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PARIMUTUEL BETTING ON THE ESPORTS DUELS: REVERSE FAVOURITE-LONGSHOT BIAS AND ITS DETERMINANTS

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PARIMUTUEL BETTING ON THE ESPORTS DUELS: REVERSE FAVOURITE-LONGSHOT BIAS AND ITS DETERMINANTS

We analyse betting behaviour patterns of the visitors of the specialized betting website dedicated to the popular eSports game Counter-Strike: Global Offensive. The reverse favourite-longshot bias is found both in the in-sample and out-of-sample datasets. This phenomenon is rather unusual for parimutuel betting markets because favourite-longshot bias is more common. We define simple betting strategies based on the bets on underdogs and show that these strategies make a sufficiently large positive profit, which is a sign of market inefficiency. Next, we investigate determinants of the reverse favourite-longshot bias. We hypothesize that popular teams attract more unsophisticated gamblers which adds to the stronger reverse favourite-longshot bias in matches with such teams. Geographical proximity is found to be a significant factor that increases the bias, whereas the effect of internet popularity measured by the number of team players' followers on Twitter surprisingly follows the U-shape curve.

Keywords: eSports; betting; market inefficiency; favourite-longshot bias.

JEL Classification: Z23, G14

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1 Introduction

According to the general economic definition, the market is more efficient if the prices better reflect available relevant information about the traded goods. With regard to the betting markets, the concept of market efficiency is associated with the existence of strategies that generate positive economic profits. Each sports betting market is characterized by its own peculiarities such as rules for making bets, the size of the bookmaker's cut, the sports-specific rules, etc. Therefore, the bettors' behaviour could be very different across the markets, and the emergence of the new markets could possibly bring unprecedented phenomena. In this paper, we consider a relatively new market of betting on the eSports duels. Due to the skewed sample of bettors in comparison to the more popular sports such as soccer or more aristocratic sports such as horse racing, we can potentially predict new betting behaviour patterns. We investigate the parimutuel betting market for one of the most popular eSports disciplines *Counter-Strike: Global Offensive* (CS:GO) organized on one of the most popular discipline-related betting websites `csgopositive.com`. We demonstrate the existence of the so-called reverse favourite-longshot bias, the phenomenon of the overbetting on the favourites[1]. We hypothesize that popular teams attract more unsophisticated gamblers, which adds to the stronger reverse favourite-longshot bias in matches with such teams. Different proxies for team popularity, such as geographical proximity and number of team players' followers on Twitter, are used to determine the nature of the bias. The bias is found to be persistent and strong enough to be exploited to make profits.

The literature on the efficiency of sports betting markets is rather extensive. Scholars come to different conclusions depending on the betting mechanism, betting restrictions, the type of sport and other factors. The impossibility of beating the market was demonstrated for such sports as horse racing (Figlewski, 1979), baseball (MLB[2], Woodland and Woodland, 1994), American football (NFL[3], college football, Golec and Tamarkin, 1991), and soccer (Croxson and Reade, 2013).

A wealth of other papers demonstrate various betting market inefficiencies. First, there exist arbitrage opportunities across the bookmakers (Vlastakis, Dotsis, and Markellos, 2009). Second, home-field advantage can be incorrectly estimated by the market. Home team win chances in NFL were found to be exagerrated by the market in Borghesi (2007) and Dare and Holland (2004) (in the latter paper, overestimated coefficients were detected only for

[1]Vice-versa, favourite-longshot bias stands in the literature for overbetting on longshots, or underdogs.

[2]Major League Baseball.

[3]National Football League.

underdogs playing at home). Third, analyses of tweets can at times help to beat the market by revealing additional information about the teams, as shown by Brown et al. (2016) for the English Premier League soccer matches. Fourth, some information can be (correctly or incorrectly) derived from the previous seasons of competition. Bennett (2019) found that the inefficiency of the college football betting market is a result of the overestimation of information obtained from the previous seasons. Also, inefficiencies of the betting markets can be country-specific. For example, Angelini and De Angelis (2019) report mixed evidence regarding the efficiency of betting markets for European soccer leagues matches: 8 out of 11 markets were found to be efficient, whereas 3 markets were inefficient.

