Uncertainty of Outcome and Superstar Effect on Esports Viewership

Joe Patten

May 2021

Abstract

In this paper, I evaluate the Uncertainty of Outcome Hypothesis (UOH) as well as the superstar effect on viewership in two esports: Counter-Strike: Global Offsensive and Dota 2. I find evidence of uncertainty of outcome on viewership in Counter-Strike, but no evidence of uncertainty of outcome on viewership in Dota 2. I also find evidence of superstars increasing viewership in Counter-Strike as well as Dota 2. The results found in Counter-Strike more closely resemble previous results found in traditional sports than Dota 2.

Contents

1 Introduction **3**

1.1 UOH in Sports Leagues 4

1.2 Superstar Effect in Sports Leagues 4

1.3 Esports 5

1.3.1 Counter-Strike 6

1.3.2 Dota 2 6

1.4 Streaming Platforms 7

1.5 Uncertainty of Outcome 7

2 Data **7**

3 Methods **9**

4 Results **10**

4.1 Counter-Strike UOH 10

4.2 Counter-Strike Superstars 11

4.3 Dota 2 UOH 14

4.4 Dota 2 Superstars 14

5 Discussion **15**

5.1 Competitive Balance in esports 17

6 Conclusion **18**

1 Introduction

There is a popular hypothesis, the uncertainty of outcome hypothesis (UOH), which states that a more balanced sporting competition leads to greater interest and demand (Rottenberg, 1956). In other words, the UOH says that spectators generally prefer sporting events where two teams are of similar ability. At the league level, a league where the outcome of its matches are highly uncertain is deemed a balanced league. If the UOH were to hold for a certain league, that league would want to organize the matches where teams were evenly matched as doing so would generally increase match viewership. Increasing match viewership would benefit the league hosting the match, the teams participating in the match, and the advertisers and broadcasters. Over the last decade, leagues and tournaments in esports have become more structured . Attempts have been made to create sustaintable competition in these events. One such example is the Louvre Agreement made by the world's largest esports network, the ESL. The agreement has ensured that 13 Counter-Strike teams will not only share a portion of the revenues and profits from Pro Tour competitions, but that these teams will also have a guaranteed long-term slot for participation. As this agreement is fairly recent, it still remains to be seen if it increases competition or not.

There have been a multitude of studies that have explored the UOH on spectator demand. The studies that have focused on traditional sports leagues have shown mixed results. The majority of the studies that focus on stadium attendance have found evidence that contradicts the UOH; however, more recent studies that focus on TV viewership have generally found evidence that supports the UOH (Cox, 2018). The question is do we see similar results in esports viewership? Currently, there are no studies evaluating if the UOH holds in esports. In 2021, it has been projected that global esports revenue will amount to over $1 billion, with more than 75% of that revenue coming from media rights and sponsorship (Newzoo, 2021). As many esports matches draw in hundreds of thousands to millions of viewers, it becomes very important to determine the factors affecting spectator demand.

Another potential booster to spectator demand comes from the presence of superstars. Hausman and Leonard (1997) were one of the firsts to empirically study this "superstar effect". They found that NBA superstars increased attendance and television ratings. This also resulted in an increase in revenue for the superstars' team, and the teams they played. Multiple studies have also shown that there exists a superstar effect on attendance and television ratings in the English Premier League, the Bundesliga, and the MLS (Buraimo and Simmons (2015), Jewell(2017), and Brandes et al. (2008)).

The purpose of this study is two-fold. First, I evaluate whether UOH holds in esports. Specifically, I evaluate whether online viewership of esports matches is greater when the outcome of matches is relatively uncertain. Second, I evaluate whether the presence of superstars in a match contributes to greater viewership. This study contributes to the literature as it is the first study to assess how outcome uncertainty and star quality impact spectator demand in esports. Since esports is a sector that is rapidly growing, and is predicted to keep growing at a fast pace, this study will give more insight into the preferences of esports viewers. I also compare the results from this study with what has been found in the sports literature. For Counter-Strike, I find that a 10% decrease in absolute difference in win probability between two teams for a match (meaning that the match outcome is more uncertain) comes with a 3% increase in match viewership. I also find that a match with a "superstar" increases game viewership by 18-19%. For Dota 2, I do not find evidence that outcome uncertainty increases match viewership. I do however find that matches with superstars do increase game viewership.

1.1 UOH in Sports Leagues

In many conventional markets, competition is encouraged or essential in order to maximize consumer welfare. However, in professional team sports, economic cooperation is often considered necessary in order to maximize consumer welfare (Buraimo and Simmons, 2015). Neale (1964) explained that the product generated by sports leagues or even matches is not divisible between teams; this product is dependent on each team in a match. Neale (1964) further postulated that it would be of maximum interest to the league to organize matchups of evenly matched teams. Many sports leagues have tried to capitalize on UOH by introducing policies that would distribute player talent across teams. Player drafts, salary caps, luxury taxes, and revenue sharing are examples of policies implemented in top sports leagues with the aim of keeping leagues balanced. The question is: does preserving uncertainty of outcome actually maximize welfare?

