The Effect of Franchising on the Competitive Balance in eSports

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Abstract

I analyse the impact of a change in league system from a non-franchised structure with relegation and promotion to a franchised structure without relegation and promotion on the competitive balance in eSports. Using player level data I find that the probability of competing for players has diminished significantly. The reason for this is that the change in the league format made it more likely for new players to enter into the competition. This suggests that the overall level of play has increased as bad players are being wedged out and only the high performing players remain. Lastly, using the standard deviation of wins, a common competitive balance estimator, I find that the competitive balance has decreased after the treatment. Since there is an increase in new player talent, the distortion in the competitive balance implies that the already successful teams are investing more into new talent compared to unsuccessful teams.

Keywords: Sports Leagues, eSports, video games, competitive balance

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1 Introduction

Over the past decade eSports, competitions using video games, has emerged from a small subculture to a multi billion industry involving superstar players, high prize money, and interest from media and politics alike. Today eSports events fill up huge stadiums all over the world. In 2021, over 489.5 million people watched eSports events over the internet or via television, which is more than 10% of the total online population (4.397 million) Newzoo [2022]. Likewise, today's top games' prize pools outrank those of traditional sports such as Dotas International 2021, which had a prize pool of 40 million, thus exceeding the prize pool of the NBA Statista [2022]. Moreover, by the end of 2022 eSports revenue is projected to be 1.38 billion dollars Newzoo [2022].

Just like traditional sports, eSports has two main league structures. There are non-franchised leagues, which are prevalent across all European traditional sports, and there are franchised leagues, such as the NBA. In non-franchised open systems new teams enter by being promoted from a lower tier league by taking the spot of the lowest performing teams in the higher tier league. However, in franchised leagues teams usually have to buy their spot and can only enter into an existing league when an incumbent is selling their spot. Additionally, franchised leagues usually implement a revenue sharing deal between teams and the league organiser. This is to help improve the competitive balance between teams. Recently, the arguably biggest eSports title League of Legends (Lol), a battle based strategy game, has moved from a non-franchised league to a franchised league in all of its mayor regions. Whether the change in the title's league structure is considered a success or not is yet to be answered by the literature.

Hence, in this study I analyse the impact of a change in the type of league from a non-franchised to a franchised system in the competitive structure of tournaments, using evidence from eSports Lol competitions. I use four difference-in-differences models, with the treatment being the time when the franchising took place to answer the following: First, whether the change in league system affected the probability of players competing. Second, whether this change comes from new players entering into the competition or Third, from players leaving the competition. Lastly, what the treatment means for the competitive balance in the league. The question of competitive balance is central here because fans usually prefer leagues in which the outcome is unclear. Also a more balanced competition increases demand and revenue for the league, which is of course of particular interest for the game's publisher and team owners.

My findings suggest that the change in the league system had an impact on the skill levels of competing players. The treatment reduced the likelihood for players to compete in the league, as low performing players were pushed out by new talent. In addition, the ratio of high quality players to low quality players increased, which improved the level of play further. Finally, my results also indicate that the competitive balance has plummeted. Teams invest more into playing talent after the treatment, but it mainly seems to be the already top performing teams investing in new players. This leads to a distortion in the league's competitive balance. However, given the lack of parallel trends the last result seems questionable and would require further research.

My results contribute to the extensive literature of competitive balance in traditional sports in open non-franchised leagues versus closed franchised leagues (i.e. Szymanski and Valletti [2010], Buzzacchi et al. [2010] or Noll [2002]). My findings confirm results made by Szymanski [2003] or [Buzzacchi et al., 2010] that the competitive balance in franchised leagues is lower than in non-franchised leagues. However, my work is unique as it studies the move from one system to another within the same league. Previous studies, such as the above, compared the competitive balance between different leagues of the same sport, specifically comparing European open leagues to North American closed leagues. Furthermore, I expand on the literature of competitive balance by using the use case of eSports.

In addition, I add to the new and diverse strain of eSports literature. Most of the literature has focused on comparing traditional sports to eSports ([Jenny et al., 2017]) and only little work has been done for economic testing, such as [Coates and Parshakov, 2016]. They analysed the tournament pricing schemes in eSports in relation to effort. But none to my knowledge have analysed the competitive structure and competitive balance within a league.

My paper is structured in the following way; Section (2) describes the franchising deal in each region and its implications for the stakeholders. Section (3) lays out the previous literature and connects my work to prior research. Section (4) presents my data sample and descriptive statistics. Section (5) shows my empirical approach and results on the impact of the franchising on the probability of playing. Section (6) examines whether the results from (5) come from new players entering or players leaving. Section (7) explores the impact on the competitive balance. Section (8) presents additional robustness checks, and section (9) concludes and discusses this paper.

2 Policy Background

Lol is a real time team based strategy game where two teams of five compete against each other. In simple terms the goal is to destroy the enemy's base. It was first published in 2009 by Riot Games and is now owned by Tencent, which is the biggest company by market capitalisation in China. A big feature of competitive games such as Lol are professional competitions or tournaments, which started in 2011 with the Season 1 World Championship. Currently, regional league systems exist all over the world for Lol in which teams compete against one another in a league and gain points, similar to traditional sports such as Football. There are two seasons per year called Spring split and Summer split, and the top teams then advance to a play-off round which is a knock-out tournament like the play-off systems of the NBA or NFL. Hence, there are regular season winners and play-off winners. My research only considers the regular season results. Among the regional leagues are the North American, European, Korean and

Table 1: Introduced changes after Franchising in each League

	China	North America	Europe	Korea
Started Franchising	Summer Split 2017	Spring Split 2018	Spring Split 2019	Spring Split 2021
Entry Cost				
For new teams	80 mil. Chinese RMB (*)	$13 mil.	$13.02 mil.	$10.5 mil.
For existing teams		$10 mil.	$9.93 mil.	$8.8 mil
Revenue Sharing	Yes details unknown	Players receive: 35% Teams: 32.5% Riot Games: 32.5%	Players receive: 35% Teams: 32.5% Riot Games: 32.5%	Yes details unknown
Minimum Player Salary	unknown	$75.000	$75.000	60 mil. KRW
Introduced Home and Away System	Yes	No	No	No

Note: (*) the exact amount for new teams to enter for the second half of 2017 is unknown, but during the expansion of their league in 2020 new teams had to pay 80 mil. Chinese RMB. as shown in the table.

Chinese league, which are considered the mayor regions. These leagues are all run by Riot Games and in some cases by Riot Games in cooperation with local publishers.

By the year 2021 all four major regions decided to move to a franchised league model. Because each league is governed by different local entities the timing of the change in the league system is different for each and the franchising specific rules are also different. Table (1) shows an overview of the league changes after the franchising was introduced. What follows is a detailed description of the different franchise systems.

The first league to remove relegation and promotion was the LPL, the Chinese league. The franchise system was launched for the 2017 Summer split, future league expansion was planned and by 2022 there are now 17 teams in the league. While it is unknown how much the initial entry fee in 2017 was, during their expansion in 2020 teams had to pay a minimum 80 million Chinese RMB, which is roughly $11.63 million Chen [2019a]. Furthermore, what is unique for the Chinese league is that a home and away system was introduced. Six teams have their own home venue across five different cities in a similar fashion to how traditional sports leagues are physically structured. The Chinese league also has some form of revenue sharing to which participating teams are entitled to, but the exact details are unknown to the public Chen [2019b].

After China, North America removed promotion and relegation for the start of the 2018 season. The North American Challenger series, which was their second tier league was abolished. Furthermore, they implemented a drafting round which gives amateur players the opportunity to show their talent and helps teams to source new players. The format is comparable to franchised leagues such as the NFL. As usual, to participate in the new franchised system teams would have to pay buy in prices. These were $10 million dollars for existing teams and $13 million for new teams. According to [Lolesports-Staff, 2016] revenue is shared three ways between players, teams and Riot Games. The player's minimum salary is increased to $75k and they receive 32.5% of league revenue. Essentially, players receive at least their contract salary, and if player's share of league revenues is greater than the total salaries of all players, then the difference will be paid to them. Conversely, players do not get any additional money if their share is less than the combined salaries. On the other hand, teams will receive 32.5% share of league revenue. Half of this revenue will be shared equally through pool revenue sharing, while the other will be distributed according to seasonal finishes and contribution to viewership and fan engagement. The remaining 32.5% will used by Riot Games to finance the broadcasting, production and live events among others.

