The effect of emerging online new media on traditional media consumption. The case of eSports and Traditional Sports

Sandeep Gangarapu

ganga020@umn.edu

Internet changed the way people consume media every day. People read their news online, catch their favorite TV show online and stay in touch with their friends online. There are many studies that investigate how online media affects offline traditional incumbents. However, we do not know how new forms of entertainment that are created and exist only on the internet like Vlogging, Podcasts, eSports affect traditional media consumption. In this paper, we investigate this question in the context of eSports viewing, a new leisure activity afforded by the internet and exists only on the internet. We study how eSports effect one of the most favorite leisure time activity of Americans, watching sports on TV. We use panel data on the TV viewership of popular traditional sports and exogenous scheduling of popular eSports watched in the United States in order to estimate the effect that eSports have on traditional sports viewership. Though we find the negative relationship indicating that traditional sports viewership drops on the days' eSports are scheduled, we do not find a statistically significant effect with the data at hand.

Introduction

The Internet has fundamentally changed the way people do many day-to-day activities. From watching movies on Netflix to playing online video games, people spend a significant amount of their leisure time online (Wallsten (2013)). The adoption of the Internet is so widespread that there are new genres of entertainment like Vlogging, Podcasts, eSports that are created on the Internet and exist only on the Internet. Manovich (2003) termed these forms of entertainment as 'New new media'. There are many studies that empirically investigate the effect of Internet on traditional platforms (Waldfogel (2009), Seamans and Zhu (2013), Danaher (2017)). Waldfogel (2009) shows that web viewing of conventional TV programs substitutes TV watching time, but overall watching time of the program increased. Seamans and Zhu (2013) find that newspapers in a geographical location experience a decrease in circulation because of the entry of Craigslist in that location. Danaher (2017) shows that the availability of a product on Netflix has no effect on DVD sales of that product. While these studies look at whether online substitutes of the same offline media displace or coexist with the offline media, we do not know how emerging online new media effects related offline media. In this paper, we study this question in the context of eSports and traditional sports consumption.

eSports are a form of sports where the primary aspects of the sport are facilitated by electronic systems (Hamari and Sjöblom (2017)). It is a multi-player video game played competitively for spectators, typically by professional gamers on the internet. The eSports market in the US is on an astronomical rise. A recent survey conducted by the consumer marketing company Newzoo suggests that eSports among the age group of 21-35 are as popular as Baseball or Ice hockey. Over a million viewers watched the major finals of a recent CounterStrike: GlobalOffensive major championship, which is the most popular eSport in America. Though watching eSports on the Internet is a form of watching sports, it is not the same as watching traditional sports on TV. It is a new media, which is made possible by the Internet and exists only on the Internet. Therefore, this context offers a unique opportunity to investigate the research question.

Though eSports are a new genre of sports, it can be treated as a new product entering a market to rival traditional sports market. When a new product enters a competitive market, it results in expansion of market or diversion of the market from incumbent competitors or a combination of both (Mahajan et al. (1993)). The market expansion may occur when the new product creates a distinct market of its own or when consumers consume both the products. In the case of eSports introduction, we have reasons to believe that eSport market could have been the output of any of the above mechanisms.

First, eSports might create a market of its own. In the context of online sharing economy platforms for the hotel industry, Zervas et al. (2017) show that when AirBnB, an alternative to traditional hotels, enters a new city, it creates a new market of its own. They find that the flexible supply model of Airbnb attracts consumers who were previously constrained by the high prices imposed by traditional hotels during peak seasons and special events. They also find that 70% of listings on Airbnb are located outside traditional hotel districts thereby opening up a new market that did not exist before. In a similar way, we have reasons to believe that eSports cater to a new market that was previously not captured by traditional sports. Unlike traditional sports, eSports do not need a person to be physically active to play and enjoy a sport. Also, eSports are more flexible compared to traditional sports as they can be played at any time of the day, for longer periods of time. So, eSports might be attracting new consumers who were earlier constrained by traditional sports requirements.

Second, it is possible for traditional sports consumers to additionally consume eSports. Media consumption literature shows that people consume eSports and traditional sports for different reasons. Wann (1995) find eustress, self-esteem, escape and group affiliation to be motivations behind people watching traditional sports. Hamari and Sjöblom (2017) find no significance for group affiliation while they do find eustress and self-esteem to be significant motivation factors behind watching eSports. It is possible that people who consume eSports for eustress and self-esteem continue consuming traditional sports in order to satisfy all group-affiliation needs.Aguiar et al. (2017) suggest that leisure demand has increased by 2.3 hrs a week over the last decade. While time spent watching TV has remained constant, they notice an increase in time spent playing video games. They also attribute 50% of leisure time increase to video games growth.

Third, it is possible for eSports to divert consumers from traditional sports to eSports. A recent survey conducted by an eSport market intelligence company, Newzoo claims that 76% of eSports enthusiasts say that the time spent watching eSports is taking away from the time they used to spend watching traditional sports. When people have finite capital available to them, consumption of one resource crowds out consumption of other resources especially when the resources are related. Wallsten (2013) shows that increase in time spent on the internet crowds out time spent on other activities like working, sleeping, travel, household and educational activities. This leads us to believe that time spent consuming eSports might crowd out time spent consuming tradition sports as people have a finite amount of time in a day.

