- In the model in our paper, we assumed that people used the pattern just documented to construct their beliefs about the outcome of soccer matches.
- We assumed that each person had a belief $\tilde{p}_F$ about the probability of the favourite winning and, as usual, we assumed the distribution of these beliefs across the population was uniform over $[p_F - \sigma, p_F + \sigma]$.
- We then assumed that, given their beliefs about the strength of the favourite, they would use the pattern documented in the graphs on the previous page to construct beliefs about the draw $\tilde{p}_D$ and the longshot win $\tilde{p}_L$ so that the probabilities sum to one.
- We specify beliefs as

$$\begin{aligned} \tilde{p}_D &= (\delta_0 + \delta_1 \tilde{p}_F)(1 - \tilde{p}_F) \\ \tilde{p}_L &= (1 - \delta_0 - \delta_1 \tilde{p}_F)(1 - \tilde{p}_F) \end{aligned}$$

  using the data from a regression based on the right panel of the previous graph to give us estimates of δ_0 and δ_1.
- With these beliefs, we can predict whether people will accept bets on teams at given odds, using the usual $\tilde{p}D > 1$ rule.

Our calibration of beliefs about draws and longshot wins



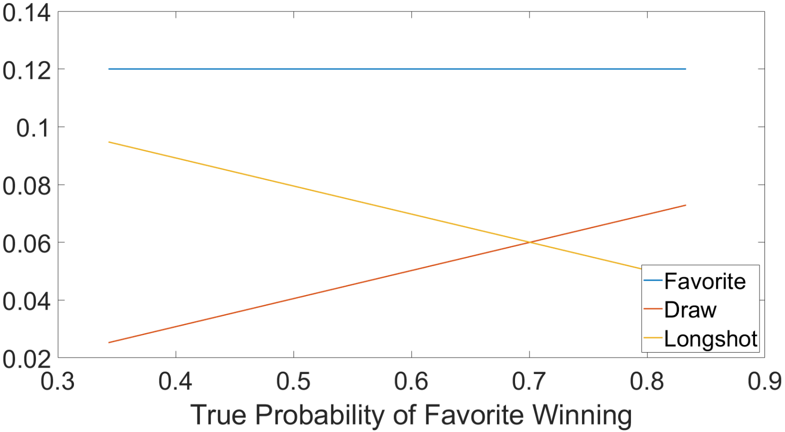
The Monopolist Takes Bets on Soccer

- Once we know people's beliefs, we know how they will bet when offered specific odds.
- This means we can solve the monopoly model for these beliefs to figure out the expected profit maximising odds.
- This problem is a bit more complicated than the two-team case, so we used numerical methods to solve it rather than calculus—basically we guess lots of possible different odds and find out which of them maximises the bookmaker's profits.
- But the principles are the same:
  - Odds will feature a favourite-longshot bias, so that the the probability of a bet's success will have a positive effect on its expected payouts.
  - The odds will also depend on how much disagreement there is. The more disagreement about the probability of an outcomes, the worse the odds will be.
- We will show the optimal odds in a second but first let's think about how they might look.

Disagreement and Its Implications

- As before, we have a constant level of disagreement about favourites.
- In our paper, we choose $\sigma = 0.06$ because delivers an average predicted overround that is very close to the average in our soccer dataset.
- The chart on the next page show the amount of diagreement among the bettors in the model, defined as the difference between the person that is most pessimistic about a bet winning and the person that is most optimistic.
- For beliefs about favourites with uniform odds on $[p_F - \sigma, p_F + \sigma]$, this measure of disagreement is 2σ.
- But the model predicts the amount of disagreement about draws and longshots will vary depending on the true value of p_F.
- If there is only a weak favourite, there is more disageement about whether there will be a longshot win than a draw.
  - Example: If Arsenal v Chelsea is a toss up that's equally likely to be home win, away win or draw, one person might think Arsenal are 40% likely to win and the other think Chelsea are 40% likely to win but they would agree on the likelihood of a draw.
- If there is a very strong favourite, there is more disageement about whether there will be a draw than a longshot win.