After the North American initiative, Europe franchised their regional league in the Spring split of 2019. To be part of the new league, existing teams had to pay $13.02 million and new teams $9.93 million. Their second tier division was abolished and instead they created the EU Masters as a successor to the former tier two league. Amateur national leagues were created across Europe and the best teams are then sent to represent their country in the semi-professional tournament of EU Masters. But, winning the EU Masters did not mean promotion now any more after the franchising. As in North America the minimum player salary was increased to roughly $75.000. According to [Wolf, 2018] the European league system is identical in structure and revenue share to the North American model.

The last region to move to a franchise system was the Korean league which started at the beginning of the 2021 season. Likewise, their relegation and promotion was removed and a revenue sharing model was introduced, however the exact details of it are not public knowledge [LCK, 2020]. Also, the minimum salary for player is set at 60 million KRW.

3 Literature Review

First and foremost my research paper extends the literature of competitive balance in traditional sports by utilising the use case of eSports. Many economists have thereby analysed contest design of open and closed leagues and their effect on competitive balance. Noll [2002] studies the European non-franchised system of relegation of promotion, in which the best performer of a inferior league is promoted to the next best one and the worst performer is relegated into the inferior league. He finds that the European system has a net positive effect on attendance, players earn higher wages and the effect on competitive balance is ambiguous. Likewise, Ross and Szymanski [2002] conclude that a promotion and relegation system would be welfare enhancing for US taxpayers and consumer. More recently, Szymanski and Valletti [2010] find that the North American franchised leagues are more competitive balanced, dynamically, but that there is more equality of opportunity in European leagues. Their model also suggests that teams have a higher incentive to invest in effort under a system with promotion and relegation, but that there are fewer incentives to encourage competitive balance. Similarly, Dietl et al. [2008] find that teams over invest more in talent in open leagues, because there is a higher incentive to do so in order to not demote.

Other empirical studies analyse the effect of competitive balance or compare it between different leagues. ([Buzzacchi et al., 2010]; [Lenten, 2015]). [Buzzacchi et al., 2010] compare the different league systems of North American and European leagues regarding their competitive balance and find that open leagues are less competitively balanced contrary to some theoretical models. (e.g. [Szymanski and Valletti, 2010])

Moreover, an essential part of most franchised systems in traditional sports is revenue sharing as is the case for Lol. Thus, there exits much literature on the effect of revenue sharing on competitive balance, but the literature does not agree on its impact and this depends heavily on the assumptions made. Initially it started with Rottenberg [1956]'s famous 'Invariance Principle' which suggests that revenue sharing does not influence the competitive balance. Since then many economists have challenged this principle. Such as Fort and Quirk [1995] or Vrooman [1995] who show that gate revenue sharing, the sharing of revenue generated through the sale of tickets, has no effect on talent allocation, thus confirming the Invariance Proposition. Using a broader revenue function, that accounts for the visiting team's chance to win or the absolute quality of a team Atkinson et al. [1988], Marburger [1997] and Késenne [2000] find that competitive balance can be improved by revenue sharing. These models generally assume that the supply of talent is constant. Meaning that hiring a player not only benefits the buyer but also weakens the other teams in the same league, which impacts the marginal revenue of talent. In a closed franchise system, like North American leagues, this assumption may make sense, but it seems implausible in open European markets without any foreign player quotas and is difficult to expand for the use case of Lol. [1]

As such, several works using non-cooperative game theory arose showing that in the open European leagues of football, the invariance proposition does not hold and that revenue sharing decreases competitive balance (Szymanski [2003], Szymanski [2004], Szymanski and Késenne [2010]). This results from the dulling effect, in which teams have less incentive to invest into extra talent because teams have to share an amount of their marginal gain from the investment between each other. What is important to note is that here teams are assumed to be profit maximisers. Yet, there is reason to believe that teams especially in Europe may be win maximisers ([Késenne, 1996], [Sloane, 1971], [Vrooman, 2000]). Késenne [2000] shows in his more general n team model with constant and fexible talent supply that pool revenue sharing, in which teams share a percentages of their revenue, can worsen competitive balance if teams are profit maximisers. Whereas it can improve if teams are win maximisers. This result, however, does

[1] This definition for open and closed leagues, however, cannot be readily applied to the case of Lol. In 2014 a quota for foreign players was introduced, in which teams were only allowed to have two imports actively playing. After playing continuously for 4 years in a foreign league imports can apply for residency. Hence, before and after franchising Lol leagues were somewhere in between a constant and flexible talent supply. Similarly, there is a strong difference regionally on the reliance of imported players. North America has been heavily reliant on imported players, because of their small player pool. Here one could assume that their talent supply is rather constant. Other regions such as Europe with a vast player pool have mainly moved away from importing players over last year, here a flexible supply of talent may seem more adequate.

not also imply that gate revenue sharing affects competitive balance in such a way.

Further papers extended the assumption of purely win- or profit maximising leagues and introduce mixed models in which there are win- and profit maximising clubs. Lang et al. [2011] verify the aforementioned dulling effect in a two club model containing one profit maximiser and one "sugar daddy" club. The sugar daddy uses vast amounts of money to invest into the club to gain full control of it. Their main goal is sporting success and they care little about any financial losses. Additionally, Dietl et al. [2009] also show that competitive balance decreases in a two team model consisting of one win and one profit maximiser.

However, empirical evidence from European and North American leagues suggests that teams trade off financial gains and wins. (e.g. [Atkinson et al., 1988], [Garcia-del Barrio and Szymanski, 2009]). Dietl et al. [2011] use a contest model where teams maximise a weighted utility of profit and wins. They find that revenue sharing does not always reduce the incentive to invest in new playing talent. They define a "sharpening effect" that increases competitive balance in a league. Specifically, for their two team model, they find that the small market team will invest more into playing talent than the large market club, if the winning preference is high enough for the small market team.

As stated in the previous section, Lol also has a form of revenue sharing. However, testing the effect of revenue sharing for Lol can be difficult, since every league has a different model and the impact of revenue sharing on competitive balance depends heavily on the assumptions one makes. Nevertheless, the use case of eSports can give valuable insight on the effect of revenue sharing in a complex and new environment, which can be of use for future revenue sharing models in professional gaming.

On the other hand, my work adds to the new and diverse field of eSports. This category of literature is still in its infancy, but it offers vast research opportunities not only in the field of eSports, but also in economics as a whole. For example, the tournament setting of eSports enables researchers to empirically test whether agents induce enough effort. Original models by Lazear and Rosen [1981] and Rosen [1986] suggest that rewards have to be heavily concentrated towards the highest ranking participants in order to maximise contestant's effort. Using tournament prize data in eSports Coates and Parshakov [2016]'s findings show that the prize structure is convex in rank order. Meaning that each time participants advance to the next round their rewards increase more heavily. Hence, eSports tournament prize schemes are aimed at increasing contestant's effort as in Lazear and Rosen [1981] and Rosen [1986]. Effort plays a central role in my work too as the league structure may induce players and team owners to put in less effort as the cost of not inducing effort may decrease with the abolition of relegation.

Moreover, literature in traditional sports demonstrates that factors such as political institutions, economics and geographical conditions and human resource attributes' impact a nations sporting performance (e.g. [Bernard and Busse, 2004], [Johnson and Ali, 2004], [Noland and Stahler, 2016]). Parshakov and Zavertiaeva [2018] highlights key differences between traditional sports and eSports. The cost of participation is much lower in eSports and athletes can participate in different eSports titles, because they do not need intense physical form, nor certain climate conditions or specific expensive infrastructure. Also governments are yet to step in and develop national teams. This implies that country specific fixed effects are if anything likely to be marginal. However, using a sample of money won by players each year Parshakov and Zavertiaeva [2015] show that country level fixed effects are important and similar in degree to traditional sports.

