Betting on intuitive longshots

Philip W. S. Newall^{A,B*}, Lukasz Walasek^A, Rebecca Vázquez Kiesel^C, Elliot A.

Ludvig^A, Caroline Meyer^A

^A University of Warwick, Coventry CV4 7AL, United Kingdom

^B Experimental Gambling Research Laboratory, School of Health, Medical and Applied Sciences, CQUniversity, 120 Spencer St, Melbourne, VIC 3000, Australia

^C Technical University of Munich, Arcisstraße 21, 80333 Munich, Germany

Running head: Betting on intuitive longshots

* Corresponding author: Dr. Philip Newall. Present address: Experimental Gambling Research Laboratory, School of Health, Medical and Applied Sciences, CQUniversity, 120 Spencer St, Melbourne, VIC 3000, Australia

Email. p.newall@cqu.edu.au

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Abstract:

Sports betting markets are a laboratory for studying probabilistic judgments in the field. Here we present a study of a new gambling product that allows customers to easily design custom bets via Twitter: a “request-a-bet” service. We use large volumes of Twitter data to demonstrate that soccer bettors use request-a-bet services to create “intuitive longshots” – combinations of (individually) representative events with high potential winnings. Pairing these requests with historical data illustrated that these requested bets would lead to substantially higher losses than conventional soccer bets. Compared to conventional sports betting products, these preferences are associated with two ordinarily contrasting cognitive biases: the overweighting of small probabilities, and the representativeness of individual events. Moreover, these results suggest that more datasets of actual sports betting behavior should be shared with researchers to fully investigate the welfare effects of novel sports betting products.

Keywords: decision-making, gambling, representativeness, longshot bias, social media

Sports betting markets are a natural laboratory for studying probabilistic judgments in the field because gamblers are financially incentivized to correctly forecast one-off events. Previous field sports betting studies have primarily inferred gamblers' preferences through the investigation of past betting *odds*, for which large datasets can be collected and which tend to reflect gamblers' biases (e.g., Thaler & Ziemba, 1988). This is because few historical datasets of past betting *choices* have been made available to researchers (Chagas & Gomes, 2017), perhaps due to the economic risk to gambling operators from releasing valuable data (Cassidy, Loussouarn, & Pisac, 2013).

Here we leverage a new approach of utilizing large datasets to investigate the drivers of everyday gambling behavior (Otto, Fleming, & Glimcher, 2016). We take advantage of a new gambling product that allows gamblers to easily design custom bets via Twitter: a “request-a-bet” service. By studying these requested bets, we are able to unobtrusively measure gamblers' preferences and find that these preferences reflect two ordinarily contrasting cognitive biases: the overweighting of rare events and the representativeness of common outcomes.

In horse racing, gamblers put more money on unlikely “longshot” horses winning than is justified given the objective probability of success (Thaler & Ziemba, 1988). Unlikely longshot bets offer high potential payoffs, which, like a lottery ticket, provide gamblers with a cheap dream of hitting it big. This reflects the cognitive bias that people tend to overestimate the probability of rare events (Kahneman & Tversky, 1979).

A further bias has been shown in NFL betting, where a skill adjustment known as “the spread” equalises the potential payoff from betting on any team. This skill adjustment means that bets on the best and worst team “to beat the spread” in any encounter will usually receive the same payoff: \$100 for every \$110 bet. In this sports betting market gamblers have a bias

toward betting on strong teams (Simmons & Nelson, 2006). Betting on a strong team feels “intuitive,” even when the odds have been experimentally manipulated to make betting on strong teams a losing strategy (Simmons, Nelson, Galak, & Frederick, 2011). This matches the evidence from the laboratory studies, which show that probability judgments are often influenced by the representativeness of information, rather than objective statistical facts (Kahneman & Tversky, 1972).

In conventional sports betting markets, and in life in general (Pleskac & Hertwig, 2014), the potential payoff from any bet varies inversely with its probability of success, creating a separation between bets that are intuitive and bets with high potential payoffs. However, we hypothesise that Twitter users will use the flexibility inherent in request-a-bets to uniquely combine both sports betting biases, thus creating “intuitive longshots.”