Understanding whether and how eSports effect traditional sports have implications to various entities. If eSports is creating a new market of its own, Marketers who advertise in traditional sports have now uncovered an entirely new segment that they could not reach before. They can now form strategies to reach these audiences through eSport medium and market their products to them. Traditional sport governing bodies and franchises can find ways to attract this new market to traditional sports. Content producers on traditional media can now come up with newer formats of content that can appeal and capture this market. If eSports is diverting the existing traditional sports market, governing bodies of traditional sports can find ways to retain them. This may include changing game formats to appeal to the diverting market.

In this paper, we provide insights into the effect that eSports has on traditional sports viewership and understand which of the above mechanism is at play. We use Nielsen data on TV program viewership for six traditional sports leagues (NFL, NBA, NCAA Basketball, NCAA Football, MLB and MLS) and data on eSport scheduling and viewership to create a panel. We then use panel data with traditional sport and time fixed effects in order to estimate the effect that eSports have on traditional sports viewership. Though we find a negative relationship between eSport scheduling and traditional sports viewership, we do not find a statistically significant effect.

In the next section, we review prior literature related to the consumption of media and viewing motives of sports. We then understand the context of our research setting in depth, describe data, empirical strategy and present the results.

Related Literature

Effects of Internet on traditional media consumption

With increasing adoption of Internet, researchers have studied digital media and digitization of content extensively (Zentner (2012), Smith and Telang (2010), Seamans and Zhu (2013)). The literature in this area can be broadly divided into three main streams. The first line of literature looks at the broader question of how Internet adoption affects consumption of traditional media. The second line of literature looks at the response of advertisers on traditional media to this changing consumption behavior. The third line of literature looks at how content producers react to Internet adoption through the digitization of content and distribution of content through digital media.

There are many studies that look at how Internet adoption changes consumption behavior of traditional media like Newspapers, TV and DVD's. Researchers argue that Internet adoption affects media consumption in two different ways. On one hand, convenience and personalization afforded by the Internet might cannibalize traditional media consumption (Liebowitz and Zentner (2012), Cho et al. (2016)), while on the other hand, Internet might also act as a low-cost channel for promoting and selling the content thereby increasing the consumption (Smith and Telang (2010)).

Traditional media platforms like TV, Radio, and Newspapers are typically two-sided markets. On the cost side of the market, there are consumers who consume content. On the revenue side of the market, there are advertisers who reach their target audience by marketing products through these platforms. Rysman (2017) states that behavior change on one side effects the other side. Researchers have studied how increasing Internet adoption changes advertising revenue on traditional media platforms. The results are mixed. For media platforms like TV and Newspaper that have close Internet substitutes, they find that increasing Internet adoption decreases advertising revenue on the traditional platforms as Internet provides better targeting opportunities for advertisers (Zentner (2012), Seamans and Zhu (2013)). For platforms that do not have closer substitutes, Internet adoption has no effect on advertiser revenue (Zentner (2012)).

Another line of literature studies the effects of content digitization on consumption of the same content through traditional media. The effect is different for different kinds of content. Researchers find that for content that is serial in nature like soap operas, digitization and web distribution not only acts as a distribution channel but also acts as an advertising channel and a way to reach more audience. In the context of television shows, Waldfogel (2009) finds that while web distribution of content slightly reduces the time spent on television viewing, the overall time spent consuming the content through all channels increases significantly. This is true for unauthorized distribution too. Literature in the area of piracy shows that for the content that is consumed more than once, unauthorized distribution acts as a way to sample the content thereby stimulating the interest and increasing long-term authorized consumption Smith and Telang (2010).

While the above literature extensively discusses how consumption of traditional media has changed with the advent of Internet, little is known about how emerging media that exists only on the Internet effects traditional media. While the digitization of traditional content and web distribution has increased the reach and consumption of traditional media content Waldfogel (2009), emerging media like vlogging, podcasts, and eSports that are created purely for the Internet might affect their consumption. As discussed in the previous section, the emerging media might have an audience of its own (Zervas et al. (2017)) or crowd out the consumption of traditional media due to time constraints (Aguiar et al. (2017)).

Sport Viewing Motivations

There is a length of literature that studies why people view sports. Gantz (1981) explored the viewing motives and behaviors associated with television sports. He found that the thrill of victory, escapism, learning about the game, and passing time were the leading reasons why people watch sports. He also found that people prefer to watch team sports more than individual sports. However, the lab experiment involved asking participants many questions and underlying themes/motives were derived using factor analysis. These themes varied from author to author in different research until Wann (1995) formalized the motivations into a valid and reliable measure called Sports Fan Motivation Scales (SFMS), an instrument designed to measure eight different motives of sports fans. They are eustress (i.e., positive levels of arousal), self-esteem benefits, escape from everyday life, entertainment, economic factors (i.e., gambling), aesthetic (i.e., artistic) qualities, group affiliation, and family needs. In a later study, Gantz et al. (2006) explored the differences between sports fans and fans of other television entertainment genres. They found that sports fans are different from other types of fans in their pre-viewing and post-viewing behaviors. For sports fans, viewing is more often proactive rather than a last-ditch alternative when there is nothing else to do or nothing else to watch on television.