There have been several studies on multiple sports that have shown mixed results for UOH. Older studies tend to focus on stadium gate receipts and stadium attendance, whereas more recent studies have started evaluating TV audiences. Multiple studies found that evenly matched games bring in larger TV audiences for the NFL, the English Football League, and the Spanish Football Primera League (Buraimo (2008), Paul and Weinbach (2007), Tainsky et al. (2014), Buraimo and Simmons (2009), and Cox (2018)).

1.2 Superstar Effect in Sports Leagues

Rosen (1981) developed a model that explained why a small group of people in certain occupations earn significantly larger salaries and dominate their occupations. Rosen (1981) further theorized that high-talent performers, i.e. those performers that have marginally more talent than the rest of the performers, attract larger audiences and more fans when compared with their peers. Adler (1985) extended this work and theorized that superstardom may not be due to differences in talent, but rather could be due to popularity.

Hausman and Leonard (1997) were the first researchers to empirically test whether superstars increased spectator demand in sports. The authors analyzed the effect of superstar players on TV audiences and attendance in the NBA. Superstars, who were defined as players that were the top 25 players to receive all-star votes for a season, increased stadium attendance and TV ratings. Furthermore, Hausman and Leonard (1997) focused on the top superstars of the NBA, Michael Jordan, Larry Bird, Magic Johnson, and Isiah Thomas. In the 1989-1990 season, Michael Jordan and Larry Bird increased over-the-air TV ratings by 28% and 27% respectively. Magic Johnson had the largest effect, increasing TV ratings by 31%. When focusing on specific channels (such as TNT and NBC), the authors found similar effects.

Jewell (2017) found that marquee players in the MLS from 2007 to 2012 increased stadium attendance. David Beckham brought an estimated 25% increase attendance, while Cuauhteámoc Blanco brought an estimated 13% increase in attendance. In order to evaluate the effect of superstars in the English Premier League on TV viewership, Buraimo and Simmons (2015) used combined relative wage, defined as a team's wage bill for a season divided by the average wage bill for the league, as a measure of superstardom in a matchup. The authors found a statistically significant positive coefficient on combined relative wage giving evidence that the presence of superstars increase TV viewership.

Defining what makes a player a superstar is fairly subjective. Multiple studies have defined superstars to be the top paid players in league or sport. Brandes et al. (2008) found that choosing what percent of top paid players to define as superstars affected results. For example, when analyzing the German Bundesliga, Brandes et al. (2008) found evidence of the superstar effect when defining superstars to be the top 2% of players. However, when expanding the definition to being the top 5 or 8% percent of top paid players, this effect disappears. Other studies have used popularity, like all-star votes, to indicate which players are superstars. Again, depending on how one specifies how many players are superstars could affect results.

1.3 Esports

According to Newzoo (2018), the top esports by viewership in 2018 were: League of Legends (347.4M hours viewed), Counter-Strike: Global Offensive (274.9M hours viewed), and Dota 2 (250.4M hours viewed). League of Legends and Dota 2 are both multiplayer online battle arena games, and the gameplay is very similar. Counter-Strike: Global Offensive is a first person shooter game. For my analysis, I focus on Counter-Strike and Dota 2 viewership. Revenues for relevant stakeholders come from the following streams (Deloitte, 2019):

1. Sponsorship deals for esports teams, leagues or event organizers
2. Advertising revenue gained from live streams as well as Video-on-Demand content
3. Revenue from media rights for broadcast esports content
4. Ticket sales for live events and merchandising (team jerseys, chairs, in-game skins, etc) revenue

5. Game publisher fees paid by the publishers both to independent esports organizers for hosting events and to esports teams for marketing rights

Sponsorship deals, advertising revenue, and revenue from media rights for broadcasting made up more than two-thirds of total revenue in esports in Europe in 2018 (Deloitte, 2019). As these areas make up the bulk of revenues, online viewership is of major importance.

1.3.1 Counter-Strike

Counter-Strike is a first person shooter game series in which a team of terrorists tries to plant and activate a bomb while the counter-terrorists try to prevent it through either eliminating the terrorist team before the bomb has been planted, or through defusing the bomb after it has been planted. Each team consists of two 5-person teams who take turns playing as each faction. The game can be played on one of several maps previously chosen by the teams before play commences. Generally, the first team to win 16 rounds[1] wins the map.

Counter-Strike has had a long history of esports competitions. The first “Major” tournament was hosted in Dallas, Texas at the 2001 Cyberathlete Professional League (CPL) Winter Championship. The tournament had a prize pool of $150,000. The eports scene for the game started to die until the next iteration of Counter-Strike, Counter-Strike: Global Offensive, was released in 2012. The esports scene picked up again, and the number of tournaments with large prize pools increased year after year. In 2020, there were 26 planned “Major” tournaments that had prize pools of $100,000 or more. Each one of these tournaments invites the top teams in the world to participate. Some tournaments also allow teams to qualify for the tournament by beating other teams wishing to participate in the tournament. Some of these tournaments are held online, where teams connect over the internet to play each other, or at a LAN setting, where teams convene at the same location to play each other.