[Parshakov and Zavertiaeva, 2018] investigates this further by aggregating prize money rewarded to players at the country-level. They include country-level factors that may help to understand contestants performance in eSports. These characteristics cover factors that contribute to traditional sports, like GDP per capita or population, and eSports related components, such as percentage of internet users. The authors find that GDP per capita does not impact the probability of a country entering in an eSports tournament, but it has positive effects on the amount of money won by a country. This approves the low entry cost hypothesis mentioned earlier. Also, the percentage of internet users positively affects a country's participation, but not the amount of money won.

Researchers have compared the differences between traditional sports and eSports. An apparent difference seems to be the athlete's physical activity. According to Jenny et al. [2017] traditional sports utilise large muscle groups , while eSports require the use of small muscle groups. Hence, the level of physicality related to typical definition of sports does not translate to eSports. Similarly, eSports is organised differently. Karhulahti et al. [2017] states one needs equipment and commercial products owned and controlled by private entities. This violates a criteria defined by the GAISF (Global Association of International Sports Federations), which states that sports should not need to depend on the gear or equipment supplied by a single distributor.

In essence, what the above mentioned papers in eSports of Parshakov and Zavertiaeva [2015], Parshakov and Zavertiaeva [2015] and [Jenny et al., 2017] do is comparing models or structures from traditional sports to the eSports environment. Similarly, my study does exactly that. I extend on the literature of competitive balance in traditional sports by applying it to the field of eSports competition to gain insights on how the a change in system affects competition in eSports.

4 Data

To conduct this research I use individual player data from individuals who have competed in at least one of the four main regions in League of Legends eSports, namely Europe, North America, Korea, and China. Player statistics is taken from Sevenhuysen [2022] and player demographic data from lol.fandom

[e]. I reconstructed the sample to show whether a player has competed or not from 2013 to the first half of 2022 except for Korean players where the dataset starts from 2015. The reason for this is that before 2015 Korea used to run a knock-out tournament twice a year instead of a seasonal championship like the other regions. This gives me 19 observations per player except for players who started playing in Korea. Furthermore, to set up the panel I deleted observations in which players have changed teams during a split. I delete the team the player left and the new team the player has joined is kept in my dataset. I then used the wiki API from lol.fandom [e] to extract data on each players birthday and reformatted the output from an unstructured non tabular layout to a tabular format. By cleaning and deleting observations such that only the players who have competed in atleast one of the top regions remained, allowed me to merge the two datasets together. In conjunction the two datasets enable me to define the time at which a player is of the required age to compete professionally in Lol, which I discuss in my robustness checks.

Overall my sample amounts to a total of 76 seasons and 1198 different players which gives me 21506 observations. Most work regarding competitive balance use team data. However, for my special case, I use player level data to ensure that the treated do not have an effect on the untreated. If I were to use team data, then the treatment in China might well impact the untreated in Korea as the growth in financial stability of Chinese teams may cause more Korean players to play for Chinese teams. I overcome this problem by defining treatment at player level instead of league/region level.

Furthermore, the dataset includes in game statistics such as Kills, deaths, assists, the ratio of Kills and Assists to death, the win rate, the player's position, and the team and region a player has played in. Players can change between regions, but there is an import rule. Meaning only a maximum of two imports from a foreign region can be playing at the same time. Additionally, region for my case is important, because it determines the time when the franchising has been introduced. I define region not in terms of residency or nationality as has been done in the rulebooks of Lol-eSports. If a player is competing then the region they are competing in defines his region. This region also defines their region prior to playing and after having stopped playing. Once a player changes teams to another league, then the region changes to the corresponding region and once playing stops the region will remain to the one last played in.

In addition, the dataset includes the time when the franchising has been introduced, which differs across regions. China moved first in Summer of 2017, then North America in Spring 2018, then Europe in Spring 2019, and lastly Korea in Spring of 2021. To measure the competitive balance, I calculated the standard deviation of wins (SDW) as I will explain in detail later.

I use another two datasets which are edited versions from the first one for model 2 (Impact on First Entry) and 3 (Impact on First Exit) that I will explain later. The second one shows when a player first entered the game and excludes observations after having entered. The third shows when the player first

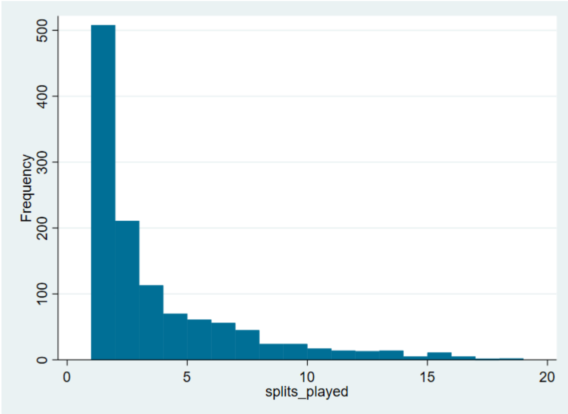

Figure 1: Professional Career Length before Leaving for the First Time

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left the game after having played previously. Observations before the player entered into the league and after having first stopped playing actively are excluded. The average time a player is competing actively is 3.29 seasons (around 1.5 years) compared to 8.2 years as a professional NBA player [Baker et al., 2019]. Figure (1) shows the number of players that have played for a specific amount of time before first leaving, ranging from one split to 19 (half a year to nine and a half years). It can be seen that there is a negative almost convex relationship between the number of splits played and the amount of players having played for that time. This seems to be a common relationship in the field of professional sports, but in eSports the decrease may be much sharper, since the average professional career is that much shorter.

Table (2) depicts concentration measures for each league. The Herfindahl-Hirschman Index (HHI) was calculated using team data of first place finishes in each region from lol.fandom [b], lol.fandom [a], lol.fandom [c] and lol.fandom [d]. The HHI index suggests that there are some regional difference, since in some cases, such as EUW (Europe), the index increases after the treatment. Whereas in others, it decreases after the treatment, such as in China. It is important to note that the high increase in the HHI of the Korean league is due to there only being three splits after the treatment, because the franchising was introduced in 2021. This explains the sharp increase in the index. Overall, the index does not tell us what to expect regarding the competitive balance after the introduction of franchising. Also, the Gini coefficient shows that there is little variation in the spread of win rates before and after the treatment.

Lastly, Figure (2) shows the SDW across all four leagues and the dotted line marks the timing of the treatment. It is clear to see that there is a lot of variation between the years and regions. Looking at the Chinese league, for example, it seems that the competitive balance was already on a downward trend before the treatment and retained at a fairly low level without too much fluctuation after the treatment. The leagues in Europe and North America share a similar sentiment. Fluctuations after the treatment reduced and it seems the trend was already downwards before the treatment. For the case of Korea little can be said since the league was only recently treated.

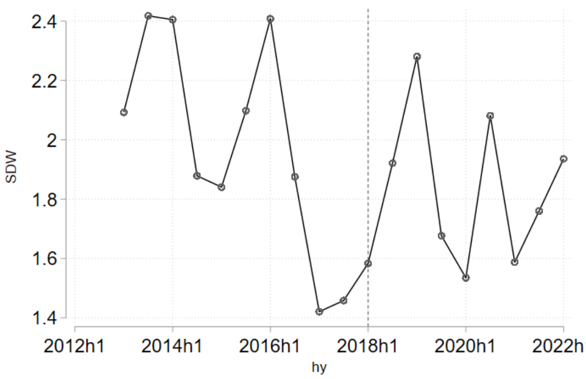
Table 2: Concentration Measures of first place regular season placements

Region	HHI of first place regular season finishes		Gini of Win-rate	
	Before Franchising	After Franchising	Before Franchising	After Franchising
NA	0.36	0.34	0.212	0.207
EUW	0.26	0.51	0.207	0.208
KR	0.17	0.56	0.221	0.200
CN	0.53	0.34	0.212	0.209

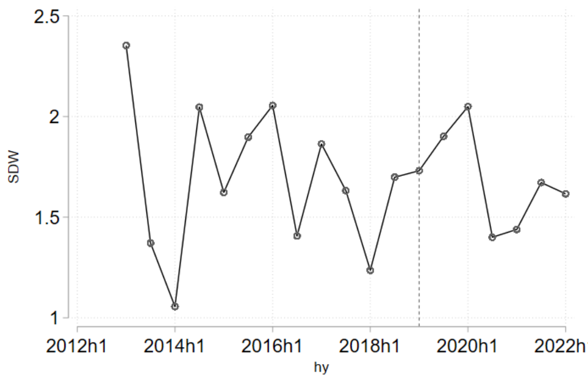
Note: NA stands for North America, EUW for Europe West, KR for Korea and CN for China. For the calculation of the HHI of EUW the season of 2018 was left out, because the league format was changed such that team were divided into two groups, hence there was no clear regular season champion. Likewise, in CN the league was also divided into two groups for the seasons of 2016,2017 and 2018. Also teams that rebranded, such as Longzhou Gaming to Kingzone Dragon were treated as the same team if they won a regular season under different sponsors.