Borghesi (2007) raises the question of why more recent studies (Dare and MacDonald, 1996; Gandar et al., 2001) demonstrate the effeciency of markets that were found by previous studies to be inefficient (Golec and Tamarkin, 1991). One of the possible explanations Borghesi offers for these inconsistencies is that more advanced econometric methods were used in later papers. In addition, it is possible that inefficiency cannot be maintained for a number of years, and the markets gradually adapt.

Probably the most well-known sports betting market inefficiencies are favourite-longshot and reverse favourite-longshot biases. In studies conducted by Woodland and Woodland (2001) and Gray and Gray (1997), authors provide simple profitable strategies, such as betting on the underdogs of the NHL[4] and NFL matches, respectively. Gil and Levitt (2012) prove the inefficiency of the betting market for the soccer World Cup 2002 matches by showing profitability of the strategy of betting on the underdogs. Berkowitz, Depken, and Gandar (2017) demonstrated that it is possible to generate close-to-zero positive profit by betting on the favourites of football and basketball NCAA[5] matches.

The favourite-longshot bias was persistently documented on parimutuel betting markets — the markets where two or more sides make their bets into the same pot, and the winners get the losers' money (minus the bookmakers' comission). Betting on horse races is usually organized in the form of parimutuel market. We mention Asch, Malkiel, and Quandt (1984); Ali (1977); Ziemba and Hausch (1986) among the first papers that describe the favorite-longshot bias in horse races betting and refer the reader to Sauer (1998) for a more detailed survey.

There are a number of explanations for the favourite-lonshot bias including those based on Kahnemahn-Tversky prospect theory (Thaler and Ziemba, 1988; Snowberg and Wolfers,

[4]National Hockey League.

[5]National Collegiate Athletic Association.

2010), risk-loving behaviour (Quandt, 1986), information asymmetry (Hurley and McDonough, 1995), and evolutionary perspectives (Kajii and Watanabe, 2017).

A brief summary of the results of studies concerning the effeciency of sports betting markets is provided in Table 1.

Paper	Sport	Tournament	Betting market	Market efficiency
Ali (1977)	harness horse racing	20247 races	parimutuel	favourite-longshot bias
Angelini and De Angelis (2019)	soccer	European leagues	fixed-odds	mixed evidence
Asch, Malkiel, and Quandt (1984)	horse racing	712 races	parimutuel	favourite-longshot bias
Bennett (2019)	American football	college football	spread betting	reverse favourite-longshot bias (and other biases)
Berkowitz, Depken, and Gandar (2017)	basketball American football	college basketball college football	fixed-odds fixed-odds	favourite-longshot bias but efficient market
Borghesi (2007)	American football	NFL	spread betting	temperature is underestimated
Brown et al. (2016)	soccer	EPL	fixed-odds	Tweets contain information not included in the odds
Croxson and Reade (2013)	soccer	Various tournaments	fixed-odds	efficient market
Dare and Holland (2004)	American football	NFL	spread betting	reverse favourite-longshot bias for home underdogs
Dare and MacDonald (1996)	American football	NFL college football Superbowl	spread betting	efficient market efficient market favourite-longshot bias
Figlewski (1979)	horse racing	thoroughbred horse races	parimutuel	efficient market
Gil and Levitt (2012)	soccer	World Cup 2002	fixed-odds	reverse favourite-longshot bias and delayed reaction to goals
Golec and Tamarkin (1991)	American football American football	NFL college football	spread betting spread betting	favourite-longshot bias and bias against home teams unspecified biases
Gray and Gray (1997)	American football	NFL	spread betting	profitable betting on home underdogs
Vlastakis, Dotsis, and Markellos (2009)	soccer	Domestic and international European soccer matches	fixed-odds	favourite-longshot bias and arbitrage between different bookmakers
Woodland and Woodland (1994)	baseball	MLB	fixed-odds	minor reverse favourite-longshot bias but efficient market
Woodland and Woodland (2001)	hockey	NHL	fixed-odds	reverse favourite-longshot bias
Ziemba and Hausch (1986), see also Thaler and Ziemba (1988)	horse racing	50000 races	parimutuel	favourite-longshot bias