There are some studies that explore the motivations for playing eSports. Yongjae and Ross (2006) used uses and gratification theory to explore the motivations behind people playing sport video games, i.e., video games that mimic real-life traditional sports. They found evidence of motivations of knowledge application, identification with the sport, fantasy, competition, entertainment, social interaction, and diversion. However, the motivations behind playing might not be the same as the motivations behind viewing. Hamari and Sjöblom (2017) study motivations behind people playing eSports. They find that escapism, acquiring knowledge about eSports, novelty, enjoyment of aggression are the leading reasons why people watch eSports. While there are some overlapping motivations between watch traditional sports and eSports (escapism, acquiring knowledge about eSports), there are also other reasons why people watch eSports specifically (novelty, enjoyment of aggression). This leads us to believe that while eSports might act as a substitute for some motivations, viewers might consume both eSports and traditional sports for other motivations.

Context

When people hear about eSports, they often confuse it with video games. There is a subtle difference between eSports and video games. eSports are a subset of video games and a video game is considered an eSport if it is played competitively for spectators by professionals (Hamari and Sjöblom (2017)). Most of the eSports are played by two competing teams with an objective of winning the game just like any traditional sport. CounterStrike:Global offensive, League of Legends, Dota 2, Call of Duty are some of the most popular eSports in America. The beginning of eSport tournaments goes as far as 1990 when Nintendo organized Nintendo world championships. However, viewing eSports as an activity became mainstream after the launch of Twitch.tv, a live streaming video platform in June 2011. Prior to the launch of Twitch, fans watched eSports either at the tournament venues or through the gaming software itself. Twitch centralized the streaming of all eSports under one umbrella and played a crucial role in the growth of eSports. The League of Legends world championship in 2016 had 43 M unique viewers and 14.7 M concurrent peak viewers clocking over 370 M unique hours watched (Kresse (2018)). Compare that to the deciding match of the NBA Finals in 2016 on ABC network had 31 M unique viewers (tvb (2016)).

There are many factors that distinguish eSports from traditional sports. First, unlike traditional sports where the games of the most popular league of each sport are broadcasted on TV, eSports are broadcasted online on platforms like twitch.tv or gaming.youtube.com. Second, traditional sports have year-long league games with a fixed schedule that repeats each year while eSports scheduling does not follow that format. eSport have discrete tournaments which have unique qualifying rules and there is no schedule that the games follow year on year. Third, most traditional sports have a team that is affiliated to the state or a city. But, eSports teams are generally franchisee based and do not represent any geographical entity.

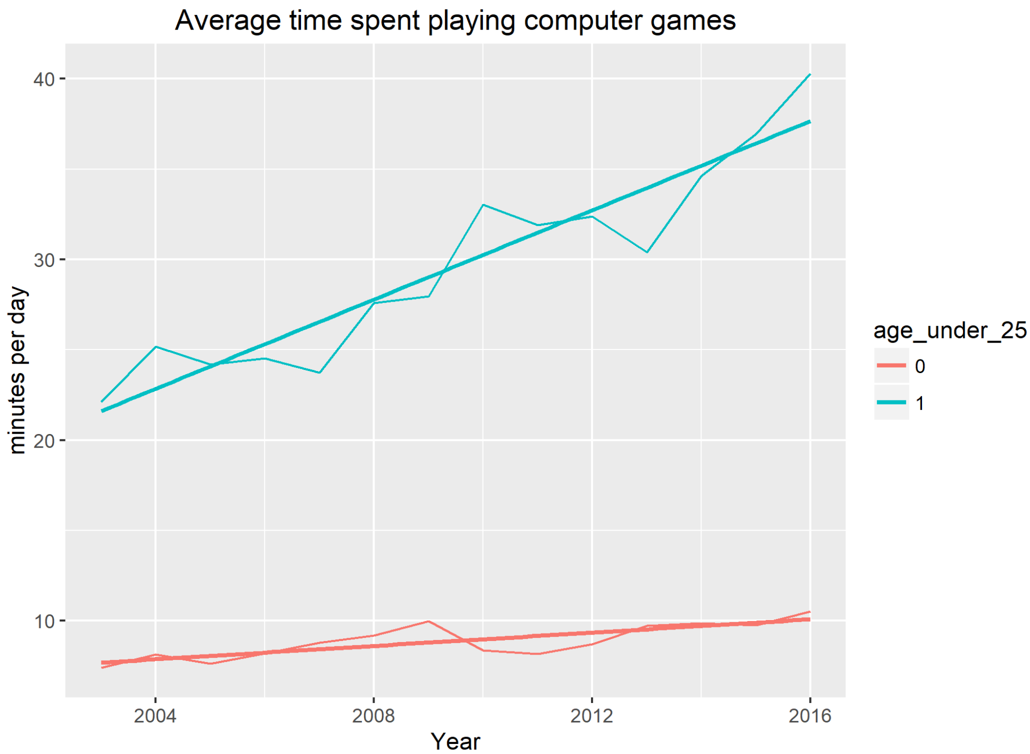
While mainstream media dismisses eSports as not even a sport, eSport market rises YoY at an astonishing rate and are as popular as Baseball and Ice Hockey among the age group of 21-35. There are many statistics supporting the rise and popularity of eSport but we are yet to establish empirically how eSports affect traditional sports. In this paper, we answer the question of where the viewers of eSports are from. Do eSports appeal to new audiences who weren't interested in traditional sport before? Are eSports cannibalizing the traditional sports viewers? or Do audience view both eSports and traditional sports?