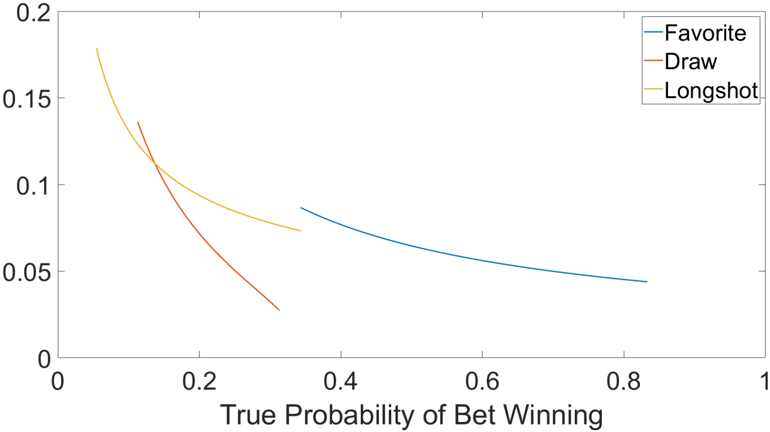
Disagreement in the home/away/draw model, $\mu = 0.02$ and $\sigma = 0.06$



Implications of Varying Disagreement

- As with the two-team case, there will be a favourite-longshot bias, so expected loss rates will get bigger as the probability of the bet winning falls.
- But disagreement also matters: The model predicts that **as disagreement increases, the bookmaker offers worse odds**.
- For most of the values of p_F, there is less disagreement about the draw than about the longshot win.
- This should mean lower expected loss rates for draws for most values of p_F.
- But when p_F is particularly high, so p_D and p_L are particularly low, there is more disagreement about the draw than the longshot win.
- So for the lowest values of p_D and p_L, the expected loss rates for draws could be higher than for longshots.
- These patterns explain the model's predicted expected loss rates shown on the next page.

The monopolist model's predicted loss rates for home/away/draw model, $\mu = 0.02$ and $\sigma = 0.06$



The Evidence on Loss Rates

- We used our data on 151,683 matches to calculate the average loss rates for bets on favourite win, bets on longshot wins and bets on draws, sorting each of them into deciles.
- Home/away/draw betting is dominated by the traditional retail European bookmakers.
- We have described before how these bookmakers engage in anti-competitive practices such as restrictive stakes for people who have a record of winning.
- And there is not as much competition via offering better odds as you might think from checking sites like OddsChecker.
- So perhaps this industry can be treated as though odds are effectively set by a monopoly.
- And the next page shows the evidence on loss rates for the 3 types of bets. It matches very closely with the model's predicted pattern, most notably with draws often having very low loss rates despite a low chance of success.

Loss Rates Home, Away and Draw Bets

Part II

Advertising and Proposition Bets

Advertising Patterns for Bookmakers

- We have discussed how retail bookmakers do not seem to compete much in terms of the odds they set.
- But they do spend a lot of money on marketing attempting to attract and retain customers.
- In relation to advertising of bets, however, most of the emphasis is on promoting "proposition bets" which combine multiple different individual bets into a single bet.
- The most obvious such bets are accumulators—you agree to roll over your winnings on one bet to be placed on second bet, and then those winnings onto a third bet and so on. You only win if all your picks win but, typically, the amout you win would be large relative to your original stake.
- The other type of proposition bets are combination bets such as "Man United to win, scoring more than 3 goals, including one in the second half."
- We are going to describe how our monopoly model predicts advertising spending will be larger for proposition bets.

Example: Paddy Power Super Sub

- Paddy Power's current big promotional campaign "Super Sub" advertises that if you place a bet on a player to do something (pretty much anything ...) then the bet rolls over to the substitute that replaces them.
- Look at the list of things you can bet on, mostly with low probabilities of happening.

What markets will Super Sub apply to?

Super Sub is available on:

- Player to commit 1 or more fouls
- Player to be fouled 1 or more times
- Player to commit 1 or more fouls in 1st Half
- Player to have 1 or more shots on target
- Player to be shown a card
- Player to score
- To score or assist
- To score or to be shown a card
- Anytime assist
- Player to have 1 or more shots on target in 1st half
- Player to have 1 or more shots

Manufacturing More Profitable Bets

- By definition, these are longshot bets.
- It is likely that people have trouble calculating the correct probabilities associated with these bets but, even if they were correct on average, our monopoly model says profits on these bets are bigger for bookmakers.
- This suggests a way for bookmakers to make more profits.
- There are only so many sporting events out there with extreme underdogs and many of them might be events that people are not interested in or are unaware of.
- But proposition bets are a way for bookmakers to invent bets with low probabilities of success which will have high profit rates for them.
- This suggests there is an incentive to spend money advertising these bets.
- We can add advertising as a feature of our model and confirm this is the case.