Figure 2: Standard deviation of wins across leagues

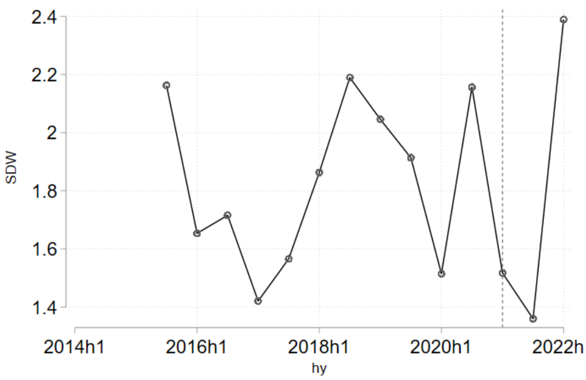
The dotted line shows the timing of the treatment in each league



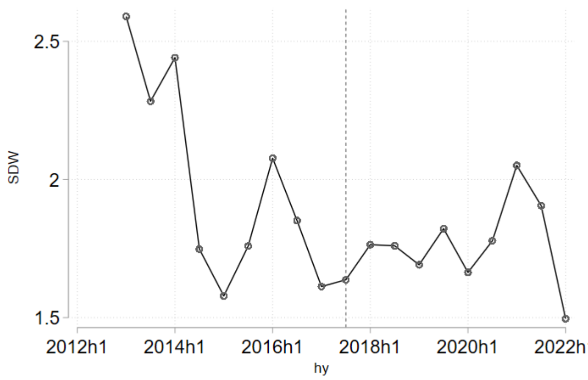
(a) SDW in North America



(b) SDW in Europe



(c) SDW in Korea



(d) SDW in China

Legend: The graphs show the standard deviations of wins over the idealised standard deviation of wins, which is the standard deviation if all teams had the same probability of winning against one another over the time period of 2013 to the first half of 2022. The exact definition used can be found in the empirical strategy of section (5). Graph (a) shows the SDW in North America, graph (b) in Europe, graph (c) in Korea and graph (d) in China.

5 Empirical Strategy and Results on the Impact of Playing

This paper aims to look at the impact of the type of league on four different game outcomes: (1) The probability of being in the game, (2) The probability of first entering the game, (3) The probability of first leaving the game and (4) the competitive balance. I define the league type as F, with F being equal to one if the league is franchised and zero otherwise. All my specifications follow the twoway fixed effect difference-in-differences approach of de Chaisemartin and D'Haultfœuille [2020]. In the following I will present each specification and their results one after another.

5.1 Model 1: Specification

I analyse outcome (1) with the following model:

$$Playing_{it} = \alpha_t + c_i + \sum_{\tau=0}^{4} \beta_\tau F_{r\tau} + \sum_{\tau=-4}^{-1} \delta_\tau F_{r\tau} + \eta_{it}, t = 1, 2, ...T \tag{1}$$

I utilise a staggered difference-in-differences design using a twoway fixed effects estimator with player and time fixed effects presented by [de Chaisemartin and D'Haultfœuille, 2020]. This estimator solves the bias problem that can arise if average treatment effect are heterogeneous across groups and time periods. I use a logistic regression to analyse how the treatment affects the change in the league system. The treatment is assumed to be exogenous, since it is Riot Games, Lol's publisher, who decides on the league format and not the players themselves.

The data is on individual (i) and half year (t) level. The dependent variable $Playing_{it}$ captures the amount of times a player is competing. It is constructed as a dummy variable that equals one if player (i) is actively playing during a split (t). Player fixed effects are described by c_i. I control for time fixed effects with α_t. The treatment variable $F_{r\tau}$ equals one, if the franchising system has been introduced at time (t) in region (r), zero otherwise. The variable of interest β shows the impact of the treatment on the dependent variable.

I use an event study model to be able to see if the effect changes over time. This allows me to see if there is a dynamic treatment effect. In this dynamic setting the estimand is a weighted average of DiD estimands that compares the evolution of the outcome from the period just before the event (t-1) to the period after the event (t+1), of groups which experience treatment at (t), and groups which are not yet treated at (t+1). Thus, the control group consists of players who are still untreated at (t+1). This approach gives a larger control group than other estimators, like [Callaway and Sant'Anna, 2018], which may yield more precise results.

5.2 Model 1: Results

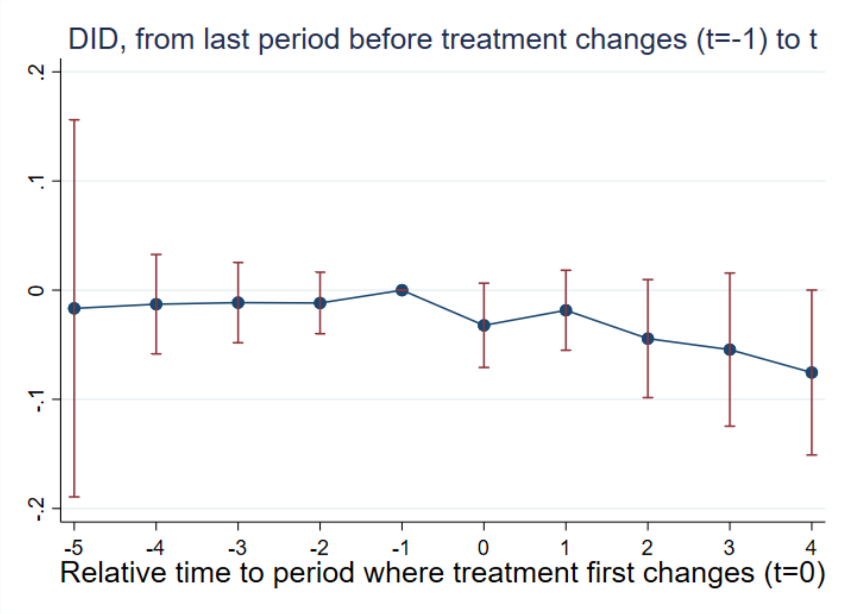


Figure 3: Impact on Probability of Competing Event Study Graph

Note: The above figure 3 shows the DiD coefficients with 95% confidence intervals from equation 1 on the probability of competing. Standard errors are cluster on player level. The x-axis shows time to treatment in half year intervals. The y-axis shows the coefficients of equation (1). Treatment is defined as the time at which a region introduced the franchising. The control group consists of players who have not yet been treated at time (t+1). The sample is defined as players who have competed at least once in a mayor region.

My results indicate that the change in the league system affected the probability of competing negatively. This implies that competition around new talent has increased after the franchising and teams seem to be investing more and recycling through new players. Table (3) column 1 in the appendix shows the coefficients from model 1 and it is clear to see that the franchising at the time of treatment had a significant effect of -0.0322. Likewise, all other leads are also negative, but only the lead 2 periods after the treatment is statistically significant.

Figure (3) shows the event study graph of model 1. The treatment took place at period zero and after the treatment the coefficients start decreasing. The picture tells a clear story of parallel trends as there is no treatment effect before franchising as the coefficients are all close to zero with no statistical significance. This validates my results as the parallel trends assumption is satisfied. Before the treatment there is hardly any effect, only when the league systems change does the treatment have its effect and the pre-treatment trends diverge while the treatment effect increases over time reaching an estimate of -0.0167 in period t=4 and resulting in an average effect of -.043. Hence, we can assume that the players leaving are the under performing players and the high performers remain. This can also be seen at the number of observations which are decreasing in time. So as the number of observations decreases and the probability of participating also decreases, the ratio of competitive players to low performing players shrinks even more over time. This indicates that the overall level of play in the league also increased as a result.