Preliminary Analysis

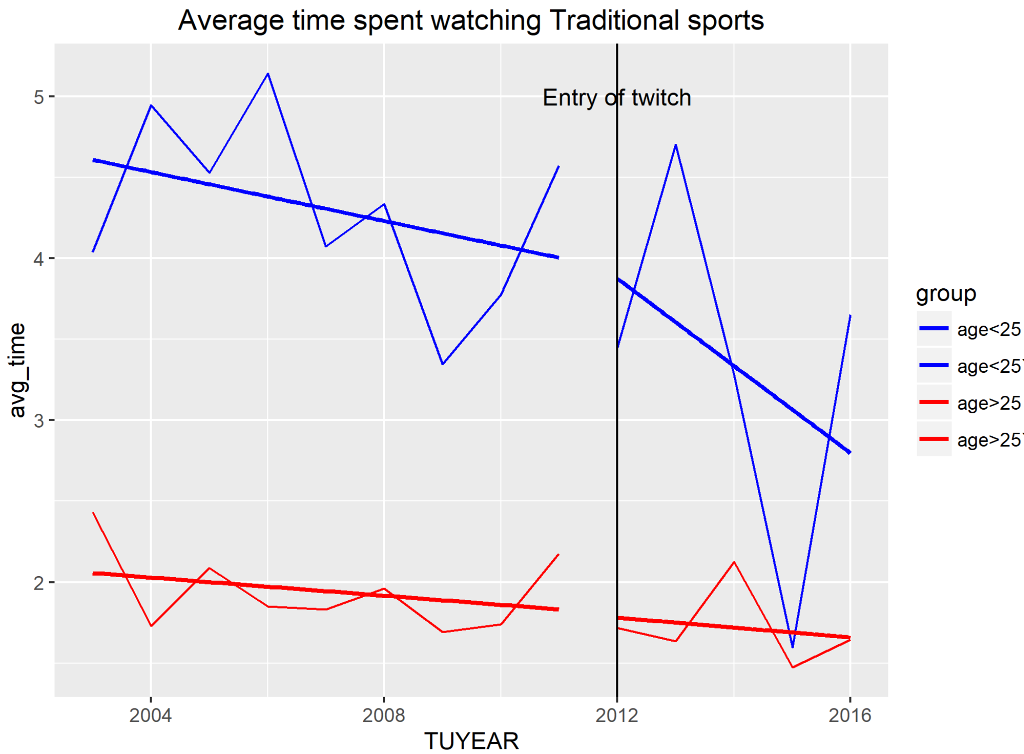
In order to check the trends in time spent on traditional sport and eSport related activities, we use data from the American Time Use Survey (ATUS) that measures the number of time people spend doing various day to day activities and collected by the Department of Labor Statistics. Participants who have completed all eight months of the Current Population Survey (CPS) are sampled and one member from the household is asked questions about time use. The collection of data started in 2003 and continues every year. The activities groups include personal care, household, care, work-related, education, purchase, eating, socializing and leisure, sports and recreation, volunteer activities. Each of the above activity groups has several sub-activities. Participants are asked questions about how much time they spent during each activity, duration of the activity, the start and end times of activity. We are particularly interested in socializing and leisure, sports, and recreation.

Socializing and Leisure section contains sub-activities like relaxing, watching television, communicating with other people, attending events etc. Sports and recreation contain time use data about sub-activities related to watching and playing various sports outdoors. In this context, we are interested in trends of people watching and playing various traditional sports activities. Relaxing and Leisure activity has a sub-activity called 'playing games' which corresponds to playing computer games. (Aguiar et al. (2017)).

We have year wise data on average time spend doing various activities. First, we check whether the trend of people playing video games has gone up. We plot the average time spent playing computer games across years. The figure shows that time spent playing video games has increased for people below the age of 25 but not so much for people above the age of 25. We take 25 as the cutoff age as the majority of the people who watch and play eSports are generally below the age of 25.



In a similar way, we use the entry of twitch.tv as a treatment and see how this treatment changed the way people consume traditional sports. We consider the year 2012 as the first period of post-treatment as twitch.tv was introduced in the second half of 2011. We again consider people above the age of 25 as the control group and others as the treated group. The graph for the pre-period shows that the trend was parallel between the people who received treatment and those who did not and the trend after the treatment is not parallel anymore. There is decline is viewing time for those below the age of 25. The trend continues to stay the same for those above the age of 25. This clearly shows there is indeed a decreasing trend in time spend on traditional sports among young people since 2012. This is by no means causal. There could be many macroeconomic factors that could have caused the declining interest in traditional sports among the younger people. This analysis was done just to check independently, the hypothesis about the growing interest in eSports and decreasing interest in traditional sports.



Data

Nielsen, a global measurement and data analytics company uses a proprietary metering technology to estimate the viewership of programs broadcasted on TV. However, this data is not publicly available. We collect the data on traditional sports viewership from a website called `http://www.showbuzzdaily.com/`. This website publishes Nielsen TV viewership data of all sport-related programming broadcasted on major television networks in the USA. We gather data on six popular traditional sports leagues like NBA, NFL, NCAA Football, NCAA Basketball, MLB and MLS broadcasted on Saturday and Sunday from Oct 2016 to April 2018. The website provides information on three metrics that indicate the viewership of a program. They are *Persons, Adults, Rating*. *Persons* indicates the estimated total viewers watching a program while *Adults* indicates total viewers that are in the age group of 18 to 49. *Rating* indicates the percentage of TV viewers watching a program. For our analysis we only consider *persons* and *adults* as the variables directly measure the viewership of a program. For each day, we aggregate the viewership of all the programs broadcasted at sports level for all days in the period of analysis. The panel consists of viewership data indicated by *persons* and *adults* for 6 different sports on 143 days. Table 1 contains summary statistics of both *persons* and *adults* for all traditional sports.