A Monopoly Model with Advertising

- Consider the following extension of the monopoly model.
- We add an extra step to the demand for bets. The demand for bets is now

$$V(A, D) = G(A) B(D)$$

  so that in additional to our previous demand function for bets as a function of odds, $B(D)$, there is another term $G(A)$ that depends on how much money A has been spent on advertising.
- Think about it this way: Before placing a bet, people have to know the bet is available and the more advertising there is, the more people will know about it.
- If $G(A) = 1$ then all potential bettors know about the existence of the bet and if $G(A) = 0$ then none of them know about it.
- We will assume that $G'(A) > 0$ and $G''(A) < 0$ so that advertising increases awareness of bets but with diminishing marginal returns.
- We will also assume that the cost of unit of advertising is δ.

Profit-Maximising Strategy for the Bookmaker: Odds

- The bookmaker's expected profit on the bet is

$$E(\Pi) = (1 - \mu - pD)\, G(A)\, B(D) - \delta A$$

- Taking derivatives with respect to D, the condition for optimal odds is

$$\frac{\partial E(\Pi)}{\partial D} = (1 - \mu)\, G(A)\, B'(D) - pG(A)\, B(D) - pDG(A)\, B'(D) = 0$$

- The $G(A)$ terms all cancel out so this solves to give

$$D = \frac{1 - \mu}{p} - \frac{B(D)}{B'(D)}$$

- This is the same formula as for the model without advertising.
- So adding advertising does not change the profit-maximising odds for a bet with probability p of success.
- And our previous results still hold: Profits per bet are higher for bets with low values of p because they have lower elasticity of demand.

Profit-Maximising Strategy for the Bookmaker: Advertising

- The bookmaker's expected profit on the bet is

$$E(\Pi) = (1 - \mu - pD)\, G(A)\, B(D) - \delta A$$

- Taking derivatives with respect to A, the condition for optimal advertising is

$$\frac{\partial E(\Pi)}{\partial A} = (1 - \mu - pD)\, G'(A)\, B(D) - \delta = 0$$

  This condition equates the marginal product of advertising in raising profits with the cost of a unit of advertising.

- This condition can be re-written as

$$G'(A) = \frac{\delta}{(1 - \mu - pD)\, B(D)}$$

- The assumption that $G''(A) < 0$ means $G'(A)$ is a negative function of A.
- This means A will depend negatively on δ (the cost of advertising) and positively on $(1 - \mu - pD)\, B(D)$ (the profit on the bet at the chosen odds if everyone knew about the bet).
- Bets with low values of p have higher expected profit and so higher advertising.

Specifying Demand and Awareness

- To give a specific illustration of how this model works, we need to specify beliefs of bettors and also how the awareness of bets depends on advertising.
- As before, we will assume the distribution of beliefs among potential bettors is uniform on $[p-\sigma, p+\sigma]$ so the demand for bets when everyone knows about the bet is

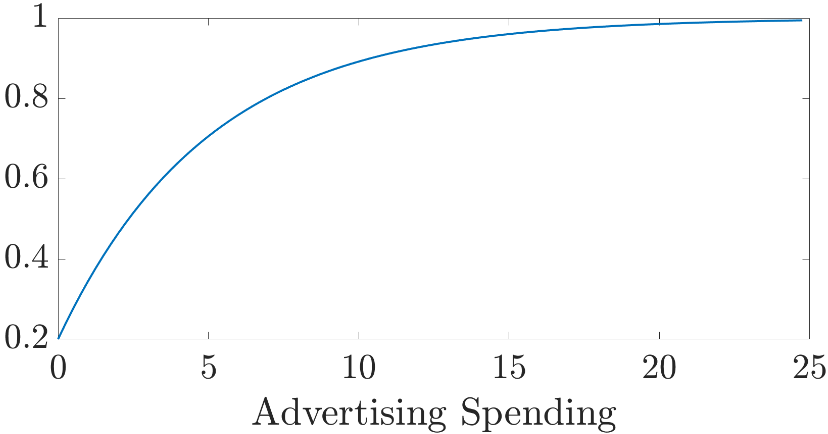
$$B(D) = \frac{p+\sigma-\frac{1}{D}}{2\sigma}$$

- We specify $G(A)$ as follows

$$G(A) = 1 - \gamma e^{-\alpha A}$$

  a specification that is commonly used in economics models of advertising.
- This means that if there is no advertising $(A = 0)$ then a fraction $1-\gamma$ of potential bettors will still be aware of the bet and as advertising rises then eventually everyone knows about the bet.
- This function has been used a lot in the economics of advertising. It arises from assuming that for every advert placed, there is a probability $1-\alpha$ that someone didn't see the ad.