Additionally, the confidence intervals of Figure (3) are all fairly small, but periods further in the past show larger confidence intervals. At its extreme four periods before the treatment the confidence interval is at its biggest. The placebos compare first time switchers' outcome evolution with not yet switchers' outcome evolution, before the first time switchers' treatment changes. At the point of (t=-4) there are only 1643 number of observations to calculate the estimator of this placebo compared to 2357 for the placebo at (t=-3). Likewise, there are only 957 switchers compared to 971 switchers at (t=-3). Moreover, the average professional career of a Lol player is very short with only around one and a half years, i.e. 3 periods. As it gets closer to the treatment time there fewer players actively playing and more players not playing any more. This and the smaller number of observations and switchers may explain why the confidence interval is so large for the fourth placebo.

6 Impact on First Entry and First Exit

The previous model highlighted that the treatment had a clear negative impact on the probability of players competing, which suggests that the overall skill level of the league has improved as low performing players have left the league and only high performers remained. I develop the next two models to gain some insights behind the mechanisms of the first model. Specifically, the results of the first entry and the first exit models allow me to check whether the probability of competing has shifted after the treatment; because of new players entering into the league (first entry model) or competing players leaving the league (first exit model). What follows is the empirical strategy of both models and then their subsequent results separately.

6.1 Model 2: Empirical Strategy First Entry

I use the following logistic regression to analyse the impact of the treatment on the probability of first entering the competition.

$$Entry_{it} = \alpha_t + c_i + \sum_{\tau=0}^{4} \beta_\tau F_{r\tau} + \sum_{\tau=-4}^{-1} \delta_\tau F_{r\tau} + \eta_{it}, t = 1, 2, ...T \tag{2}$$

Here the dependent variable $Entry_{it}$ takes on the value one, if a player (i) has entered a league at time (t) and has played a positive number of games conditional on not having played previously. Observations after having entered are excluded here. Again F defines the treatment and I use time and player fixed effects. All the other variables are defined as in equation (1).

6.2 Model 2: Results of First Entry

Again I use the model 2 of equation (2) to understand if the effect on the total probability of playing from equation (1) comes from new entries. Estimates of equation (2) displayed in Figure (4) suggest that the change in league has increased the probability of first entering into the league. I find an average effect of

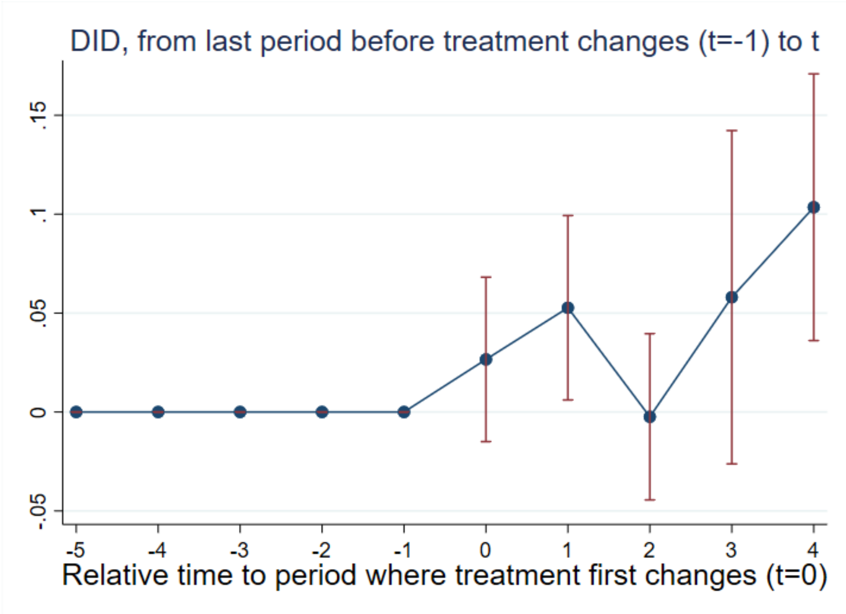


Figure 4: Model 2 Event Study Graph

Note: The above figure shows the DiD coefficients with 95% confidence intervals from equation (2) on the probability of first entering. Standard errors are cluster on player level. The x-axis shows time to treatment in half year intervals. The y-axis shows the coefficients of equation (2). Treatment is defined as the time at which a region introduced the franchising. The control group consists of players who have not yet entered into the league and have not yet been treated at time (t+1). The sample is defined as players who have competed at least once in a mayor region. Observations after having first entered into the league are excluded.

0.059, which is a small increase in the log odds probability of first entering into the league. This translates to a 1.1% increase in the log odds of first entering. The results imply that the introduction of the closed league has increased demand for new talent and that teams are investing in new talent. Teams are trying to be more competitive by using new players to strengthen their team. Hence, the reason why the probability of competing has decreased, as shown in model 1, may be because of new talent entering the game.

Additionally, the event study graph of Figure (4) shows a clear treatment effect. Before the treatment there was no effect, only after the treatment is an effect is noticeable, which gives evidence to the parallel trends assumption. However, the flat line without zero confidence intervals before the treatment is likely due to the way the model has been shaped. Remember, in this model observations after first entering the league are excluded, like a survival model. This event is similar to a one time event such as death after which there are no further possible observations. Hence, all the players acting as control groups for any effect at (t+l) with l >=1 have not been playing since t-1, which are 1+l periods. So, there are a large amount of players who are neither in the control nor treatment group, because they entered the game before the treatment, which explains the flat line without the confidence interval.

Likewise, the number of observations and the number of switchers decreases as the time after the treatment increases. The number of observations reduces by around 20% between most periods. At the treatment there are 975 observations and 366 switchers, while at the last period (t+4) there are a total of 325 observations and 160 switcher.

Lastly, table (3) column 2 in the appendix depicts the coefficients of equation (2) and only he coefficients at (t+1) and (t+4) are statistically significant while the rest are insignificant.

6.3 Model 3: Empirical Strategy First Exit

Again I use a difference-in-differences logistic regression to analyse the effect of the treatment on the probability of first leaving the competition. I estimate,

$$Exit_{it} = \alpha_t + c_i + \sum_{\tau=0}^{4} \beta_\tau F_{r\tau} + \sum_{\tau=-4}^{-1} \delta_\tau F_{r\tau} + \eta_{it}, t = 1, 2, ...T \tag{3}$$

The outcome variable of equation (3) $Exit_{it}$ equals one, if player (i) has stopped playing for a team at time (t) and is not continuing playing conditional on having competed previously at time (t-1). The variable being equal to zero indicates that a player is actively playing. Observations in which the player does not play are excluded, with the only exception being at time (t) when the player first stops playing. I again control for time and player fixed effects and the other variables in equation (3) are the same as in equation (1).

6.4 Model 3: Results of First Exit

The results of equation (2) have shown that at least some of the effect found from the probability of playing comes from new entries. The results of equation (3) depicted in Figure (4), on the other hand, show that the change in league system actually decreased the probability of first leaving the league with an average effect of -0.0141. This implies that the effect from equation (1) is solely coming from new entries into the league and that these new entries outweigh the effect of existing players staying in the league. This is likely, because the average effect is very small and close to zero, compared to 0.059 from the previous model of equation (2). Again, the figure presents evidence of the parallel trends assumption and shows a clear treatment effect, which validates my conclusion.