Table 1 Summary Statistics of viewership information

Statistic	N	Mean	St. Dev.	Min	Max
persons	1,364	10.5M	22.4M	0.15M	184M
adults	1,364	3.9M	8.9M	0.013M	67M

Unlike traditional sports, eSports do not have one major league played throughout a year. Instead, eSports are played at various tournaments that take place for 2-3 days and are organized by different entities. We gather the data on eSport scheduling from a website called `esc.watch`. We only consider the eSport tournaments that are popular, broadcasted on twitch.tv and have high prize money. We collect data for three popular eSports; CSGO, DOTA2, LOL.

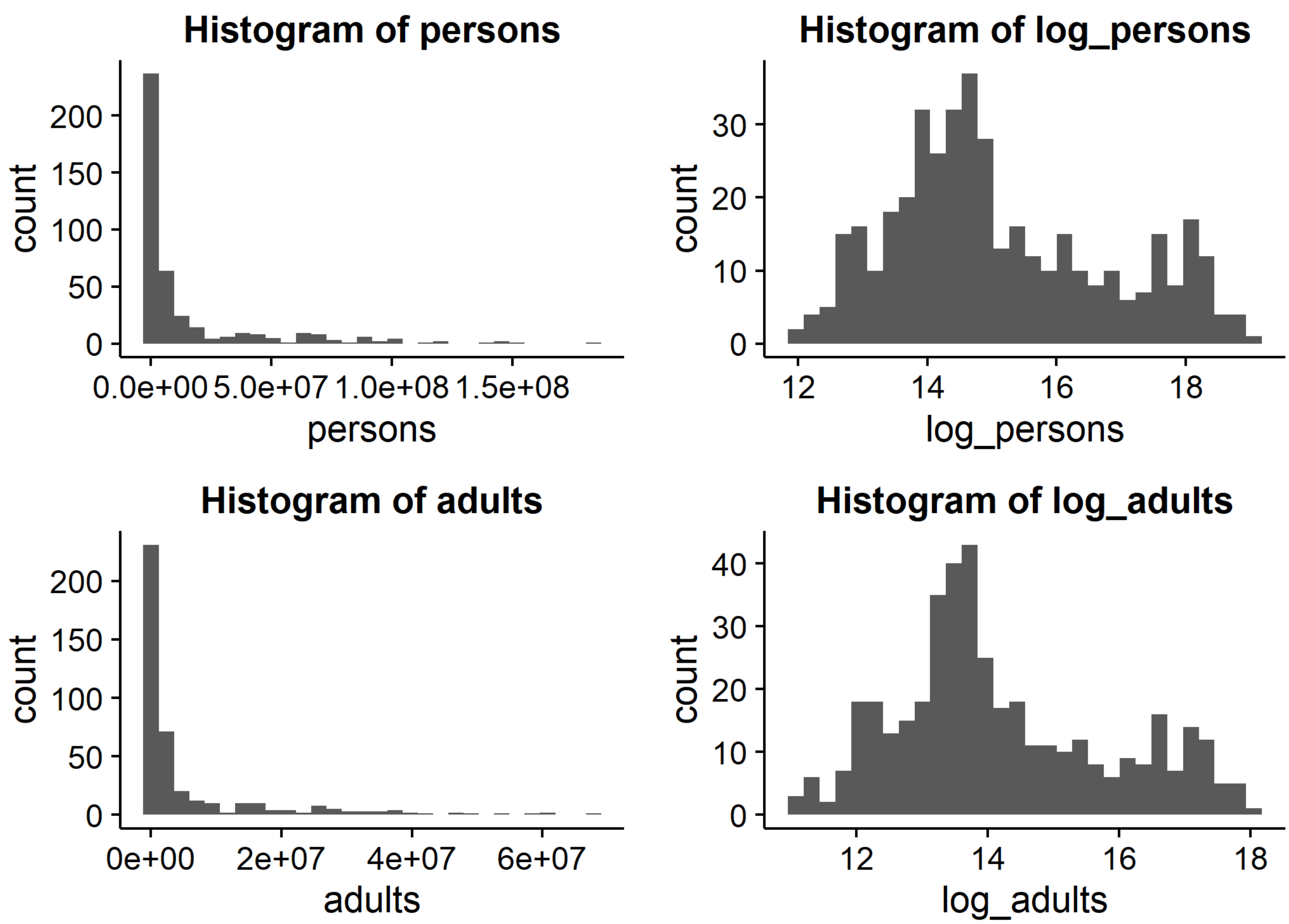
Empirical Analysis

We use panel data with traditional sport fixed effects and week fixed effects model in order to estimate the effect of eSport scheduling on traditional sport viewership. There is considerable heterogeneity in average viewership of various traditional sports with NFL attracting the highest audience compared to other sports. The traditional sport fixed effect controls for this unobservable effect of popularity. There is also heterogeneity in viewership across different types of games in each traditional sport like preseason games, regular league games, playoffs and finals. However, the scheduling is consistent across years. Month fixed effect controls for this seasonality in the viewership of traditional sports. The equation 1 is the model specification we use for the estimation of the effect of eSport scheduling on traditional sport viewership.

$$log(vtSp_{it}) = \beta eSp_t + tSp_i + month_t + \nu_{it} \tag{1}$$

$vtSp_{it}$ represents the viewership of traditional sport i on day t. We use $persons_{it}$ and $adults_it$ as a measure of $vtSp_{it}$. Both $persons_{it}$ and $adults_it$ follow power law distribution. So, we transform the scale using the logarithmic value of the variable. Figure 1 shows the distribution of both $persons_{it}$ and $adults_it$ as well as the log transformed version of them.