1.3.2 Dota 2

Dota 2 is a multiplayer online battle arena video game where two teams of 5 players each battle to defend their base on the map. Each player can choose a unique character that has special abilities. Players collect experience points and items for their characters that can aid them in defeating the other team’s characters. A team wins when they have destroyed the other team’s “ancient”, which is a large structure located within the other team’s base.

Dota 2 esports teams can compete in tournaments in the Dota Pro Circuit in order to accumulate points. Teams with the most accumulated points qualify to play in the annual “The International”

[1] In order to win, a team must be the first to win 16 rounds, and must win by ”2 rounds” (the other team must have won 14 rounds or less). If the score is 15-14, play continues. If score becomes 16-14, the team with 16 points wins. If the score becomes 15-15, overtime commences. The team to win the most rounds in overtime wins.

tournament. Teams participating in this tournament can win a share of a large prize pool. In 2019, the total prize pool was $34 million.

1.4 Streaming Platforms

In addition to the large prize pools, one major reason that allowed Counter-Strike and other large esports scenes to flourish was the advent of streaming platforms like Justin.tv, UStream, and Twitch. These platforms allowed individuals to easily view esports matches via the internet. Tournaments (both online and LAN) continue to be streamed to individuals across the world in a number of different languages. One of the most popular streaming platforms as of 2021 is Twitch. Twitch not only houses channels that stream professional esports events, but is also home to 2 million active individuals who stream various video games.

1.5 Uncertainty of Outcome

Uncertainty of outcome can be viewed at the match level, the season level, and the long run (Cox, 2018). The focus of this study explores the uncertainty of outcome at the match level. Uncertainty of Outcome (UO) can be measured in a few ways. Past studies have primarily used betting odds or predicted outcome (usually using a probit model) to calculate the probability each team in a match would win. These probabilities give a sense of how fans and analysts believe the two teams will match up. Many traditional sports studies evaluate the home team's probability of winning as a measure of UO (particularly when measuring the impact of UO on stadium attendance. The closer this probability is to 50% the more uncertain the match. A major difference between esports and traditional sports is that even though esports teams might be region-based (in Counter-Strike, there exists Europe, North America, South America, Asia, Oceania, and Commonwealth of Independent States regions), esports lack geographical "localness" when compared with traditional sports. There are no home or away teams in esports like there are in traditional sports.

Since there are no home or away teams in esports, the measure of UO I use in this study is the absolute difference in the probability of each team wining a match (Buraimo, 2008). The closer this value is to 0, the more uncertain the outcome of a match is. In this study, I use historical betting odds to estimate the probability that each team will win a certain match; the absolute difference in probability is then calculated. Using this measure, I evaluate how uncertainty impacts viewership.

2 Data

Viewership data is taken from Twitch. SullyGnome.com collects data from all active channels every 15 minutes. I have obtained data for 63 different Twitch channels that have streamed esports tournaments.

In total, I have nearly 700,000 data points that contain information about the number of viewers during a certain time watching a certain channel. For both Counter-Strike and Dota 2, I take the max viewership during the duration of each match. I then use information from each tournament (specifically which channel streams each match) in order to match these data points with matches played.

Odds data from 2017-2020 was scraped from Oddsportal.com. This site keeps historical odds data for each match from various betting sites. The odds data is then converted to the probability that each team will win a certain match. Using the estimated probabilities for each team to win the match, I can derive the absolute difference in win probabilities (which will be the UO variable of interest). The closer this number is 0, the more uncertain the outcome of the match is predicted to be. The data on Oddsportal.com is not complete in the sense that it does not list odds for all matches. Matches in smaller tournaments (less significant matches) are more likely to be missing.

	Observation	Mean	SD	Min	Max
Viewership	882	67,650	73,261	504	472,726
Absolute Difference in Win Probability	882	0.33	0.22	0	0.92
Playoffs	882	0.22	0.41	0	1
Grand Finals	882	0.04	0.19	0	1
Semifinals	882	0.07	0.26	0	1

Table 1: Summary Statistics for Counter-Strike matches played from 2017-2020. Playoffs is a dummy variable indicating if a match is a playoff game, Grand Finals is a dummy variable indicating if a match is a grand final of a tournament, and Semifinals is a dummy variable indicating if a match is a semifinals of a tournament.

	Observations	Mean	SD	Min	Max
Viewership	769	48,945	53,682	274	424,852
Absolute Difference in Win Probability	769	0.38	0.24	0	0.91
Playoffs	769	0.47	0.50	0	1
Grand Finals	769	0.04	0.20	0	1
Semifinals	769	0.14	0.35	0	1

Table 2: Summary Statistics for Dota 2 matches played from 2017-2020. Playoffs is a dummy variable indicating if a match is a playoff game, Grand Finals is a dummy variable indicating if a match is a grand final of a tournament, and Semifinals is a dummy variable indicating if a match is a semifinals of a tournament.