Additionally, one can see that right at the treatment the effect of first leaving increases with a coefficient of 0.062, which is statistically significant at 10 percent. This suggests that the surge in new sponsors and the new revenue share deal, together with the financial stability of the new system, increased teams willingness to invest in new talent and rotate poorly performing players out. Likewise, the Chinese league increased their league size one period after the treatment. This might explain why the coefficient is still positive at (t+1). Besides, before 2021 the maximum contract length of pro players was three years. One can expect that most contract lengths are either one or two years in duration. Thus, if we look at (t+1) the probability of exiting decreases compared to the previous period with a coefficient of 0.020, which is not statistically significant however. Teams made big acquisitions the previous period so there was no need for new players any more. Also, it is important to note that most transfers happen at the start of each year. All regions, except China, franchised their league at the start of the year in the

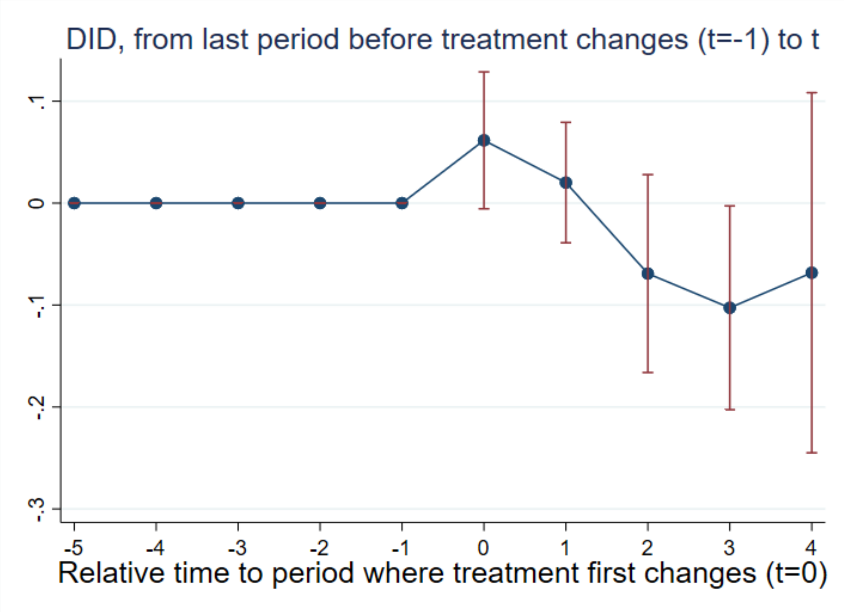


Figure 5: Model 3 Event Study Graph

Note: The above figure shows the DiD coefficients with 95% confidence intervals from equation (2) on the probability of first entering. Standard errors are cluster on player level. The x-axis shows time to treatment in half year intervals. The y-axis shows the coefficients of equation (3). Treatment is defined as the time at which a region introduced the franchising. The control group consists of players who have not yet left the league the league conditional on having played continuously and have not yet been treated at time (t+1). The sample consists of only the observations in which players have played a positive number of games.

Spring split. The period (t+1) would then refer to the Summer split in which there is less player movement between teams. This also explains why the probability of first exiting reduces at (t+1) compared to (t).

Then for the first time at t+2 the outcome becomes negative with a coefficient of -0,69. There is a similar evolution in the outcome when comparing the paths of Figure (4) of equation (2) up until this point. From (t) to (t+1) the probability of entering is positive in model 2, while the probability of leaving is also positive for the same time span. Then at period (t+2) we see a shift. The probability of first entering drops to zero, while in Figure (3) the probability of first leaving drops to a negative coefficient.

Moving on to period (t+3) we see that the effect stagnates with a coefficient of -.103 at five percent statistical significance. Then at (t+4) the effect increases slightly to -0.68 compared to the previous period. Again this reduction in the probability to leave is likely due to the contract length and the large acquisitions done at the time of the treatment and one period later. However, the standard error at (t+4) is very large and there is no statistical significance.

7 Impact on the Competitive Balance

7.1 Model 4: Specification

The previous three specifications examined how player investment by the teams have shifted and showed that in game competition has increased as the probability of playing had decreased, because of an influx of new people. However, unless I know which teams invest into new talent then there is little to say about the competitive balance in the league. For example, if only the top teams are the ones pursuing new athletes then the competitive balance in the league will decrease and shift more towards the already winning teams. To solve this problem, I present a fourth model that uses a common competitive balance estimator, that is similar to the one presented by Noll [1988] Scully [1900], as the outcome variable. I call this variable standard deviation of wins (SDW).

The competitive balance estimator of Noll [1988] Scully [1900] has the following form:

$$Noll - Scully - estimator = \frac{actual\ standard\ deviations\ of\ wins}{idealised\ standard\ deviation\ of\ wins/sqrt(N)} \tag{4}$$

,where N is number of games per season.

The idealised standard deviation of wins corresponds to the standard deviation one would have if all teams have an equal chance of winning against each other. The estimator I use is a slight variation of the above, since the leagues I compare are of different sizes.

$$SDW_{rt} = \frac{\sqrt{\frac{\Sigma_i^N (winrate_{irt} - \mu_{rt})^2}{N_{rt}}}}{\frac{0.5}{\bar{N}_t}} \tag{5}$$

,where SDW_{rt} is the standard deviation of wins in region (r) at time (t) and $\bar{N}_t$ corresponds to the average amount of actively competing players across all regions at time (t), and N_{rt} is the number of observations at time (t) in region (r).

The main difference from my estimator to equation (4) is that I divide the idealised standard deviation of wins by $\bar{N}_t$ the average number of observations across time. This simple change should allow me to make comparisons across leagues with different sizes as the benchmark to which each league is compared is the same.

Additionally, the SDW, like other competitive balance estimators, are usually calculated using team data. However, in my case I use individual player data to increase the statistical power of my regressions. Using player data instead of team data should not cause a problem, since team data is just the aggregate of player data.

Finally, the equation I estimate has the following form:

$$SDW_{irt} == \alpha_t + c_i + \sum_{\tau=0}^{4} \beta_\tau F_{r\tau} + \sum_{\tau=-4}^{-1} \delta_\tau F_{r\tau} + \eta_{it}, t = 1, 2, ...T \quad (6)$$

All variables except the dependent variable are the same as in equation (1). SDW_{irt} denotes the standard deviation of wins as described earlier for player (i) in region (r) at time (t). Again I use leads and lags to be able to see a change over time.

7.2 Model 4: Results of Competitive Balance Model

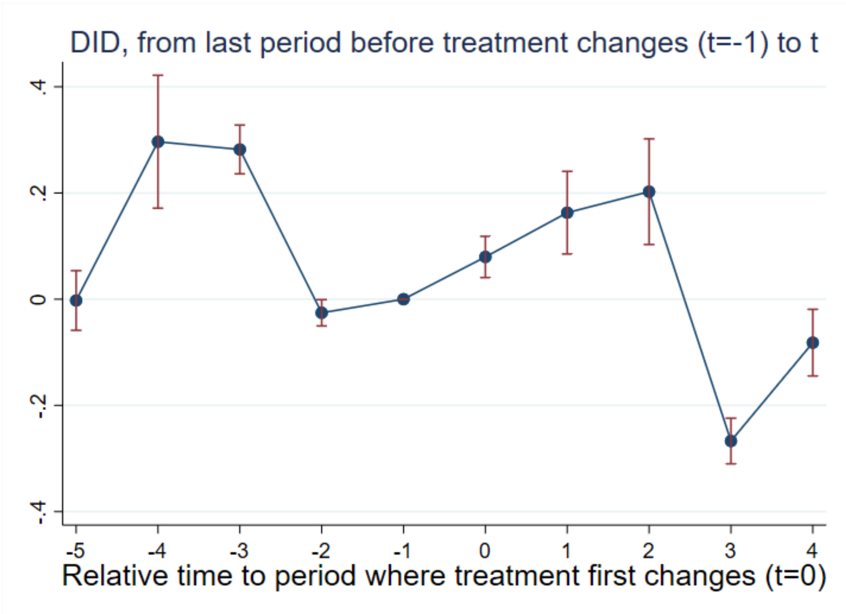


Figure 6: Model 4 Event Study Graph

Note: The above figure shows the DiD coefficients with 95% confidence intervals from equation (6) on the effect on the competitive balance. Standard errors are cluster on player level. The x-axis shows time to treatment in half year intervals. The y-axis shows the coefficients of equation (6). Treatment is defined as the time at which a region introduced the franchising. The control group consists of players who have not yet left the league the league conditional on having played continuously and have not yet been treated at time (t+1). The sample is defined as players who have competed at least once in a mayor region. Observations before having played professionally and after having left the league are excluded.

To understand whether the already top or low performing teams are investing more into new talent I created the model of equation (6). The results depicted in Figure (6) show that the change in the league system led to a decrease in the competitive balance overall. This means that the already successful teams are investing more into new talent compared to unsuccessful teams. This leads to a distortion in the competitive balance in the league. For the low performing teams the abolishment of relegation means that they are happy with being in the league and generating revenue from sponsors and the revenue sharing deal between Riot Games and the other participating teams.