Figure 1 **Histograms of dependent variables**



β is the coefficient of interest which estimates the effect of eSport scheduling on traditional sports viewership. eSp_t is a dummy variable that equals 1 if an eSport is scheduled on day t and equals 0 otherwise. tSp_i represents traditional sport fixed effect. $month_t$ represents month fixed effect that controls for seasonality in traditional sports viewership. ν_{it} is the error term of the regression equation.

While month fixed effects control for the seasonality in viewership, week fixed effects are more granular as it controls for a particular game that might receive significantly different viewership like Super bowl or playoff games. While week fixed effects might capture more granular variations, we might lose power in the estimation of smaller effects as we have reduced data for each week and sport group. Equation 2 is the model specification that estimates the effect of eSports on traditional sports viewership with traditional sport and week fixed effects.

$$log(vtSp_{it}) = \beta eSp_t + tSp_i + week_t + \nu_{it} \tag{2}$$

Both the above specification give unbiased estimates of β only if the scheduling of eSports is exogenous to the scheduling of traditional sports. There are three reasons to believe that eSports scheduling is exogenous. First, unlike traditional sports eSports have a global audience. Even for the tournaments conducted in the USA, the percentage of US viewers are just around 28%. Second, each eSport has multiple tournaments scheduled throughout the year and there are many such eSports. There are also multiple traditional sports to compete with and traditional sports programming happens throughout the year. While many traditional sports and eSports might avoid scheduling during major programs like the super bowl, carefully scheduling by avoiding every traditional sport and eSport programs while catering to a global audience is difficult. Third, eSports are broadcasted online, which, unlike traditional sports broadcasts do not need to compete with television networks and other traditional sports for time slots. All the above reasons lead us to believe that eSport scheduling is exogenous to traditional sports scheduling.

The specification also relies on the assumption that eSport viewers go back to watching traditional sports when there is no eSport scheduled on a given day. Even if this assumption does not hold and only some viewers go back to watching traditional sport, the above specifications underestimate the effect that eSports have on traditional sports viewership.

We further analyze the effect of individual eSport on traditional sport viewership using the specifications in 3 and 4 using month and week fixed effects

$$log(vtSp_{it}) = \beta_1 lol_t + \beta_2 dota2_t + \beta_3 csgo_t + \beta_4 other_t + tSp_i + month_t + \nu_{it} \tag{3}$$

$$log(vtSp_{it}) = \beta_1 lol_t + \beta_2 dota2_t + \beta_3 csgo_t + \beta_4 other_t + tSp_i + week_t + \nu_{it} \tag{4}$$

To take into account the variability in the popularity of eSport tournaments, we change the above specification to use viewership numbers of an eSport event instead of a dummy variable that indicates the scheduling of eSport on a particular day. Equations 5, 6, 7, 8 give the specifications that estimate the elasticity of viewership of traditional sports with respect to eSports.

$$log(vtSp_{it}) = \beta log(eSp_t) + tSp_i + month_t + \nu_{it} \tag{5}$$

$$log(vtSp_{it}) = \beta log(eSp_t) + tSp_i + week_t + \nu_{it} \tag{6}$$

$$log(vtSp_{it}) = \beta_1 log(vlol_t) + \beta_2 log(dota2_t) + \beta_3 log(csgo_t) + \beta_4 log(other_t) + tSp_i + month_t + \nu_{it} \tag{7}$$

$$log(vtSp_{it}) = \beta_1 log(vlol_t) + \beta_2 log(dota2_t) + \beta_3 log(csgo_t) + \beta_4 log(other_t) + tSp_i + week_t + \nu_{it} \tag{8}$$

Results

Table 2 reports the estimation results of the coefficients from fixed effects models from equation 1 and equation 4. There are a total of six models in the table with three models with dependent variable as $log(persons_{it})$ and the other three models with dependent variable as $log(adults_{it})$. The first two models are specified using only traditional sport fixed effects and no time fixed effects. The next two models are specified with traditional sport fixed effects and month fixed effects. The final two models are specified with traditional sport fixed effects and week fixed effects.

As can be seen from the table, the coefficient of interest ($esport\_dummy$) is negative for the models without any time fixed effects and for the models with month fixed effects. This suggests that for model 1 and model 2, on the days when there is an eSport scheduled, the traditional sports viewership drops by 10% among all viewers and 11.3% among viewers of ages 18-49. However, these results are not significant.

This could be because of many reasons. First, eSports may not indeed have any significant effect on the traditional sports viewership. Second, we do not have sufficient power to find an effect that is significantly small. There is a reason to believe this as the period of analysis only has 267 days considered and out of which only 54 days have at least one eSport scheduled. The power reduces further as we add month and week fixed effects.