Table 1: Summary of the results on sports betting market efficiency

To the best of our knowledge, this paper is the first to investigate the efficiency of the betting market for eSports duels, which is a parimutuel market[6]. At the moment of making a bet on the duel, the agent knows the current distribution of bets and the current odds (coefficients). The coefficients depend on the distribution of bets and may vary over time. When the deadline expires, the final winning coefficients are determined. All winning bets will be multiplied by the final coefficient, not by the coefficient at the time of the bet.

[6]This is typical for betting markets organized on the eSports platforms.

Despite the similarities to the parimutuel structure of the horse races betting market, we will demonstrate the reverse type of the inefficiency. In order to explain this result, we will closely look at how team popularity affects the bettors' behaviour.

The structure of this paper is as follows. Section 2 describes the database. Section 3 tests for market inefficiencies and analyzes the possible reasons for these inefficiencies. Section 4 outlines and evaluates simple strategies that can allow bettors to make money from these market inefficiencies. Section 5 concludes.

2 Data

In order to conduct this study, we collected a dataset that includes information about 2412 CS:GO matches played by professional eSports teams at various tournaments. Two teams participate in each match. The outcome of a match is a victory by one of the parties. For any two teams that were listed among the top 30 teams of the world between September 25, 2017 and September 17, 2018 for at least one week according to `hltv.org`, we included in the dataset 6 last matches played by these teams by September 24, 2018. If less than 6 matches took place between these teams, all such matches were included. A complete list of the teams included in the dataset is presented in Table 6 (see Appendix). We will call this dataset as in-sample.

In the out-of-sample data, we included matches between the same teams as in the in-sample that took place in a different time interval. In the out-of-sample, for any pair of the same teams we included the last 6 matches played by these teams by November 24, 2018, excluding matches that were played before September 24, 2018. Once again, if less than 6 matches were played, all matches were included in the out-of-sample. The out-of-sample dataset consists of 717 matches.

There are a number of websites accepting bets on the outcome of eSports matches. Usually, bets are accepted in the currency of a particular website. However, players can convert the local currency into the real money, so bets on such websites can be considered as responsible and aimed at generating positive profit. One of the most popular websites that organize bets on the outcomes of the CS:GO matches is `csgopositive.com`.

The website `csgopositive.com` accepted bets for each of the 2412 matches in our in-sample. The betting mechanism follows typical parimutuel market rules. Each user has the opportunity to bet almost any amount of money (not less than approximately 15 US dollar cents and not more than approximately 7800 US dollars for one account) on one of the two teams. Those who predicted the outcome of the match wrongly, lose the bet. Those who predicted the outcome of the match correctly get their bet back, multiplied by the coefficient that is a function of the ratio of the sums put on each of the teams. Both the bets ratio and the multiplication coefficient are changing dynamically and are public information at any point. After the time for making bets expires, the final multiplication coefficient becomes fixed and will be applied for each winning bet. Interim values of the multiplication coefficient are for information purposes only.

If bettors put less than 50% of money on a team, we will call this team an underdog (of the match) and denote it as $Team_1$. We will call the underdog's opponent a favourite and denote it as $Team_2$. The share of the money put on the underdog of a match M is denoted by $\alpha(M)$. All matches M with $\alpha(M) = 0.5$ were excluded from our databases. After this operation, our in-sample dataset consists of 2371 observations and out-of-sample contains 704 matches. For any $\alpha \in [0, 0.5)$, by P_α we denote the share of the underdogs' victories in matches M with $\alpha(M) = \alpha$.

In order to analyse the role of the geographical location of a team, for each team we determine the country this team is attributed to. We will use the dummy variable Eu, indicating whether the team represents a European or Post-Soviet country ($Eu = 1$ if yes; $Eu = 0$ if no). The number of teams in a match representing this region is denoted by Eu_sum. If the number of teams from this region in a match is i, we set $TEu_i = 1$, otherwise $TEu_i = 0$, $i = 0, 1, 2$.