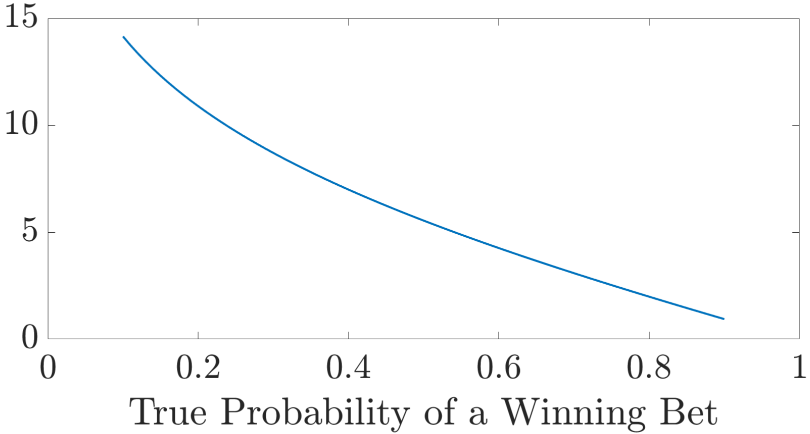
The $G(A)$ function: Awareness as a function of advertising spending, for $\gamma = 0.8$, $\alpha = 0.2$



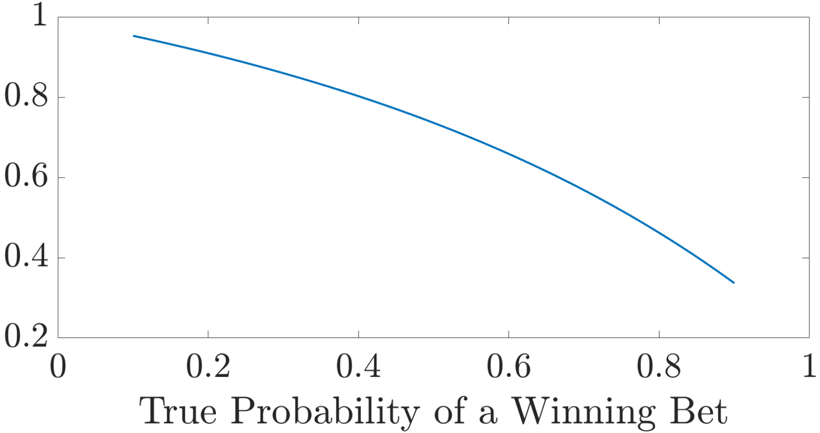
Results of the Model

- The charts on the next few page show the results from solving this model with the $G(A)$ function just shown (which has $\gamma = 0.8$, $\alpha = 0.2$), with disagreement parameter $\sigma = 0.06$ (which is the value that worked best in our European soccer application) and cost of advertising $\delta = 0.0005$.
- Advertising spending is highest for the bets with the lowest probability of success, like proposition bets.
- For a fixed value of γ, awareness rises as winning probability falls.
- This isn't saying that people will always be most aware of bets with low probabilities of success. For example, when Liverpool play Man City, everyone is aware that this is something they can bet on. In that case, $\gamma = 0$.
- But explains why, for high profile events, the advertising focus is on proposition bets: People know the game is happening and that you could bet on either team. But they don't know about proposition bets unless you get them the information that they exist.
- Hence, for the Super Bowl, bookmakers don't push bets on the teams but instead advertise loads of prop bets, from who will score the first touchdown to the length of the pre-game national anthem.