Method

Various gambling companies’ Twitter accounts now offer “request-a-bet” services, which respond to betting odds requests on custom bets from the public. Betting odds requests can be sent by any member of the public via a message accompanied by a hashtag. The bookmaker replies to betting odds requests with the custom bet’s quoted odds and a link where the bet can be placed via their online platform (the bookmaker may also refuse to quote odds). In the present study, we collected large volumes of such requests to test whether their properties align with a demand for intuitive longshots.

Data Extraction

The leading British bookmaker William Hill runs a request-a-bet service on Twitter via the hashtag #MyOdds. We used the StreamR package (Barbera, 2015) in R to collect bet requests with the #MyOdds hashtag and William Hill’s reply using Twitter’s official API.

Data were collected between August 11th and September 27th, 2017, coinciding with the start of the 2017/2018 English Premier League soccer season. During this time period, only two British bookmakers that we were aware of, Paddy Power and William Hill, had request-a-bet products. William Hill has a much larger presence in the UK gambling market, and created its product first, in January 2017 (Roarty, 2017).

Data Processing and Coding

After removing non-English characters and tweets containing only links, we obtained a total of 9,443 tweets. William Hill refused to quote odds on 1,066 requests. As our data collection had precise time cut-offs, we also did not find requests for 1,426 odds provided by William Hill. After further excluding all requests that did not include at least one Premier League soccer event (the UK's highest level of soccer, and one of the most globally followed sports leagues), our final sample consisted of 2,889 requests and corresponding quoted odds.

First, we determined whether individual bets would have paid off. Calculating bet payoffs was done after completion of the 2017/2018 season. At this point events corresponding to a small number of requests had not yet occurred, leading to a loss of seven observations. Although detailed match statistics are freely available online, e.g., from premierleague.com/results, these statistics do not include information on some requested events, such as the number of throw-ins or goal-kicks. This led to the loss of another 385 observations. A further 29 observations included specific players who took no part in the match, invalidating the request and the bookmaker's quoted odds. This reduced the sample size to 2,468 requests for which average bet pay-offs were calculated.

From the full sample of 2,889 requests we manually categorized individual events within each requested bet, excluding any requests that did not relate to a well-defined number of matches (e.g., "Manchester City to win the FA cup;" – here Manchester City might get

knocked out after only one match). We also excluded requests that did not relate to actual match events (e.g., a request that a specific player would transfer to join a new team). This reduced the sample size to 2,681 requests for the content variables that follow.

For each request, we counted the number of individual soccer matches that a request related to, as well as the number of teams that either were required to, or could, satisfy a request's required events (maximum = 20 for the number of teams in the English Premier League). Finally, we counted the number of individually-specified conditions that a bet would need to satisfy to be successful. An individually-specified condition was coded as a set of statements involving events which must happen in a single match for a request to pay-off, as separated by a comma, an "and," or as should be given a grammatical English description of the required events (the original tweets were of variable written quality).

Consider the following hypothetical request "Romelu Lukaku to score a header and Manchester United to win, and Harry Kane to score a header and Tottenham to win." This example refers to two matches, one match involving Manchester United and the other match involving Tottenham. This example also refers to two specified teams (Lukaku was a Manchester United player, and Kane a Tottenham player) who were either required to, or could, satisfy a request's required events. The teams playing against Manchester United and Tottenham did not have to do anything to satisfy the request's conditions, and were therefore not included in the count, despite taking part in these matches. This example also refers to four individually-specified conditions, corresponding to the events separated by an "and" or a comma.

Two researchers performed the manual coding. A 10% random sample was dual-coded to determine inter-coder reliability. Percentage agreement was 98.3% (profitability), 95.2% (number of matches), 93.2% (number of teams), and 85.8% (number of conditions).

These are all above suggested minimum threshold of 70% agreement for acceptable inter-rater percentage agreement (Stemler & Tsai, 2008). Full coding instructions and coder output variables are available from <https://osf.io/2g8y5/>.

Follow-up Survey

Since our initial study, at least six additional gambling operators began offering request-a-bet services on Twitter. For exploratory purposes, from December 2018 to March 2019 we collected usernames associated with any of the following request-a-bet hashtags: #pickyourpunt, #priceitup, #betyourway, #buildyourbet, #getaprice, #requestabet, #yourodds. Using the streamR package, 4,584 unique usernames were obtained for potential recruitment to a short online survey. All Twitter users can be contacted publicly by default, but Twitter users may also opt-in to allow anyone with a Twitter account to message them privately as well. Non-commercial user accounts who had opted-in to receiving private messages ($N = 779$) were contacted with a link to a five-question survey. Ethical approval was obtained prior to collecting the data. The survey asked participants to recall how many request-a-bet bets they had made, whether the participant had won or lost overall at request-a-bets, and contained the PGSI Short Form problem gambling screener (Volberg & Williams, 2012). In total, 55 participants completed the survey. Questionnaire materials and anonymous responses can be downloaded from <https://osf.io/2g8y5/>.