To test the hypotheses associated with the popularity of team on the Internet, for each player the number of his or her followers on Twitter was found (variable $Twit$). For each team $Twit\_av$ denotes the average number of followers on Twitter across all team members. If for any team $Twit\_av > 50000$, then we will consider this team as popular ($Pop = 1$), otherwise — unpopular ($Pop = 0$). The list of popular teams is provided in Table 6 (see Appendix). If the number of popular teams in a match is i, set $TPop_i = 1$, otherwise $TPop_i = 0$, $i = 0, 1, 2$.

Tables 2 and 3 represent all variables in consideration. Table 4 provides descriptive statistics for some variables.

3 Market efficiency analysis

Efficient market hypothesis states that available relevant information is immediately reflected in the stock price (in the case of bets, in the odds). We say that the betting market

Variable	$Team_1$	$Team_2$	α	$Result$	Eu	$Twit$
Description	Underdog (a team on which bettors put less money)	Favourite (a team on which bettors put more money)	Share of money bettors put on the underdog of a match	Match result 1, if $Team_1$ won 0, if $Team_2$ won	Is a team European or ex-USSR? 1, if yes 0, if no	The number of player's followers on Twitter
Source	csgopositive	csgopositive	csgopositive	csgopositive	liquipedia.net	twitter.com

Table 2: Description of variables collected from the open sources

Variable	P_α	$Twit\_av$	Pop	Pop_sum	$TPop_i$	Eu_sum	TEu_i
Description	The share of underdogs' wins in matches M with $\alpha(M) = \alpha$	average value of $Twit$ across teams' members	1, if $Twit\_av$ > 50000; 0, otherwise	the sum of variables Pop for both teams in the match	1, if $Pop\_sum = i$; 0, otherwise	the sum of variables Eu for both teams in the match	1, if $Eu\_sum = i$; 0, otherwise

Table 3: Description of computed variables

is inefficient if there exists a strategy that allows bettors to generate positive profit. The existence of a strategy that beats the market indicates that some information is available but not included in the odds. The form of market efficiency may vary. A strategy that allows bettors to make the profit on the in-sample dataset indicates that the market is inefficient at a certain moment of time. However, if the same strategy is also profitable on the out-of-sample dataset, then the market is inefficient to a greater extent since in this case the inefficiency is stable and is not a temporary characteristic of the market. In this section, we analyse the betting market efficiency by studying the distribution of P_α (see definitions in Section 2).

As with the studies of Gray and Gray (1997) and Woodland and Woodland (2001), where profitability of betting on the underdogs of NHL and NFL matches was demonstrated, we are looking for a similar effect for CS:GO matches. Our hypothesis is that for low values of α the share of wins P_α of teams, on which the share of α of all bets was set, is greater than α. We also expect that while α increases, the difference $P_\alpha - \alpha$ decreases. The latter means that players who bet on the underdogs perform better than those who bet on favourites.

Though close connection between P_α and α is very expected, P_α can depend on other factors. We think that popular teams accumulate more bets made by less-informed website visitors. Unsophisticated bettors' actions may be associated with the desire to maintain one's interest to the match and enjoyment of it, not with the objective analysis of the team's chances of winning. Therefore, in matches between popular and unpopular teams,

	variable	n	mean	sd	median	min	max
player characteristics	Twit	177	72427.44	115789.7	26900	146	851000
team characteristics	Eu	56	0.64	0.48	1	0	1
	Twit_av	38	68277.5	90892.22	31261.4	432	472800
	Pop	56	0.36	0.48	0	0	1
match characteristics	alpha	2371	0.33	0.10	0.34	0	0.49
	Result	2371	0.37	0.48	0.00	0	1.00
	P_a	2371	0.37	0.10	0.37	0	1.00
	Pop_sum	2371	0.95	0.78	1.00	0	2.00
	TPop_0	2371	0.33	0.47	0.00	0	1.00
	TPop_1	2371	0.40	0.49	0.00	0	1.00
	TPop_2	2371	0.28	0.45	0.00	0	1.00
	Eu_sum	2371	1.40	0.77	2.00	0	2.00
	TEu_0	2371	0.18	0.38	0.00	0	1.00
	TEu_1	2371	0.24	0.43	0.00	0	1.00
	TEu_2	2371	0.58	0.49	1.00	0	1.00