Player and team rankings are taken from HLTV. HLTV is a website and forum dedicated to Counter-Strike Global Offensive esports news, match results and statistics. Each week, the site updates team rankings, which is based on recent performance in competitive matches over the last two months. Higher ranked teams often draw more viewers, and thus needs to be accounted for in the model. HLTV also releases annual player rankings. These rankings are based on players' in-game performances over the entire year.

In this study, Dota 2 superstars are those that have participated in the annual all-star match. Team rankings are based on the points that teams accumulate from playing in tournaments in the Dota Pro Circuit. The Dota Pro Circuit consists of "Major" tournaments that are held in a certain year. Better placements in tournaments result in higher points.

Table 1 shows the summary statistics for Counter-Strike matches, and table 2 shows the summary statistics for Dota 2 matches.

3 Methods

I evaluate the following function:

$$\text{Ln(Twitch Viewership)} = \beta\text{UO} + \alpha\text{Superstar} + X'\lambda + \phi + \omega + u \tag{1}$$

where ϕ and ω are year and tournament fixed effects. Certain tournaments are more "important" in the sense that they might offer more prize money, might have a storied history, or have more bearing on teams' futures in subsequent tournaments or leagues, and thus might attract different amounts of viewers. For example, for the game Dota 2, more viewers tune into matches for "The International" than any other tournament as this tournament not only allocates the highest prize money, but is known to be a tournament where the best teams come to compete. I add tournament fixed effects in order to avoid omitted variable bias; however, this results in conservative estimates for superstar and uncertainty of outcome coefficients. We would expect the top teams to participate or be invited to the top tournaments (those tournaments with the highest prize pools and highest spectator turnout). Thus, it would be the case that top tier tournaments have a lower variability in terms of outcome uncertainty when compared with lower tier tournaments, as lower tier tournaments would have teams of more variable quality. This would result in an increased bias in magnitude of the uncertainty of outcome variable due to their being more matches featuring evenly matched teams at top tier tournaments, which already attract more viewers. However, it can be argued that some viewers are only interested in evenly matched games, and do not care what type of tournament the game is played in. Likewise, we would expect high tier tournaments to have more matches with superstars present. Thus, controlling for tournaments would reduce the coefficient for superstar, giving a more conservative estimate.

X are match characteristics including if the match is a playoff game, a semifinals game, and/or a grand finals game. X also includes variables to control for the quality of each team by using team rankings. The team rankings variables are a set of dummy variables indicating whether each team is a top 10 team, a top 11-20 team, a top 21-30 team, or not in the top 30. As I am interested in evaluating the effect of superstars on viewership, this is an important control to add in my equation. This allows me to compare relative importance for viewership of streaming a game involving high quality teams versus showing a game involving a superstar or superstars. UO (uncertainty of outcome) in this study is the absolute difference in the probability of each team winning the match; thus, β is the coefficient of interest. If the UOH were to hold true, we would expect β to be negative (the closer in probability of each team winning a match, the more viewers we would expect). Superstar is a dummy variable indicating whether a team in the match has a superstar. For Counter-Strike, the Superstar variable is TopN, which is a dummy variable indicating whether the match features a team with a top N player. I include analyses for when N=3 and N=5. For Dota 2, the Superstar variable is All-Star, which is a dummy variable indicating whether the match featured a player that participated in the annual all-star game. We would expect α to be positive, or in other words, there is a higher demand for matches with teams that have superstars.

$$\text{Ln(Twitch Viewership)} = \beta\text{UO} + \alpha_1\text{OneSuperstar} + \alpha_2\text{BothSuperstar} + X'\lambda + \phi + \omega + u \qquad (2)$$

Equation 2 breaks up the Superstar variable into OneSuperstar and BothSuperstar. OneSuperstar is a dummy variable indicating whether exactly one team in a match has a superstar. BothSuperstar is a dummy variable indicating whether both teams in a match have a superstar. One would expect that matches where both teams have a superstar attract even more demand than matches where only one team has a superstar, thus I hypothesize that $\alpha_2 > \alpha_1 > 0$.

4 Results

4.1 Counter-Strike UOH

Table 3 shows the results to the regressions outlined in the methods section for Counter-Strike: Global Offensive. Column 1 is the equation without tournament fixed effects, column 2 is the equation including the top5 variable without tournament fixed effects, and column 3 is the equation including tournament fixed effects. The full equation (as seen in column 3) shows that playoff, semifinals and grand finals matches have higher viewership (as should be expected) than group stage or "regular season" matches. Columns 4 through 7 show results when adding the TopN, OneTopN, and BothTopN indicator variables.