Results

Twitter Requests.

Most requests involved combinations of multiple events (based on the sub-sample of $N = 2,681$). On average, requests involved 2.3 ($SD = 11.8$) soccer matches, 2.6 ($SD = 2.4$) specified teams, and 4.8 conditions ($SD = 10.4$). Furthermore, most requested bets came with

high potential payoffs. The types of bets requested likely did not reflect the average bettor's demand, because bookmakers already list many conventional bets on their websites which customers did not need to request via Twitter. Nonetheless, requested bets could return an average of £56.5 per £1 risked, if successful (based on the full sample, $N = 2,889$). By comparison, consider the fact that, historically, traditional soccer bets could return a little under £3 on average per £1 risked, given the bookmaker profit margin (Buhagiar, Cortis, & Newall, 2018). The average potential returns of requested bets in our sample were also skewed by some extremely low-likelihood requests (maximum = £10,001 return per £1 risked). The median bet request would return £9 per £1 risked.

Requested events were compared against actual match events via the data recorded on premierleague.com. The top panel of Figure 1 illustrates the distributions of potential payoffs from £1 bets (in log space to alleviate the impact of extreme payoffs) across three categories: winning bets ($N = 240$), losing bets ($N = 2,228$), and bets for which we could not determine the outcome ($N = 421$). We evaluated a strategy of betting £1 on every single bet whose outcome we could determine, with winning bets receiving the payoff implied from the bookmaker's odds. This revealed a bookmaker profit margin of 43.7%, which is almost ten times higher than the current profit margin on traditional soccer bets (Buhagiar et al., 2018). The bookmaker profit margin increased for the highest potential payoff bets, as can be inferred from Figure 1. Only three out of 724 requests with potential returns of £30 or more per £1 risked paid off, corresponding to an even higher bookmaker profit margin of 74.6% for this subset of bets.

To determine the long-run significance of the 43.7% profit margin on requested bets, we ran a simulation in which 1,000 hypothetical individuals bet on a random selection of requested bets (based on the $N = 2,468$ bets for which outcomes could be determined for). To observe the evolution of average betting returns over time, this simulation was repeated for

betting sequences of between 1 to 100 bets (this gives us $1,000 \times 100 = 100,000$ simulated outcomes). The bottom panel of Figure 1 shows the average earnings across the number of plays (bets placed). Error bars show ± 1 standard deviation, capturing the outcomes that could be expected for 68% of simulated gamblers. Consistent with the fact that most requested bets did not pay-off, most simulated gamblers lost money even with a very limited number of bets. These losses became worse as the number of bets increased, i.e., losses were not on average recovered over the betting sequence.

Fig. 1. Top panel: Distribution of potential payoff from a £1 bet in log space for a) winning bets, b) losing bets, and c) bets that could not be determined (unknown). Bottom panel: Mean earnings across various numbers of plays (bets purchased). The horizontal dashed line illustrates breaking even, and the diagonal black line represents the worst possible outcome of losing each bet. Error bars show ± 1 standard deviation around the mean.

The second property of the intuitive longshot hypothesis is the representativeness of individual events. Did Twitter users request individual events which were, in isolation, plausible? This is a difficult question to operationalize for the full dataset. For example, some teams might be perceived at this specific time as serial losers, or specific players may be notorious for having poor disciplinary records. Betting odds can be requested on essentially anything. We decided to investigate representativeness in requested bets via the subset of all requested events involving a named player scoring a goal. In total 1,067 requests identified at least one named player ($M = 1.39$) to score at least one goal ($M = 1.07$). Figure 2 shows the numbers of mentions of each individual player in the requested odds across all Premier League teams. The results show that requests were dominated by the Premier League's "top six": the teams Manchester United, Manchester City, Tottenham, Liverpool, Arsenal and Chelsea. There are multiple reasons why these teams featured most often in bet requests. For example, these six successful teams also have the largest fanbases, meaning that fans' preference to bet on their own team would predict a similar pattern of results (Massey, Simmons, & Armor, 2011).