Table 4: Descriptive statistics

we expect a larger share of wins by the underdogs than predicted by the bettors (in about 80% of matches between popular and unpopular teams, the popular team is the favourite). In a match between two popular teams, the effect is expected to have the same direction but will be less in its absolute value. As a measure of a team's popularity, we use the average number of a team's players' followers on Twitter ($Twit\_av$). If $Twit\_av > 50,000$ for some team, we call it a popular team. By Pop_sum we denote the number of popular teams in the match. For $i = 0, 1, 2$ define variable $TPop_i$. If $Pop\_sum = i$, we put $TPop_i = 1$; otherwise we put $TPop_i = 0$.

Finally, the popularity of a team among visitors of the website csgopositive.com can be influenced by the team's geographic location. Since the platform csgopositive.com is popular in Europe and post-Soviet countries, we have included in the set of explanatory variables the number of teams from this region Eu_sum. For $i = 0, 1, 2$ define variable TEu_i. If $Eu\_sum = i$, we put $TEu_i = 1$; otherwise we put $TEu_i = 0$.

We put forward the following hypotheses.

Hypothesis 1. $P_\alpha > \alpha$ for small values of α.

Hypothesis 2. P_α positively depends on $TPop_1$, $TPop_2$, and Pop_sum and negatively depends on $TPop_0$.

Hypothesis 3. P_α positively depends on TEu_1, TEu_2, and Eu_sum and negatively depends on TEu_0.

To test the hypotheses, we estimate the following models.

$$E[P_\alpha|\alpha, Tpop_0, TPop_2, TEu_1, TEu_2] =$$

$$= c_1 + c_2 \cdot \alpha + c_3 \cdot \alpha^2 + c_4 \cdot TPop_0 + c_5 \cdot TPop_2 + c_6 \cdot TEu_1 + c_7 \cdot TEu_2 + \varepsilon \qquad (1)$$

$$E[P_\alpha|\alpha, TPop_0, TPop_2, Eu\_sum] =$$

$$= c_1 + c_2 \cdot \alpha + c_3 \cdot \alpha^2 + c_4 \cdot TPop_0 + c_5 \cdot TPop_2 + c_6 \cdot Eu\_sum + \varepsilon \qquad (2)$$

$$E[P_\alpha|\alpha, Pop\_sum, Eu\_sum] = c_1 + c_2 \cdot \alpha + c_3 \cdot \alpha^2 + c_4 \cdot Pop\_sum + c_5 \cdot Eu\_sum + \varepsilon \qquad (3)$$

Estimated results are presented in Table 5. In all models, $P_\alpha > \alpha$ when α is close to 0. This means that strategies based on betting on the underdogs could be profitable. This, in turn, can potentially be an evidence of market inefficiency. The results provide strong support for Hypothesis 1.

Coefficients TEu_1, TEu_2 in model (1) and Eu_sum in models (2) and(3) are statistically significant at the 5% level. Positive sign indicates that in matches with European and post-Soviet teams, betting on the underdogs is more profitable than in matches without these teams. Close coefficients TEu_1 and TEu_2 in the model (1) report that, all else equal, the inefficiency of the betting market for matches with two European/post-Soviet teams is only slightly higher than in matches with one European/post-Soviet team. As it was conjectured in Hypothesis 3, due to the popularity of the website `csgopositive.com` in post-Soviet countries and Europe, bettors can be biased towards post-Soviet and European teams.