I find that the coefficient for the UO variable (Absolute Difference in Win Probability) is negative and statistically significant at the .01 level. The coefficient for UO is anywhere between -.26 and -.30 in the fully specified models, meaning that a 10% decrease in absolute difference in win probability (more uncertainty) comes with about a 3% increase in game viewership. These results give supporting evidence for the UOH.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Absolute Difference	-0.412**	-0.613***	-0.190*	-0.295***	-0.278**	-0.263**	-0.261**
in Win Probability	(0.188)	(0.195)	(0.100)	(0.106)	(0.106)	(0.104)	(0.103)
Playoffs	-0.071	-0.078	0.250***	0.242***	0.238***	0.239***	0.238***
	(0.125)	(0.119)	(0.079)	(0.077)	(0.076)	(0.076)	(0.076)
Grand Finals	0.406***	0.426***	0.441***	0.440***	0.438***	0.451***	0.442***
	(0.119)	(0.113)	(0.083)	(0.080)	(0.080)	(0.081)	(0.082)
Semifinals	0.192*	0.195*	0.206**	0.199**	0.196**	0.206**	0.199**
	(0.108)	(0.104)	(0.085)	(0.084)	(0.083)	(0.083)	(0.083)
Top5 (Superstar)		0.321***		0.175***			
		(0.077)		(0.054)			
One Top5 (One Superstar)					0.160***		
					(0.053)		
Both Top5 (Both Superstar)					0.346***		
					(0.101)		
Top3 (Superstar)						0.189***	
						(0.059)	
One Top3 (One Superstar)							0.178***
							(0.058)
Both Top3 (Both Superstar)							0.407***
							(0.101)
Team Rankings	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y
Tournament FEs	N	N	Y	Y	Y	Y	Y
N	882	882	882	882	882	882	882
Adjusted R-squared	0.398	0.417	0.740	0.745	0.746	0.746	0.747

Table 3: Ln(Twitch Viewership) Estimation using equation 1 for Counter-Strike Global Offensive. Standard errors are clustered by tournament. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.010$

Results could be sensitive to the uncertainty measure used (Sacheti et al., 2014). The relationship between absolute difference in probability and log viewership might not be linear. Table 4 shows the results when absolute difference in probability is converted to dummies to allow for nonlinear results (with absolute difference in probability of 0.8 to 1.0 being omitted).

As expected, viewers prefer closer matches. When compared with an expected blowout (when absolute difference is greater than 0.8), matches with absolute difference between 0.6 and 0.8 have a 25.5% increased viewership, matches with absolute difference between 0.4 and 0.6 have a 32.3% increased viewership, matches with absolute difference between 0.2 and 0.4 have a 36.2% increased viewership, and matches with absolute difference between 0.0 and 0.2 have a 38.1% increased viewership. These results give further evidence that the UOH holds in Counter-Strike.

4.2 Counter-Strike Superstars

Table 3 shows that the coefficient for the TopN variable ranges from .18 and .19, meaning that a match with a superstar (on either one or both teams) increases match viewership by between 18 to 19%. This gives evidence to the thought that the presence of superstars in a match increase spectator demand. Furthermore, I find that the coefficient for OneTopN ranges from .16 to .18, meaning that a match with

Variable	(1)
Absolute Difference in Probability: 0.0 - 0.2	0.381**
	(0.150)
Absolute Difference in Probability: 0.2 - 0.4	0.362**
	(0.149)
Absolute Difference in Probability: 0.4 - 0.6	0.323**
	(0.134)
Absolute Difference in Probability: 0.6 - 0.8	0.255*
	(0.132)
Top5	0.175***
	(0.054)
Playoffs	0.252***
	(0.076)
Grand Finals	0.425***
	(0.079)
Semifinals	0.203**
	(0.083)
Team Rankings	Y
Year FEs	Y
Tournament FEs	Y
N	887
Adjusted R-squared	0.743

Table 4: Ln(Twitch Viewership) estimation for Counter-Strike: Global Offensive when converting absolute difference of probability into dummies. Standard errors are clustered by tournament. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.010$

exactly one team with a superstar increases match viewership by between 16 to 18%. The coefficient for BothTopN is more than double that of the coefficient for OneTopN with a range of .35 to .41, meaning that a match with both teams having a superstar increases match viewership by 35 to 41%.

As done in other studies evaluating the effect of superstars (Hausman and Leonard (1997), Jewell (2017)), it is more informative to look at individual superstars and specific years in order to evaluate their effect on viewership. Table 8 shows the results when adding in dummies for specific superstars, and the years they were superstars.

In this analysis, I focus on Counter-Strike players that consistently rank high in the HLTV rankings from 2017-2020. Players that rank within the top 3 more than two times within the years 2017-2020 are included in this analysis. Table 8 shows the results for the regression that includes year and specific player indicators for superstars the year that they make top 3, and after. s1mple is a Ukranian player who has been a top 10 player every year since 2016 according to HLTV rankings. In 2018, he was ranked the best player in the world, and was top 2 in 2019 and 2020. He has received countless Counter-Strike and esports awards, including: eSports Player of the Year 2016 by Red Bull, player of the Year 2018 by Stockholm International Esports Awards, and esports PC Player of the Year 2018 by Esports Awards. The effect s1mple has had on match viewership has increased over time. Matches in which s1mple played in had 22.2%, 25.7%, and 39.8% greater viewership in 2018, 2019, and 2020.