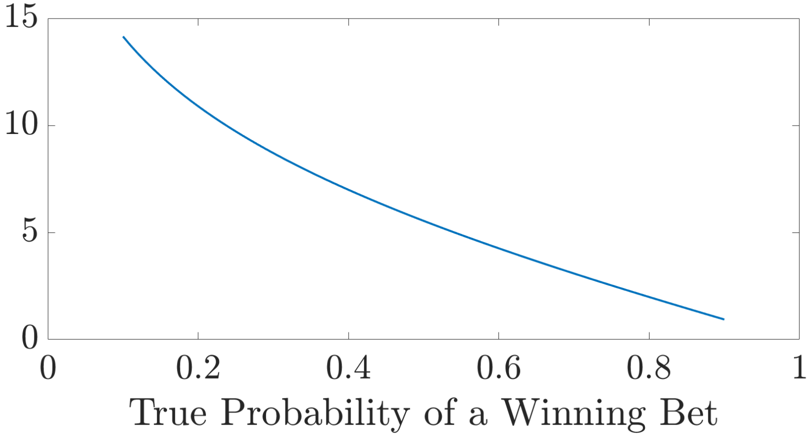
Advertising spending for $\gamma = 0.8$, $\alpha = 0.2$, $\sigma = 0.06$, $\delta = 0.0005$



The share of bettors aware of the bet for $\gamma = 0.8$, $\alpha = 0.2$, $\sigma = 0.06$, $\delta = 0.0005$



Betting volumes for $\gamma = 0.8$, $\alpha = 0.2$, $\sigma = 0.06$, $\delta = 0.0005$



Part III

Inside Information

Might Some People Have Inside Information?

- One of the themes of academic research on sports betting has been that odds might be affected by some bettors having superior information to the bookmaker.
- In 1985, economist Nicholas Crafts published a paper with UK data showing that bets on horses whose odds "plunged" on the day of a race produced better returns than other bets.
- He argued this came from some people having inside knowledge. For example, staff involved in training a horse may know it has been running fast in training.
- In cases where the horse has not run many times before, this inside information may be particularly valuable.
- In other sports, the inside information may be more nefarious e.g. the scandals in Italian soccer in which gamblers bribed referees to favour one team in a match or the "spot betting" scandals in cricket where players agreed to bowl "no balls" in return for bribes.
- In the 1990s, economist Hyun Song Shin published some papers formally modelling how the existence of insiders might affect betting odds.

Adding Insiders

- In Shin's 1991 model, a fraction z of the potential betting population are insiders who know the outcome of the contest before it has happened.
- The bookmakers knows there is a fraction z of insiders who will definitely win but can't identify these bettors.
- In the general case where demand for a bet among non-insiders is assumed to be $B(D)$, costs per unit bet are μ and the bookmaker believes the bet has a probability p of winning, the bookmaker's expected profit is

$$E(\Pi) = pz(1-\mu-D) + (1-z)(1-\mu-pD)B(D)$$

- Taking derivatives with respect to D, the condition for optimal odds is

$$\frac{\partial E(\Pi)}{\partial D} = -pz + (1-z)\left[(1-\mu-pD)B'(D) - pB(D)\right] = 0$$

- This solves to give

$$D = \frac{1-\mu}{p} - \frac{B(D)}{B'(D)} - \frac{z}{1-z}\frac{1}{B'(D)}$$

Insiders Reduce Odds

- With a fraction z of insiders, the odds are

$$D = \frac{1-\mu}{p} - \frac{B(D)}{B'(D)} - \frac{z}{1-z}\frac{1}{B'(D)}$$

- If you set $z = 0$, naturally you get the same formula for odds as we had before.
- Increasing z, the odds get lower ($B'(D)$ is positive so the final term gets more negative as z increases.)
- This happens because the insiders have zero elasticity of demand. They will accept as long as $D > 1$, which it has to be to attract any non-insiders to bet.
- So the presence of insiders reduces the overall elasticity of demand with respect to odds, which means the bookmaker sets lower odds.

A Two-Outcome Event

- Consider again a two-outcome event where beliefs about the probability p that the favourite wins are uniformly distributed over $[L, H]$.
- We can show that adding insiders to the model, the odds are

$$D_F = \sqrt{\frac{1-\mu}{p\left(\frac{z(H-L)}{1-z} + H\right)}} \qquad D_L = \sqrt{\frac{1-\mu}{(1-p)\left(\frac{z(H-L)}{1-z} + 1 - L\right)}}$$

- The ratio of odds for the favourite to odds for the longshot is

$$\frac{D_F}{D_L} = \sqrt{\frac{(1-p)\left(\frac{z(H-L)}{1-z} + 1 - L\right)}{p\left(\frac{z(H-L)}{1-z} + H\right)}}$$