In models (1) and (2), coefficients $Tpop_0$ and $Tpop_2$ are positive and statistically significant at the 0.1% level which allows us to reject Hypothesis 2. It seems that the connection between the internet popularity of the team and the willingness to bet on it is non-linear. Alternatively, the number of followers on Twitter could be a poor proxy for popularity of a CS:GO player. Not all popular players consider it appropriate to write on Twitter, and the quality of the blogs differs drastically. Therefore, the number of followers on Twitter may indicate the popularity of the blog, and not the popularity of the player.

Statistic	(1)	(2)	(3)
Intercept	0.155***	0.157***	0.158***
	(0.010)	(0.010)	(0.010)
α	0.493***	0.493***	0.501***
	(0.065)	(0.065)	(0.065)
α^2	0.332**	0.333**	0.331**
	(0.103)	(0.103)	(0.103)
$TPop_0$	0.009**	0.009**	
	(0.003)	(0.003)	
$Tpop_2$	0.011***	0.012***	
	(0.003)	(0.003)	
Pop_sum			0.001
			(0.002)
TEu_1	0.008*		
	(0.004)		
TEu_2	0.009*		
	(0.004)		
Eu_sum		0.004*	0.005**
		(0.002)	(0.002)
R^2	0.5842	0.5840	0.5814
	0.5832	0.5832	0.5807
P-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
(N)	(2371)	(2371)	(2371)

***, **, and * indicate 0.1%, 1%, and 5% significance levels, respectively.

Table 5: Results of estimation

4 Opportunities to beat the market

Despite the fact that this study successfully detected systematic underestimation of the underdogs, this does not guarantee positive profits for the bettor. In this section, we define specific strategies and analyze their profitability on the in-sample and out-of-sample datasets. By definition, profit is the difference between the amount paid by the bookmaker for the winning bet and the bet itself. Throughout this section, a bookmaker commission of 5% is included.[7]

[7]Though comission taken by the website csgopositive.com is not announced explicitly, we have not detected a match between top teams with comission exceeding 5%.

Denote by S_i, $i = 0.01, \dots, 0.49$, the obligation to bet 1 dollar on the underdogs in all matches with $\alpha \leq i$. Performance of these strategies on the in-sample and out-of-sample datasets is presented on Figures 1 and 2, respectively. Strategies S_i turn out to be profitable in-sample for $i > 0.04$ and out-of-sample for $i > 0.13$.

Expected profit of betting on one match with a particular α in the in-sample and out-of-sample data is depicted on Figures 3 and 4. Performance test for strategies S_i on the out-of-sample data confirms the profitability of betting on the underdogs, and, therefore, the market inefficiency. Finally, Figures 5, 6 display the number of observations with a given α in in-sample and out-of-sample, respectively.

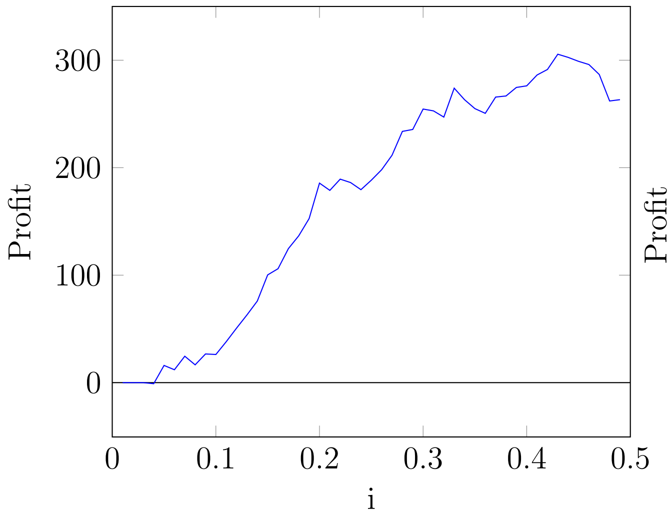

Figure 1: Total profit of strategies S_i on the in-sample data (2372 observations)