Table 2 Effect of eSport scheduling on traditional sport viewership

	(tSp FE)	(tSp FE)	(tSp FE) (month FE)	(tSp FE) (month FE)	(tSp FE) (week FE)	(tSp FE) (week FE)
	log_persons	log_adults	log_persons	log_adults	log_persons	log_adults
esport_dummy	-0.100	-0.113	-0.0967	-0.118	0.509	0.414
	(0.180)	(0.181)	(0.184)	(0.185)	(0.341)	(0.344)
_cons	15.18***	14.29***	15.08***	14.16***	14.27***	13.39***
	(0.166)	(0.167)	(0.237)	(0.238)	(0.475)	(0.478)
N	413	413	413	413	413	413

Standard errors in parentheses

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

Table 3 Effect of individual eSport scheduling on traditional sport viewership

	(tSp FE)	(tSp FE)	(tSp FE) (month FE)	(tSp FE) (month FE)	(tSp FE) (week FE)	(tSp FE) (week FE)
	log_persons	log_adults	log_persons	log_adults	log_persons	log_adults
lol_dummy	-0.0277	-0.00913	0.203	0.215	0.319	0.364
	(0.148)	(0.149)	(0.167)	(0.168)	(0.337)	(0.339)
dota2_dummy	0.144	0.117	0.00975	-0.0219	0.232	0.172
	(0.130)	(0.131)	(0.138)	(0.139)	(0.231)	(0.232)
csgo_dummy	0.0257	0.0405	-0.189	-0.173	0.196	0.172
	(0.130)	(0.131)	(0.142)	(0.143)	(0.323)	(0.325)
other_dummy	-0.102	-0.126	-0.0454	-0.0604	0.257	0.243
	(0.131)	(0.132)	(0.137)	(0.138)	(0.273)	(0.274)
_cons	15.07***	14.17***	15.05***	14.13***	14.16***	13.25***
	(0.118)	(0.119)	(0.205)	(0.207)	(0.516)	(0.519)
N	413	413	413	413	413	413

Standard errors in parentheses

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

Table 4 Effect of eSport viewership on traditional sport viewership

	(tSp FE)	(tSp FE)	(tSp FE) (month FE)	(tSp FE) (month FE)	(tSp FE) (week FE)	(tSp FE) (week FE)
	log_persons	log_adults	log_persons	log_adults	log_persons	log_adults
log_esport	-0.00580	-0.00664	-0.00526	-0.00675	0.0453	0.0377
	(0.0136)	(0.0137)	(0.0139)	(0.0140)	(0.0273)	(0.0275)
_cons	15.16***	14.26***	15.06***	14.14***	14.18***	13.30***
	(0.164)	(0.165)	(0.234)	(0.235)	(0.492)	(0.496)
N	413	413	413	413	413	413

Standard errors in parentheses

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

Table 5 Effect of individual eSport viewership on traditional sport viewership

	(tSp FE)	(tSp FE)	(tSp FE) (month FE)	(tSp FE) (month FE)	(tSp FE) (week FE)	(tSp FE) (week FE)
	log_persons	log_adults	log_persons	log_adults	log_persons	log_adults
log_lol	-0.000498	0.00105	0.0166	0.0176	0.0270	0.0307
	(0.0114)	(0.0115)	(0.0129)	(0.0130)	(0.0262)	(0.0264)
log_dota2	0.0111	0.00883	0.000815	-0.00179	0.0190	0.0138
	(0.0105)	(0.0106)	(0.0112)	(0.0113)	(0.0189)	(0.0190)
log_csgo	0.000839	0.00192	-0.0155	-0.0143	0.0156	0.0136
	(0.0104)	(0.0104)	(0.0113)	(0.0113)	(0.0263)	(0.0264)
log_other	-0.00731	-0.00918	-0.00294	-0.00418	0.0215	0.0206
	(0.0107)	(0.0107)	(0.0112)	(0.0112)	(0.0224)	(0.0225)
_cons	15.07***	14.17***	15.05***	14.13***	14.14***	13.23***
	(0.118)	(0.119)	(0.206)	(0.207)	(0.514)	(0.518)
N	413	413	413	413	413	413

Standard errors in parentheses

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

Table 3 shows the effect of individual eSport on traditional sport viewership. While LOL has a negative insignificant relationship, CSGO and DOTA2 have a positive insignificant relationship. These signs change as we add month or week fixed effects to the regression specification.

Table 4 shows the elasticity of traditional sports viewership with respect to eSport viewership. The coefficient of log_eSport indicates that an increase in viewership of eSport by 1% decreases the viewership of traditional sports by 0.0058%. However, this effect is not significant. Table 5 shows the elasticities of effect on traditional sports viewership with respect to each eSport. Again, the effects are not significant owing to the reasons discussed above.

Future analysis and Robustness checks

The results show that the negative relationship between eSport scheduling and traditional sports viewership but the effect is insignificant. This is possible because of the size of the effect and the power of the data we have at hand. We plan to collect more and granular data from Nielsen, a measurement company that collects viewership information of all programming on Television for the period of 6 years, three times more than the present period. This will help us find smaller effects with statistical significance.

Nielsen also has granular data on traditional sports viewership across different demographics, especially region. This will help us understand the effect of some eSports whose teams are region based. Finding the differential viewership of treated regions where an eSport is scheduled for the team based on that region and the control regions where an eSport is not scheduled for the team based on that region controlling for the differential viewership across those regions when none of the regions have eSports scheduled would give us unbiased estimate of the effect of that eSport on traditional sports viewership. We could use Differences in Differences methodology for the above.