- Shin's paper assumed beliefs were uniform over $[0, 1]$, so $L = 0$ and $H = 1$. In that case, the ratio of odds is

$$\frac{D_F}{D_L} = \sqrt{\frac{(1-p)}{p}}$$

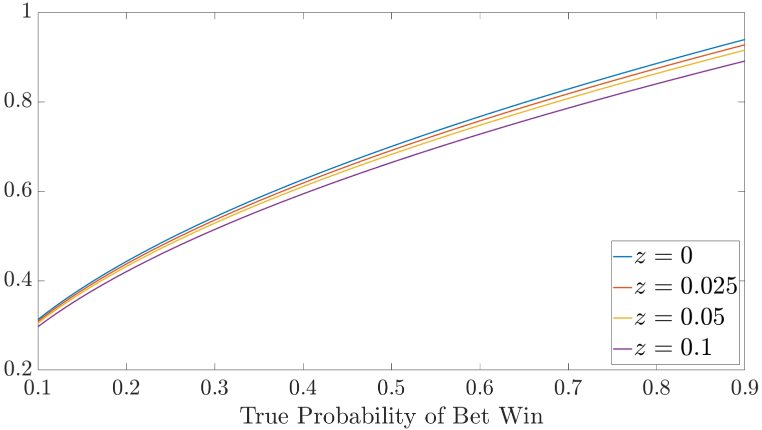
Do Insiders Cause Favourite-Longshot Bias?

- Shin's formula
$$\frac{D_F}{D_L} = \sqrt{\frac{(1-p)}{p}}$$
means the ratio of expected payouts is
$$\frac{pD_F}{(1-p)\,D_L} = \sqrt{\frac{p}{(1-p)}} > 1$$
- The expected payout for favourites is higher than for longshots.
- Economists have often interpreted Shin's paper as demonstrating that the presence of insiders generates favourite-longshot bias. After all, there are insiders in the model and there is a favourite-longshot bias.
- But we can see here that Shin did not prove this. If $L = 0$ and $H = 1$, then insiders have no effect on the relative payouts on favourites and longshots. z doesn't feature in the above formulas at all.
- In my paper "How Does Inside Information Affect Sports Betting Odds?", I show that for more realistic beliefs, a higher z does induce some favourite-longshot bias but the effect is tiny.

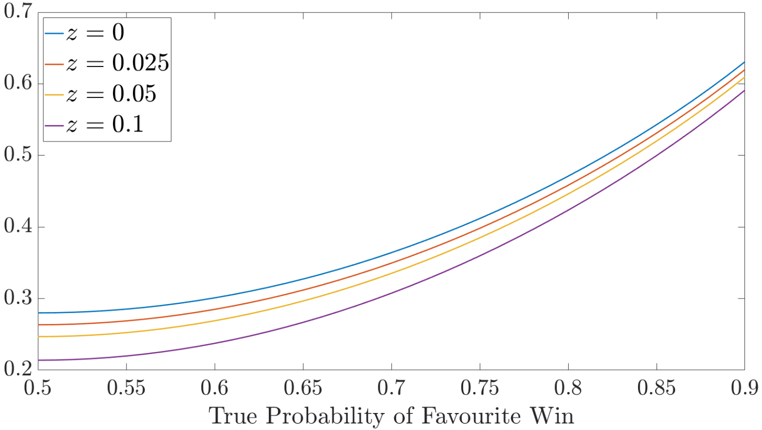
Realistic Preferences and Market Collapse

- The specification $L = 0$ and $H = 1$ is not a very good way to model the beliefs of bettors.
- It means people have essentially random beliefs and the distribution of beliefs does not depend at all on the true value of p.
- This matters because when you specify more realistic beliefs, it turns out that the market will collapse if there are more than a very small number of insiders.
- The charts on the next page shows the expected payout for bets with different probabilities of success with $L = 0$ and $H = 1$. Notice the huge loss rates from betting on longshots. It turns out that people who haven't a clue about what they are betting on lose lots of money.
- The chart on the page after shows the huge profit rate earned by bookmakers if non-insiders have these beliefs.
- These are not remotely credible. If we specify more realistic beliefs, such as beliefs being uniform on $[p - 0.06, p + 0.06]$ then loss rates for bettors and profit rates for the bookmaker are much lower (see the following two pages.)
- In fact, for very low fractions of insiders, the best an operating monopolist can do is to lose money. The optimal strategy is to close down.