Likewise, I find an average treatment effect of 0.0501. The closer the SDW is to one the more balanced the league is as the actual standard deviation is then closer to the idealised standard deviation. For my case the SDW for every league is above one in every time period, as shown by Figure (2) in the data section. Hence, for an increase in the competitive balance in the league a decrease in the coefficients needed. Since the average treatment effect is positive, the competitive balance has slightly decreased after the treatment. The only time there is a balancing effect in the league are in periods (t+3) and (t+4), one and a half years and two years after the treatment respectively.

Moreover, estimation results depicted in Table (3) of the appendix show that all coefficients are statistically significant at the one percent level. However, as shown by the Figure (6) the parallel trends assumption is clearly violated. Which implies that my above mentioned analysis is likely to be biased. As such, my conclusion on the effect of the competitive balance is questionable and the true effect may be of a different kind.

8 Robustness Checks: Adding birthday in into the dataset

A problem with the results of equation (1) are the way the data has been shaped. Every player who has been playing at a certain time also has observations at earlier periods when the player was not actively playing. During that time his dependent variable takes on the value of zero. However, some of the players who only started playing at a later more recent stage were very likely too young to be a professional player at the early periods. Riot Games sets the minimum age to 17 years old for Lol players. Chinese player Tian, for example, who won the World Championship in 2019, started playing in Spring 2019 in China at 17. However, he has an observation where he was not playing with y=0 at the start of 2013 when he was eleven years old, below the minimum age requirement. This in turn may affect my results and lead to biases. Since in some leagues, such as the European and especially the Korean, treatment was fairly recent the amount of players actively competing before the treatment may be larger than afterwards. Before the treatment there are 2587 observations of players actively playing and 9582 observations in which players were not. Whereas after the treatment there are 2298 competing and 2587 and 7039 who are not. This has clear implications for the probability of being in the league of model 1 and may explain why the outcome variable decreased after the treatment.

Thus, I revisit model 1 of equation (1) by adding the players age into the data and excluding observations in which players do not satisfy the age requirements to see if my findings change. Table (4) shows the results of model 1 in the first two columns and the results excluding players observations when they are too young in column three and four. It is clear to see that the coefficients from the new regression are very similar to the previous one. However, some results are not statistically significant any more at a certain level, such as Franchise at period t, which is only significant at a ten percent level now. Also, for the most part, the standard errors have increased in size due to the reduction in observations. Around 2945 observations were excluded. While the number of active players before the franchise has hardly changed from 2587 to 2566, observations in which players are not competing before treatment has dropped from 9582 to 6835. Overall, apart from the change in the significance the results have barely changed.

Moving on to model 4 of equation (6) I use alternative competitive balance estimators to compare their results to mine. Exact definitions of them can be found in the appendix under A.2. A simpler way to measure competitive balance is to just calculate the standard deviation between leagues without dividing by the idealised standard deviation if every team had the same probability of success against one another. Now to have a perfectly balanced league this estimator should equal zero, then there is no deviation in the probability of winning between players. The advantage of this estimator is that it makes results straightforward and leagues of different sizes and different amount of games are more comparable. [2] The Results are depicted in Table (5) column one of appendix B.2 and Figure (9 (a)) shows the evolution of the outcome variable over time. It is clear to see that the evolution path is almost identical, with the only difference being in scale. Likewise, parallel trends assumption is still violated for this model.

Instead of using the standard deviation of the winning percentage across leagues per time period I calculated individual deviation from the mean divided by the average number of players across regions in each year to describe the dispersion of winning percentages. Table (5) column 2 of appendix B2 details the results. Generally, the coefficients here are much smaller when compared to model 4 of equation (6) and none are statistically significant. The dynamic treatment effect depicted in the placebo test of Figure (9 (b)) are also quite different. There is much less pre-treatment movement than in model 4, but also the treatment effect is not as visible. Again the parallel trends assumption is violated. Moreover, what this specification predicts is that the players who are staying in the league after the treatment are better players than the ones who are entering. Model 2 suggests that the treatment forced more new players into the league. The newcomers, however, need time to adjust to the competition of the veterans, which is why we see a distortion in the competitive balance in the league, although only marginally.

Column three of table (5) shows the same estimator as above without accounting for the number of players per year. The event study graph in Figure (9 (c)) shows a similar picture to the specification of column 2 but is larger in scale, because it is not divided by the average player numbers per year. Comparing all these three specifications we can see that the general movement after treatment is similar. From (t=0) to (t=2) the coefficients are all positive and at (t=3) there is a dip. However, specification 2 and 3 show decreasing coefficients from (t) to (t=2), while specification one show increasing coefficients during the same period. In essence what these specifications show is that the results regarding the competitive balance can be somewhat different depending which estimator is used.

[2] Instead of dividing by the number of games per season I divided by the average number of games played in every split across regions in model 4 to make results comparable

9 Conclusion

In recent years franchised leagues have emerged in many eSports titles, but are also considered in traditional sports in Europe. This study provides the first analysis on the change of league system from a non-franchised league to a franchised league. My findings suggest that the treatment reduced the probability of professional players actively competing, because new talent was brought into the leagues by the teams. This fresh talent also meant that low performing players were pushed out of the competition. As a result, the number of high quality players increased and the overall level of competition surged, but conversely competitive balance diminished. This is because the top performing teams invested more into new talent than the low performing teams.

The revenue sharing deal was implemented to tackle this and increase the competitive balance in the league. But, the literature suggests that revenue sharing is not always pro balancing, and it is also decreasing in my analysis. This result is in line with work by Szymanski [2003], Szymanski [2004] and Szymanski and Valletti [2010], whose models predict that revenue sharing decreases the competitive balance due to the dulling effect.

Interestingly my analysis indicates that the dulling effect only affects certain teams and others not. Low placed teams seem to be affected by this and reduce their investment into new talent, while the top teams are the ones making most of the acquisitions. One reason for this could be according to the model of Dietl et al. [2009] that the low placed league teams are rather profit maximisers who just want to stay afloat and gain revenue while the high-quality teams are win maximisers.

But, all these models only consider one form of revenue sharing, whereas at least in some Lol leagues there are a multitude of forms. In Europe and North America there is pool revenue sharing, a performance-based revenue sharing, and revenue sharing based on contribution to viewership. As such, if all these revenue sharing systems work together the result may not align with what the literature suggests. Perhaps, for the case of Lol, increasing the share of the performance-based revenue sharing may in fact increase the competitive balance as it also gives lower performing teams greater incentive to invest in talent. All together the concept of revenue sharing is rather complex and depends heavily on the form of revenue sharing and the agents who are present in the league.

The revenue sharing deal does not only have implications for competition, but also for the finances and stability of teams. Unlike traditional sports, eSports does not have a long history and tradition, so to secure stable growth, organisations need the extra profits from the revenue sharing deal.

As a result not just the teams, but players also gained a lot. According to an anonymous survey by ESPN-Staff [2017] the average salary in 2017 for the North American league was $105,385 and $76,137 in

Europe. Whereas, in 2020 the average North American salary rose up to $410,000 Biagas [2020], which is a 400% increase over four years. It is hard to believe that without the franchising players would earn this much money only through the growth of eSports itself.

Now, several years after the franchising, team owners and community members alike, believe that overall competition and the level of play has increased and consider the move a success. Viewership numbers certainly paint the same picture. For example the 2020 Summer Split finals in Europe between *Fnatic* and *G2* saw an average audience of 819,415 per minute a 70% increase to the previous years. But, the community and team owners being content with the franchising may in fact not stem from an increase in the uncertainty of outcomes as the competitive balance decreased after the treatment. Which is something fans worried about once they heard about the potential change in the league format.

Altogether my findings have implications not only for the growing market of eSports, but for traditional sports as a whole. The historical change in the league system makes this study unique as it analyses its effect on the competitive balance and can give league designers valuable insights. The recently proposed Super League composed of top tier European football clubs might well be a good thing for the overall level of play. But my findings suggest that the competitive balance would not increase as a result.