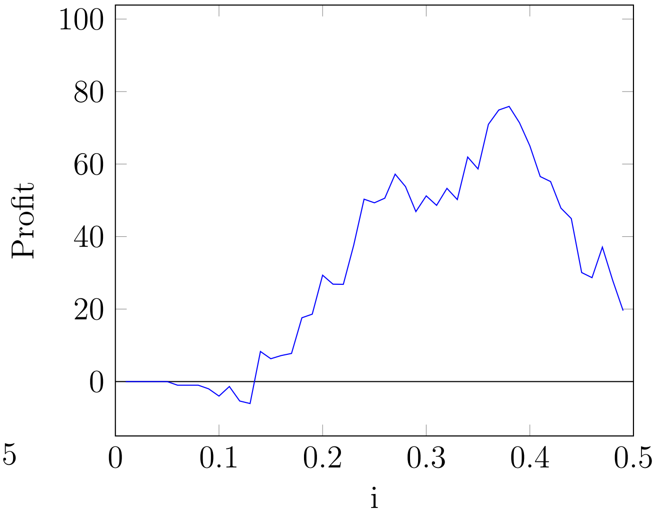

Figure 2: Total profit of strategies S_i on the out-of-sample data (704 observations)

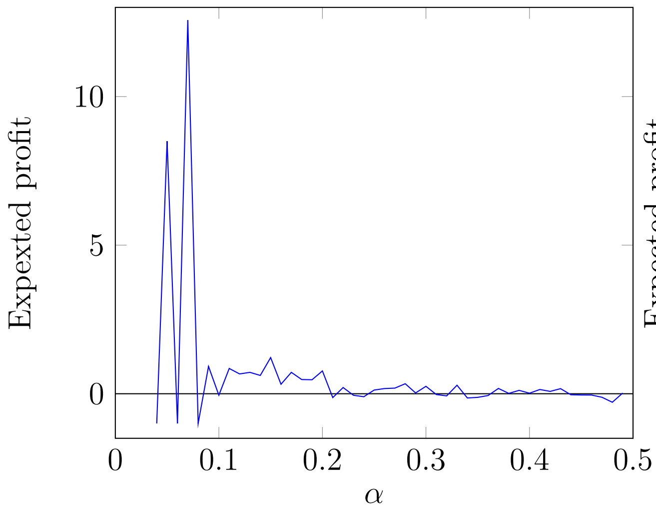

Figure 3: Expected profit on \$1 from betting on one match with particular α (in-sample).

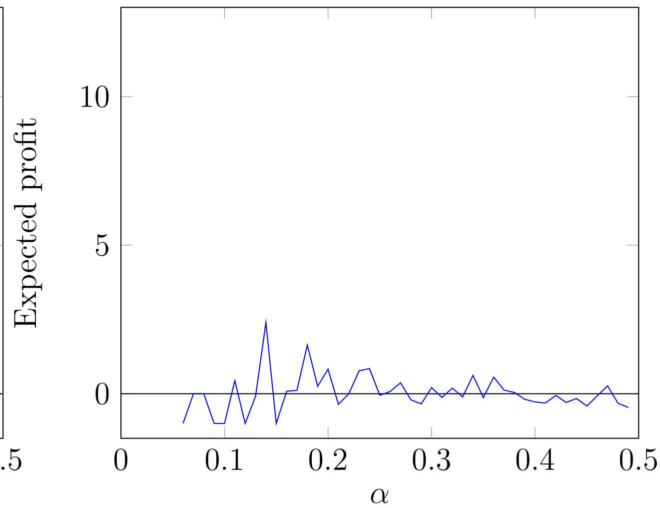

Figure 4: Expected profit on \$1 from betting on 1 match with particular α (out-of-sample).