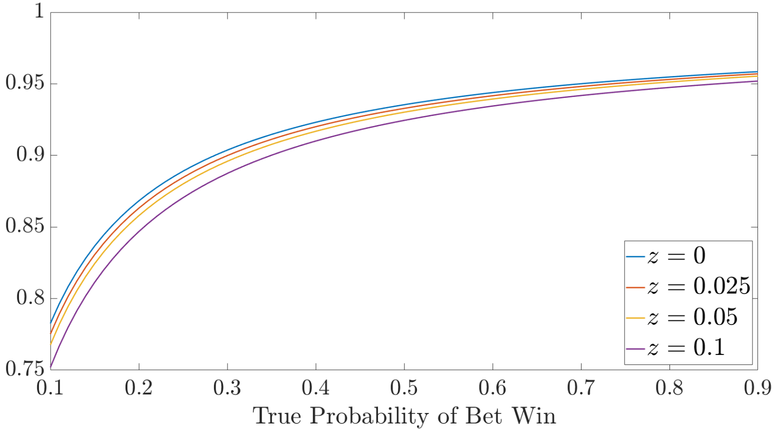
Expected payouts for bets with different probabilities of success and different values of z when beliefs are uniform on $[0, 1]$



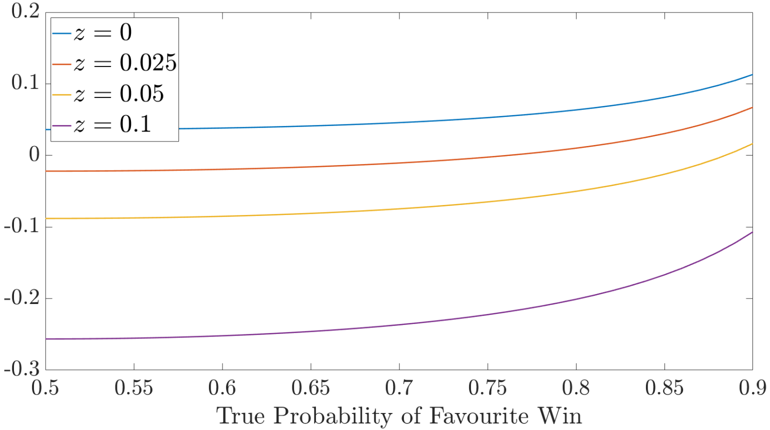
Profit rates for bookmakers for matches with different probabilities of the favourite winning and different values of z when beliefs are uniform on $[0, 1]$



Expected payouts for bets with different probabilities of success and different values of z when beliefs are uniform on $[p - 0.06, p + 0.06]$



Profit rates for bookmakers for matches with different probabilities of the favourite winning and different values of z when beliefs are uniform on $[p - 0.06, p + 0.06]$



Measuring Insiders?

- Some economists have used models like this to estimate the fraction of money placed by insiders from the odds.
- These studies generally re-porting that the share of money placed by insiders was somewhere between 3 and 5 percent across a range of different sports and times.
- These estimates implied that vast sums are being placed every day by people with privileged knowledge.
- But they are only as reliable as the assumptions they are based on. The crucial assumption in this case was that the bookmaker made zero profits. This meant that profits earned on the regular bettors were precisely offset by losses to insiders.
- But bookmakers earn big profits, e.g. Flutter's reports its gross profit margin for its UK and Ireland sports business was 13.8% in 2024.
- The insiders measure turns out to be 99% correlated with the overrounds.
- It is very unlikely this re-search is really telling us anything about the importance of insiders.

Other Reasons for Skepticism About Insiders

- There may be a lot of insider information in horse racing but the role of this sport in betting markets is declining.
- For the popular professional sports that account for the vast majority of modern betting, there is a very limited role for inside information. By the time a game between two major soccer teams kicks off, it is unlikely that anyone has information unavailable to the public that can significantly increase their chances of winning a bet.
- Academics writing on this topic regularly cite corruption as an issue. But given the high stakes for players, it is unlikely that this kind of corruption is commonplace in today's high-end sports.
- Even if corrupt activity takes place occasionally, bookmakers are unlikely to be factoring in this possibility into their odds on all events.
- These models also 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 know some people have better knowledge than them and they use betting patterns from "sharp" bettors to adjust their odds.