ZywOo is a French player that first appeared in the HTLV rankings in 2019. He was ranked the

Variable	(1)
s1mple × 18	0.222**
	(0.106)
s1mple × 19	0.257*
	(0.139)
s1mple × 20	0.398***
	(0.077)
ZywOo × 19	-0.103
	(0.135)
ZywOo × 20	0.096**
	(0.037)
dev1ce × 18	0.202***
	(0.055)
dev1ce × 19	0.392***
	(0.096)
dev1ce × 20	0.261**
	(0.119)
NiKo × 17	0.278*
	(0.153)
NiKo × 18	0.356***
	(0.070)
NiKo × 19	0.208**
	(0.092)
NiKo × 20	0.105
	(0.121)
Team Rankings	Y
Year FEs	Y
Tournament FEs	Y
N	882
Adjusted R-squared	0.754

Table 5: Ln(Twitch Viewership) estimation for Counter-Strike: Global Offensive. The model is fully specified. Absolute difference in probability, Grand Finals, Semifinals, and Playoffs variables are included in the model, but have been omitted in the output. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.010$

best player in the world in 2019, and best player in the world in 2020. Surprisingly, the marginal effects for ZywOo's participation in 2019 on match viewership is statistically insignificant and even negative. This might be due to the fact that ZywOo is relatively newer to the scene when compared with other superstars in this analysis, and thus might have not accrued as big as a following as other superstars. However, in 2020, matches in which ZywOo played in had 9.8% greater viewership.

dev1ce is a Danish player that has been a top 5 player since 2015 according to HLTV rankings, and received his best ranking of number 2 player in world in 2018. The effect dev1ce has had on match viewership has increased over time. Matches in which dev1ce played in had 20.2%, 39.2%, and 26.1% greater viewership in 2018, 2019, and 2020.

NiKo is a Bosnian player that ranked as a top 5 player in 2016-2018 and 2020, according to HLTV rankings, and received his best ranking of number 2 player in world in 2017. Matches in which NiKo played in had 27.8%, 35.6%, and 20.8% greater viewership in 2017, 2018, and 2019. The coefficient for NiKo is 2019 is smaller than previous years, and the coefficient for NiKo is 2020 is statistically insignificant. This could be in part due to his drop of performance in 2019.

4.3 Dota 2 UOH

Table 6 shows the results to the regressions outlined in the methods section for Dota 2. Column 1 is the equation without year and tournament fixed effects, column 2 is the equation including year fixed effects, and column 3 is the equation including both year and tournament fixed effects. The full equation (as seen in column 3) shows that playoff, semifinals and grand finals matches have higher viewership (as should be expected) than group stage or "regular season" matches. Columns 4 and 5 show results when adding the All-Star, One All-Star and Both All-Star indicator variables.

Variable	(1)	(2)	(3)	(4)	(5)
Absolute Difference	-0.446***	-0.449***	-0.141	-0.153	-0.120
in Win Probability	(0.138)	(0.134)	(0.110)	(0.111)	(0.119)
Playoffs	1.024***	1.024***	0.803***	0.798***	0.796***
	(0.160)	(0.154)	(0.169)	(0.168)	(0.167)
Grand Finals	0.043	0.055	0.383***	0.385***	0.394***
	(0.143)	(0.137)	(0.090)	(0.089)	(0.089)
Semifinals	-0.316***	-0.316***	0.017	0.014	0.014
	(0.093)	(0.090)	(0.071)	(0.072)	(0.074)
All-Star (Superstar)		0.400***		0.109	
		(0.137)		(0.075)	
One All-Star (One Superstar)					0.094
					(0.071)
Both All-Star (Both Superstar)					0.232*
					(0.128)
Team Rankings	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Tournament FEs	N	N	Y	Y	Y
N	769	769	769	769	769
Adjusted R-squared	0.339	0.358	0.623	0.624	0.625

Table 6: Ln(Twitch Viewership) estimation using equation 1 for Dota 2. Standard errors are clustered by tournament. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.010$

Although the absolute difference in probability has the negative sign as we would expect, when fully specifying the model (adding in year fixed effects and tournament fixed effects), the coefficients become statistically insignificant. Even when breaking out absolute difference in probability into dummies to allow for nonlinearity as shown in table 7 we do not see any evidence of viewers preferring closer matches.

4.4 Dota 2 Superstars

From the results shown in table 6, it appears that having superstars present on each team impacts viewership. Having two superstars present on each team in a match increases that match viewership by 23.2%. Besides this, the other superstar coefficients in the fully specified model are not statistically significant. However, as the definition of superstar is subjective, and has been shown to be sensitive depending on the researcher's definition Brandes et al. (2008), I will focus on individual players, and the years they became all-stars, as well as the years after. I will also narrow my definition to be players that had participated in the all-star match for at least two years.