Fig. 2. Frequency distribution of individual players (dots) and their respective teams (bars) requested for all events where an individual player was required to score at least one goal. One star player dominates most teams' requests, and the name of the most frequently requested player for each team is included.

Inspection of requested players' identities, however, shows a second level of representativeness. A single high-profile player dominated most teams' requests, even though each team starts each match with eleven players. Romelu Lukaku was the most expensive Premier League player transferred during the 2017 summer transfer window immediately prior to data collection, for £76 million from Everton to Manchester United. Lukaku was bought for the explicit reason to score goals. As an individual, Lukaku featured in more bet requests than any other team bar Manchester City. Among other most highly featured players were Harry Kane, who was the Premier League's top goalscorer for the two previous seasons, and Sergio Agüero, who would go on to break the Manchester City goalscoring record that season. However, these skilled representative players featured more heavily than their goalscoring records for the rest of the season would go on to indicate. The most highly-requested player for each team was included in 75.1% of the requests mentioning their

corresponding team, but would consequently go on to score only 24.3% of their team's goals for the season on average (which is considerably higher than the average player).

Survey Results.

From the 55 individuals who completed the survey, 51 participants indicated they had placed at least one request-a-bet wager, with a range from zero to 250 bets placed ($M = 44.4$, $SD = 65.5$). Of the participants who had bet, 37.3% reported being a winner on their request-a-bets. These results indicate that many gamblers are using request-a-bet services to gamble, rather than using the services purely for information or enjoyment. Participants scored an average of 1.39 ($SD = 1.39$) on the PGSI Short Form problem gambling screener.

Discussion

Twitter users who engaged with the request-a-bet service combined many different representative events together in order to create intuitive longshots. These requests contrasts with conventional sports betting markets, where there is a trade-off between bets with high potential payoffs, and bets that feel intuitive (Pleskac & Hertwig, 2014). This unique pattern of sports betting bias would have been economically costly to any repeat gambler, highlighting the potential dangers of the ongoing innovation in internet and mobile gambling products (Lopez-Gonzalez, Estévez, & Griffiths, 2017). These results might be especially relevant to the UK's estimated 340,000 problem gamblers (Wardle, Reith, Langham, & Rogers, 2019).

Cognitive biases in probabilistic thinking are associated with problem gambling, such as the tendency to gamble more after a "near-miss" losing bet (Walker, 1992), and many of these biases could motivate engagement with request-a-bets. For example, problem gamblers are especially attracted to high-payoff/small-probability bets (Kyonka & Schutte, 2018). A

content analysis of request-a-bet advertising shown on UK TV over the 2018 World Cup suggests bookmakers used a number of techniques to nudge gamblers toward high-payoff bets (Newall, Walasek, & Ludvig, 2019). Compared to conventional sports bets, request-a-bets allow bettors to combine the ordinarily contrasting biases toward representative events (Kahneman & Tversky, 1972) and toward overweighting small probabilities (Kahneman & Tversky, 1979). Moreover, the custom nature of request-a-bets may be particularly appealing to problem gamblers, who tend to overestimate their degree of personal control over events (Goodie & Fortune, 2013). This view is supported by a recent cross-sectional survey of online sports bettors, which found that 16.0% of respondents who had customized a sports bets were current problem gamblers, compared to 6.7% of respondents who had never customized a sports bet (Newall, Cassidy, Walasek, Ludvig, & Meyer, 2019).

The data are drawn from Twitter requests; how many of these requests were then bet on is unknown. The follow-up survey, and the fact that many gambling operators run request-a-bet services (despite the potentially high operational costs of responding to Twitter users), both suggest that many users do in fact use request-a-bet services to gamble quite frequently. Although we cannot rule out the possibility that the subsample of actual bets looks different from the overall pattern of requests, any bias would have to be large to eliminate the patterns observed here.

As the US moves closer toward legalized online sports betting, these results emphasize how the interaction between profit-making gambling firms and potentially biased consumers deserves additional international scrutiny (Newall, 2019). Future research might only be able to build on the suggestive nature of the patterns found here if gambling regulators and policy-makers enforce the sharing of proprietary betting choice data with the research community (Cassidy et al., 2013).

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