(Literally) Incredible Returns for Insiders

- Attempts to estimate z with data like our soccer dataset tend to produce estimates like $z = 0.035$.
- How do we interpret the idea that the average match has 3.5% of "insider bettors"?
- If there are bettors that regularly win because they have insider knowledge, then they are keeping very quiet about it because the best known professional sports bettors are known to make relatively modest profit margins.
- Perhaps the way it works is that there are 35% of the bettors, who get inside information for one match in 10.
- I have done calculations with the soccer data showing this would imply an average return per bet of about 11%, which would be sufficient to generate huge cumulative returns over a relatively short space of time.
- Alternatively, maybe 3.5% of bettors are chosen at random for each match to get the inside information. Again, however, calculations with the soccer data show the average return for bettors in our soccer dataset would be -1.4%.
- This low loss rate is well out of line with the actual gross profit margins that bookmaking firms report in their accounts.

Part IV

Point Shaving

Do Spread Bets Encourage Corruption?

- One concern about spread betting is that it may create incentives for corruption in sports.
- It is always possible to bribe players to throw a game but players want to win, so most of them will not be open to being bribed.
- But what if someone offered you money to go easy and only win by 10 points, so their bet on you winning by less that 12 points pays out? You still win the game and you get the bribe.
- Remember the famous economist Justin Wolfers? He wrote a paper in 2006 suggesting that this practice, known as "point shaving", was common in college basketball (NCAA) games in the US.
- College students don't get paid (and most don't get to turn professional) but lots of money is gambled on their games, so this could be exploited by gamblers.
- And some actual cases of point shaving have been uncovered.
- Generally, the players admitted that they slacked off on defense rather than deliberately missed shots on offense.

The Evidence Presented by Wolfers

- The charts on the next page show the evidence presented by Justin.
- He examined a dataset of point spreads and outcomes for 44,120 NCAA games.
- The solid line in the upper chart shows the distribution of the winning margin for the favourite for games where the spread is 12 points or less. The dashed line shows a Normal distribution with the same mean and standard deviation.
- The lower chart shows the same thing for games where the spread is greater than 12 points, so there is a very strong favourite.
- The outcomes in the upper chart are very similar to the Normal distribution.
- But the lower chart—for games with a strong favourite—shows the solid line (the actual outcomes) lower than the Normal distribution for positive winning margins greater than the spread. Strong favourites seem to beat the spread less than a Normal distribution predicts.
- In contrast, the solid line is greater than the Normal distribution at 0 to minus 12 points: Here the favourite is winning but not beating the spread. Looks fishy right?

Wolfers graph on basketball results relative to spread

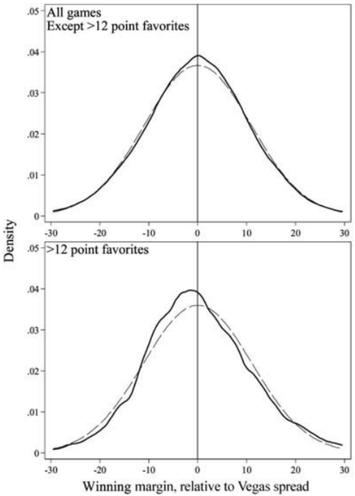


Figure 2. Probability Distribution: Game Outcomes Relative to the Spread

Note: Dashed line shows normal distribution, with mean zero. Solid line shows nonparametric estimated distribution.

Evidence Against Point Shaving

Justin's paper was clever and thought-provoking but subsequent research has mainly pointed against its conclusions. A few arguments came up.

1. **Bookmakers are not perfect**: They don't know the actual spread that equalises the chances of the two bets winning. If their estimates of the spread were on average correct but added in a zero-mean error, then an estimate of a team as having a very high spread could be partly due to this error. A paper by Neal Johnson (2009) showed even if bookmakers were very accurate in their estimation of the correct spread, favourites with very high spreads would probably "cover" a bit less than half the time.
2. **Ties**: Justin's dataset showed result at the end of the game. But Johnson pointed out NCAA games go to overtime if there is a tie. If there is a 13 point spread, then when the game ends tied, they keep playing. And in overtime favourites usually do better. Overtime games explained why more games than predicted ended with favourites winning but by a bit less than the spread.
3. **Offense/Defense**: Evidence also suggested that when teams didn't cover the spread, it was because they scored a bit less rather than conceded more points, running against what the players who did cheat had admitted to. Maybe if you're up by a lot, you don't put as much effort into scoring more points.

Supplementary Material in the Draft Book

- Chapter 16: Backing the Draw?
- Chapter 18: Insiders and Corruption