Variable	(1)
Absolute Difference in Probability: 0.0 - 0.2	0.080
	(0.088)
Absolute Difference in Probability: 0.2 - 0.4	0.091
	(0.084)
Absolute Difference in Probability: 0.4 - 0.6	0.031
	(0.104)
Absolute Difference in Probability: 0.6 - 0.8	-0.002
	(0.080)
All-Star	0.094
	(0.068)
Playoffs	0.766***
	(0.164)
Grand Finals	0.381***
	(0.087)
Semifinals	0.019
	(0.070)
Team Rankings	Y
Year FEs	Y
Tournament FEs	Y
N	769
Adjusted R-squared	0.646

Table 7: Ln(Twitch Viewership) estimation using equation 1 for Dota 2. Standard errors are clustered by tournament. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.010$

N0tail, SumaiL, UNiVeRSE, Arteezy, Solo, RAMZES666, and Miracle- are all Dota 2 players that fit into definition of superstar as defined above; in other words, they have participated in at least 2 all-star matches during their tenure as players. N0tail is regarded to be one of the best players of all time in Dota 2. Matches in which N0tail played in had a 60.8% greater viewership in 2017. The combination of SumaiL and UNiVeRSE, who were both all-stars in 2017, saw a 78.0% greater viewership in matches they participated in. These are the biggest boosters to viewership in the data. Another notable superstar is Miracle-. Miracle- is the recipient of the 2016 esports rookie of the year, and 2017 PC player of the year given by Esports Awards. Matches in which Miracle- played in had 13 to 43 percent greater viewership from 2018 to 2019. There was only one superstar/year interaction coefficient that was negative. Matches in which N0tail played in had a 19.3% smaller viewership in 2018. Although 2017 was the last year he was selected to play in the all-star match, it seems unbelievable that he would have a negative impact on match viewership in 2018.

5 Discussion

The results have shown that there is evidence of uncertainty of outcome increasing spectator demand in Counter-Strike, but they show no evidence of uncertainty of outcome increasing spectator demand in Dota 2. This suggests that (at least for Counter-Strike) preserving uncertainty of outcome is welfare maximizing. For event organizers, this is an important result as many of the streaming platforms offering

Variable	(1)
N0tail × 17	0.608***
	(0.104)
N0tail × 18	-0.193*
	(0.105)
N0tail × 19	0.349**
	(0.167)
SumaiL / UNiVeRSE × 17	0.780***
	(0.265)
SumaiL / UNiVeRSE / Arteezy × 18	0.099
	(0.122)
SumaiL / UNiVeRSE / Arteezy × 19	0.390***
	(0.116)
Solo / RAMZES666 × 17	0.243
	(0.151)
Solo / RAMZES666 × 18	0.181
	(0.122)
Solo / RAMZES666 × 19	0.146
	(0.159)
Miracle- × 17	0.274
	(0.213)
Miracle- × 18	0.125**
	(0.062)
Miracle- × 19	0.426***
	(0.127)
Team Rankings	Y
Year FEs	Y
Tournament FEs	Y
N	769
Adjusted R-squared	0.646

Table 8: Ln(Twitch Viewership) estimation for Dota 2. The model is fully specified. Absolute difference in probability, Grand Finals, Semifinals, and Playoffs variables are included in the model, but have been omitted in the output. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.010$

esports coverage make other potentially appealing content easily available to consumers. For example, on Twitch, while watching a particular stream, a viewer can see what other streamers are streaming and how many viewers are watching those other streams. Thus, if a viewer is bored, they can easily switch streams to a potentially more exciting or interesting stream.

The question now is why do we see that the UOH holds in Counter-Strike, and not in Dota 2? The two games are fairly different; however, Counter-Strike seems to have more similarities of the two esports to traditional sports. For example, Counter-Strike has an incremental point system similar to many traditional sports; and like most sports, the team with the most points wins the match. On the other hand, Dota 2 does not work on a point system. It has an "all-or-nothing" system such that a team wins when they have destroyed the other team's "artifact". In this study, I use max or peak viewership for each match. Matches that are predicted to be close are usually close contests. Potential viewers who like viewing close contests can easily determine how close a match is in Counter-Strike just by looking at the score. However, for Dota 2, it is more difficult to determine how close a match is. This might be the reason why Counter-Strike has more similar results in terms of UO to what is seen in traditional sports.

Buraimo and Simmons (2009) used the same variable for UO (absolute difference in probability) when looking at its relationship to TV viewership for the La Liga Football League. The authors found that a 10% decrease in absolute difference in win probability between two teams for a match resulted in a 3.4% increase in match viewership. For Counter-Strike, I found that a 10% decrease in absolute difference in win probability between two teams for a match resulted in about a 3% increase in match viewership.