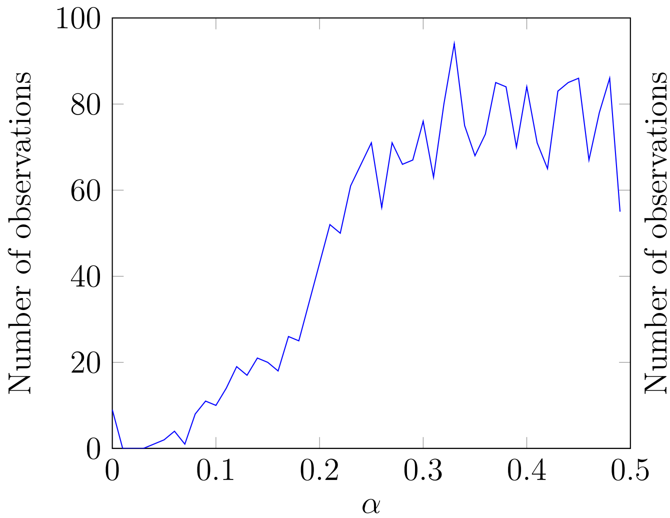

Figure 5: The number of observations (in-sample)

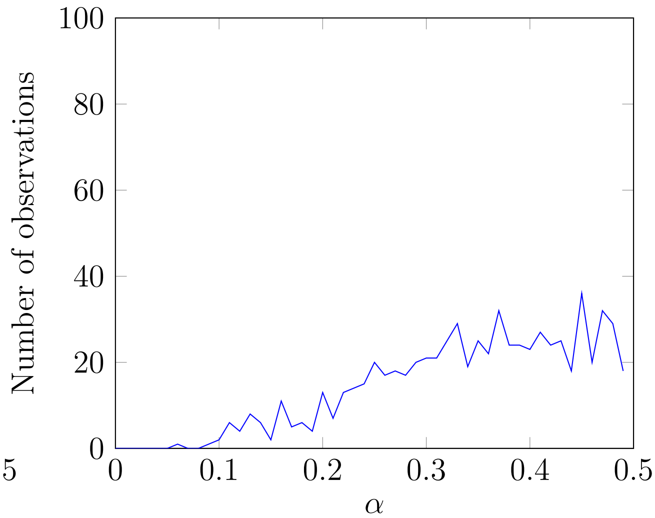

Figure 6: The number of observations (out-of-sample)

5 Conclusions

In this study, we have investigated the parimutuel betting market on the eSports discipline Counter-Strike: Global Offensive. Based on the dataset of bets on 3129 duels (in total for in-sample and out-of-sample data) among professional teams, we have shown that the market is inefficient. After documenting the reverse favourite-longshot bias, we defined simple betting strategies of betting on the underdogs and demonstrated that these strategies can beat the market. This inefficiency is not contingent on time. A test conducted on the out-of-sample data confirmed the sustainability of the favourite-longshot bias and market inefficiency over time. We suggest that more popular teams attract more unsophisticated gamblers that, in turn, leads to the market inefficiency. The geographical location of teams can play a role: the market is more inefficient in matches involving European and post-Soviet teams, and the website csgopositive.com is popular exactly in these countries. However, popularity in the media of individual players measured by the number of followers on Twitter appears to be insignificant. The results of this study offer opportunities for further research on the determinants of popularity that attract unsophisticated gamblers and lead to the market inefficiency.

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6 Appendix

Here we provide the list of the teams in the dataset.

AGO Esports	eUnited	Grayhound Gaming	Misfits Gaming	Quantum Bellator Fire	Torqued
Astralis	eXtatus	HellRaisers	mousesports	Red Reserve	TyLoo
AVANGAR	FaZe Clan	Heroic	MVP PK	Renegades	Valiance & Co
BIG	FlipSid3 Tactics	Imperial e-Sports	Natus Vincere	Rogue	Vega Squadron
Counter Logic Gaming	Fnatic	Team Kinguin	Ninjas in Pyjamas	seed	Virtus.pro
Cloud9	Fragsters	Team LDLC	North	SK	Windigo Gaming
Complexity Gaming	G2 Esports	LeftOut	NRG Esports	Space Soildiers	
ENCE	Gambit Esports	Team Liquid	OpTic Gaming	Team Spirit	
Team Envy	Ghost	Luminosity Gaming	ORDER	Sprout	
Epsilon Esports	GODSENT	MIBR	PENTA Sports	Team One	

Table 6: List of the teams in the dataset. Teams classified as popular are highlighted in blue.

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