For more robustness of the result, we can also look at twitter follower dynamics of a traditional sports handle and an eSport handle. Though the result would not be robust as there is a minimal cost involved in following a team on Twitter, this would still help us understand the growth, activity differences and involvement over time to understand the differences between those who follow only eSports, both eSports and traditional sports and only traditional sports.

Conclusion

In this paper, we empirically test the relationship that eSports have on traditional sports viewership. We take advantage of the exogenous scheduling of eSports with respect to traditional sports and use panel data of viewership of many traditional sports with traditional sport and time fixed effects to find the effect. Though we find a negative relationship between eSports scheduling and traditional sports viewership indicating that on the days when eSports are scheduled, the viewership of traditional sports goes down, we do not find a statistically significant effect. We conclude that we might need more data to have enough power to detect the small effect size that eSports have on traditional sports viewership. We also propose other methods to check for the robustness of the above result.

References

2016. Sunday final ratings: Nba finals game 7 adjusts up a little more. URL `http://zap2it.com/daily-ratings/sunday-final-ratings-june-19-2016/`.

Aguiar, Mark, Thomas Crossley, Matt Gentzkow, Patrick Kehoe, John Kennan, Pete Klenow, Alan Krueger, Fisher Hall. 2017. Leisure Luxuries and the Labor Supply of Young Men .

Cho, Daegon, Michael D. Smith, Alejandro Zentner. 2016. Internet adoption and the survival of print newspapers: A country-level examination. *Information Economics and Policy* **37** 13–19. doi:10.1016/j.infoecopol.2016.10.001. URL `http://dx.doi.org/10.1016/j.infoecopol.2016.10.001`.

Danaher, Brett. 2017. The effecting of streaming video services on film and tv consumption .

Gantz, Walter. 1981. An exploration of viewing motives and behaviors associated with television sports. *Journal of Broadcasting & Electronic Media* **25**(3) 263–275.

Gantz, Walter, Zheng Wang, Bryant Paul, Robert F Potter. 2006. Sports versus all comers: Comparing tv sports fans with fans of other programming genres. *Journal of Broadcasting & Electronic Media* **50**(1) 95–118.

Hamari, Juho, Max Sjöblom. 2017. What is esports and why do people watch it? *Internet research* **27**(2) 211–232.

Hamari, Juho, Max Sjöblom. 2017. What is eSports and why do people watch it? *Internet Research* **27**(2) 211–232. doi:10.1108/IntR-04-2016-0085. URL `http://www.emeraldinsight.com/doi/10.1108/IntR-04-2016-0085`.

Kresse, Christian. 2018. esports viewership numbers - overview (uv, peak ccu, hours watched). URL `http://esports-marketing-blog.com/esports-viewership-numbers/`.

Liebowitz, Stan J., Alejandro Zentner. 2012. Clash of the Titans: Does Internet use Reduce Television Viewing? *Review of Economics and Statistics* **94**(1) 234–245. doi:10.1162/REST_a_00148. URL `http://www.mitpressjournals.org/doi/10.1162/REST{_}a{_}00148`.

Mahajan, Vijay, Subhash Sharma, Robert D. Buzzell. 1993. Assessing the Impact of Competitive Entry on Market Expansion and Incumbent Sales. *Journal of Marketing* **57**(3) 39–52. doi:10.2307/1251853. URL `http://www.jstor.org/stable/1251853`.

Manovich, Lev. 2003. New media from borges to html. *The new media reader* **1** 13–25.

Rysman, Marc. 2017. The Economies of Two-Sided Markets **23**(3) 125–143.

Seamans, Robert, Feng Zhu. 2013. Responses to entry in multi-sided markets: The impact of craigslist on local newspapers. *Management Science* **60**(2) 476–493.

Smith, Michael D., Rahul Telang. 2010. Piracy or promotion? The impact of broadband Internet penetration on DVD sales. *Information Economics and Policy* **22**(4) 289–298. doi:10.1016/j.infoecopol.2010.02.001. URL `http://dx.doi.org/10.1016/j.infoecopol.2010.02.001`.

Waldfogel, Joel. 2009. Lost on the web: Does web distribution stimulate or depress television viewing? *Information Economics and Policy* **21**(2) 158–168.

Wallsten, Scott. 2013. What are we not doing when we're online. Tech. rep., National Bureau of Economic Research.

Wann, Daniel L. 1995. Preliminary validation of the sport fan motivation scale. *Journal of Sport and Social Issues* **19**(4) 377–396.

Yongjae, Kim, Stephen D Ross. 2006. An exploration of motives in sport video gaming. doi:10.1108/IJSMS-08-01-2006-B006. URL `http://gateway.library.qut.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true{&}db=afh{&}AN=24501438{&}site=ehost-live`.

Zentner, Alejandro. 2012. Internet Adoption and Advertising Expenditures on Traditional Media: An Empirical Analysis Using a Panel of Countries. *Journal of Economics and Management Strategy* **21**(4) 913–926. doi:10.1111/j.1530-9134.2012.00355.x.

Zervas, Georgios, Davide Proserpio, John W. Byers. 2017. The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *Journal of Marketing Research* **LIV**(October) jmr.15.0204. doi:10.1509/jmr.15.0204. URL `http://journals.ama.org/doi/10.1509/jmr.15.0204`.