In terms of the superstar effect, my estimates are similar to what is found in the sports economics literature. Hausman and Leonard (1997) found that when NBA superstars participated in a match, viewership increased by around 30%. When focusing on the top superstars in Counter-Strike as defined in section 4.2, I find similar increases in viewership due to the presence of superstars. s1mple increased viewership by between 22.2% and 39.8% from 2018 to 2020, dev1ce increased viewership by between 20.2% and 39.2% from 2018 and 2020, and NiKo increased viewership by between 20.8% and 35.6% from 2017 to 2019. In Dota 2, the effect some superstars have on viewership is much larger. This may be due to the fact that there are a variety of heroes that players can choose from. Thus, if a player is particularly effective at utilizing a certain hero (beyond what other players or even pros could do), then that would attract significantly more viewers.

5.1 Competitive Balance in esports

There have been a few examples of esports leagues implementing practices or regulations to increase competitive balance. One such example is the "Louvre Agreement" that was put into effect in 2020. This agreement ensured that 13 Counter-Strike teams would have a share of revenues and profits from Pro Tour competitions held by the world's largest esports network, ESL. This agreement also made these teams majority stakeholders and guaranteed them a long-term slot for participation (previously, participation in these tournaments was usually determined solely by past performance in other tournaments, and performance in qualification tournaments).

Another example is when Riot games, the developer of League of Legends, announced that they would offer two new products: Fan Pass and Team Pass. Fan Pass would be available to players from Brazil, Turkey, Latin America, Japan, and Oceania, and would give purchasers extra rewards for watching League of Legend events. 50% of the revenue from Fan Pass would be shared among teams participating in these events. Team pass would be available to players in Europe and North America, and would allow purchasers to get team-specific rewards. 50% of the revenue from Team Pass would go to the specifically selected teams.

As my results show that there is at least evidence of uncertainty of outcome on match viewership in Counter-Strike, these initiatives should increase consumer welfare. In addition to increasing competition between teams, it could also provide stability to leagues and tournaments. This stability, which would manifest as many of the same teams appearing in leagues and tournaments, could also lead to increased team loyalty, thus increasing viewership.

6 Conclusion

This study shows that there is evidence that UO at the match level increases viewership of Counter-Strike esport matches, but there is no such evidence for Dota 2 esport matches. Further studies should be done to evaluate why there is evidence that the UOH holds in Counter-Strike, but not in Dota 2. Using absolute difference in the probability of each team winning a match, I find that a 10% decrease in difference resulted in about a 3% increase in Counter-Strike match viewership. I also find evidence of the superstar effect on viewership in both Dota 2 and Counter-Strike. As the scene of esports is ever changing, with some esports losing fans while new esports enter the scene, it is important to evaluate the different factors that affect spectator demand. This can influence tournament and league structure in order to maximize consumer welfare as well as maximize revenue for esports teams, leagues, advertisers, and broadcasters.

References

Adler, M. (1985). Stardom and talent. *The American economic review*, 75(1):208–212.

Brandes, L., Franck, E., and Nüesch, S. (2008). Local heroes and superstars: An empirical analysis of star attraction in german soccer. *Journal of Sports Economics*, 9(3):266–286.

Buraimo, B. (2008). Stadium attendance and television audience demand in english league football. *Managerial and Decision Economics*, 29(6):513–523.

Buraimo, B. and Simmons, R. (2009). A tale of two audiences: Spectators, television viewers and outcome uncertainty in spanish football. *Journal of economics and business*, 61(4):326–338.

Buraimo, B. and Simmons, R. (2015). Uncertainty of outcome or star quality? television audience demand for english premier league football. *International Journal of the Economics of Business*, 22(3):449–469.

Cox, A. (2018). Spectator demand, uncertainty of results, and public interest: Evidence from the english premier league. *Journal of Sports Economics*, 19(1):3–30.

Deloitte (2019). The european esports market.

Hausman, J. A. and Leonard, G. K. (1997). Superstars in the national basketball association: Economic value and policy. *Journal of Labor Economics*, 15(4):586–624.

Jewell, R. T. (2017). The effect of marquee players on sports demand: The case of us major league soccer. *Journal of Sports Economics*, 18(3):239–252.

Neale, W. C. (1964). The peculiar economics of professional sports. *The quarterly journal of economics*, 78(1):1–14.

Newzoo (2018). 2018 global esports market report.

Newzoo (2021). 2021 global esports market report.

Paul, R. J. and Weinbach, A. P. (2007). The uncertainty of outcome and scoring effects on nielsen ratings for monday night football. *Journal of Economics and Business*, 59(3):199–211.

Rosen, S. (1981). The economics of superstars. *The American economic review*, 71(5):845–858.

Rottenberg, S. (1956). The baseball players' labor market. *Journal of political economy*, 64(3):242–258.

Sacheti, A., Gregory-Smith, I., and Paton, D. (2014). Uncertainty of outcome or strengths of teams: an economic analysis of attendance demand for international cricket. *Applied Economics*, 46(17):2034–2046.

Tainsky, S., Xu, J., and Zhou, Y. (2014). Qualifying the game uncertainty effect: A game-level analysis of nfl postseason broadcast ratings. *Journal of Sports Economics*, 15(3):219–236.