However, my results of the difference-in-differences model on the competitive balance depend on the parallel trends assumption, which I was not able to justify. As such, this final result may well be biased and the real effect on the competitive balance may be a different one. Future studies may expand on my work and use different competitive balance estimators. The ones I used were only simple static ones that cannot account for changes in the relative standings in leagues over time (Eckard [2001]; Humphreys [2002]). Other dynamic estimators that can account for this may show different results.

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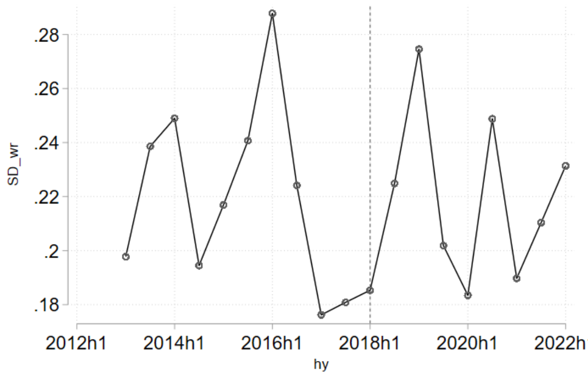
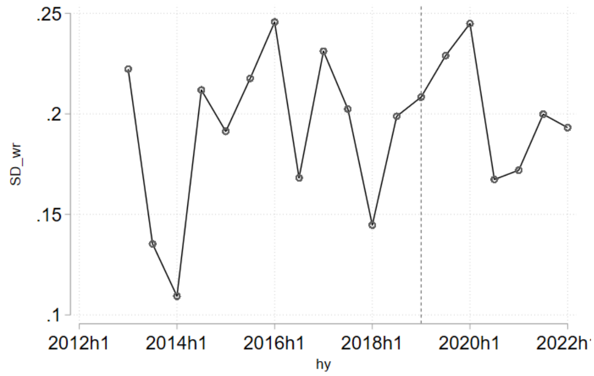
A Data Appendix

Figure 7: Standard deviation of wins without dividing by the idealised std. of wins across leagues

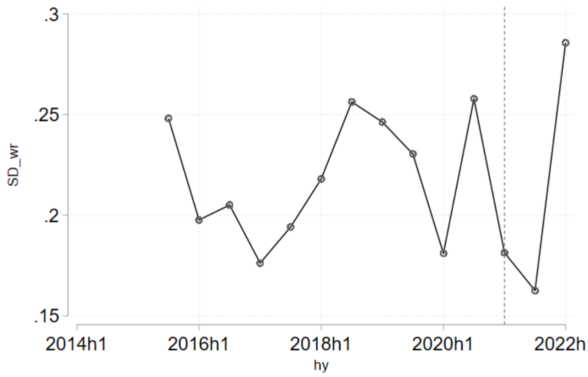
The dotted line shows the timing of the treatment in each league



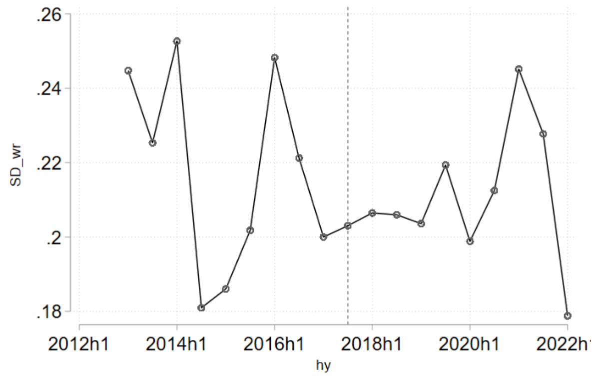
(a) SDW in North America



(b) SDW in Europe



(c) SDW in Korea



(d) SDW in China

Note: The above graphs show an alternative competitive balance estimator. It is the same as the SDW that I use in equation (6), but I do not divide by the idealised standard deviation of wins.

Table 3: Regressions

Variable	(1) Playing	(2) Entry	(3) Exit	(4) SDW
Franchise	-.0322**	.0266	.062*	.0795***
	(.0151)	(.0173)	(.0343)	(.0198)
Franchise lead 1	-.0184	.0527**	.020	.1629***
	(.0216)	(.0249)	(.0301)	(0397)
Franchise lead 2	-.0444**	-.002	-.069	.2024***
	(.0207)	(.0326)	(.0500)	(.0507)
Franchise lead 3	-.0545	.0580	-.103**	-.2671***
	(.0346)	(.0458)	(.0510)	(.0219)
Franchise lead 4	-.0755	.1035***	-.068	-.0819**
	(.0419)	(.0372)	(.0901)	(.0320)
Franchise lag 1	-.0118			-.0256**
	(.0125)			(.0126)
Franchise lag 2	-.0114			0.2820***
	(.0203)			(.0234)
Franchise lag 3	-.0128			.2965***
	(.0243)			(.0639)
Franchise lag 4	-.0167			-.0025
	(.1031)			(.0286)
Time Fixed Effects	Yes	Yes	Yes	Yes
Player Fixed Effects	Yes	Yes	Yes	Yes
Observations	21506	9547	4900	4885

Note: player-level s.e. in parentheses
***p<0.001, ** p<0.05, * p<0.1

B Robustness Checks

B.1 Adding Age into the dataset

B.2 Alternative Competitive Balance estimators

In the following I show how I defined the alternative competitive balance estimators of the robustness check in more detail. Column 1 of Table (5) shows the standard deviation in league (r) and time (t) calculated as,

$$\sigma_{rt} = \sqrt{\frac{\Sigma_i^N (winrate_{irt} - \mu)^2}{\bar{N_t}}} \tag{7}$$

,where N_t is the mean number of observations per time period in each region and μ is the mean of the winning percentage in region per time period

The dependent variable in column 2 is defined as followed,

$$\sigma_{it} = \sqrt{\frac{(winrate_i - \mu)^2}{\bar{N_t}}} \tag{8}$$

, with N_t being the average number of players across regions in period t.

The outcome variable in column 3 is just the same as in column 2 without dividing by the average number of players per time period

Table 4: Model 1 Robustness Checks: Controlling for age

Variable	Baseline Model 1		Model 1 controlling for age	
	Coefficients	Observations	Coefficients	Observations
Franchise	-.0322**	3583	-.0351*	3188
	(.0151)		(.0195)	
Franchise lead 1	-.0184	2848	-.0200	2481
	(.0216)		(.0238)	
Franchise lead 2	-.0444**	2357	-.0458*	2034
	(.0207)		(.0284)	
Franchise lead 3	-.0545	1870	-.0595*	1591
	(.0346)		(.0363)	
Franchise lead 4	-.0755	1384	-.0897**	1154
	(.0419)		(.0416)	
Franchise lag 1	-.0118	3583	-.0113	3038
	(.0125)		(.0185)	
Franchise lag 2	-.0114	2848	-.0173	2267
	(.0203)		(.0239)	
Franchise lag 3	-.0128	2357	-.0216	1724
	(.0243)		(.0359)	
Franchise lag 4	-.0167	1643	-.0526	1152
	(.1031)		(.0940)	
Time Fixed Effects	Yes		Yes	
Player Fixed Effects	Yes		Yes	

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 5: Robustness Checks

Variable	(1) Normal Standard Deviation	(2) Individual Deviation from Mean	(3) without number of players
Franchise	-.0094***	.0015	.0247
	(.0023)	(.0010)	(.0192)
Franchise lead 1	.0192***	.0010	.0191
	(.0047)	(.0011)	(.0198)
Franchise lead 2	-.0243***	.0133	-.069
	(.0059)	(.0011)	(.0205)
Franchise lead 3	-.0326***	.580	-.0002
	(.0026)	(.0013)	(.0234)
Franchise lead 4	-.0101**	.0012	.0206
	(.0044)	(.0017)	(.0248)
Franchise lag 1	-.0031*	.0008	.0130
	(.0017)	(.0010)	(.0154))
Franchise lag 2	.0037	.0008	.0137
	(.0032)	(.0012)	(.0162)
Franchise lag 3	.0361***	-.0010	-.0171
	(.0074)	(.0021)	(.0372)
Franchise lag 4	-.0006		
	(.0039)		
Time Fixed Effects	Yes	Yes	Yes
Player Fixed Effects	Yes	Yes	Yes
Observations	4885	4885	4885

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

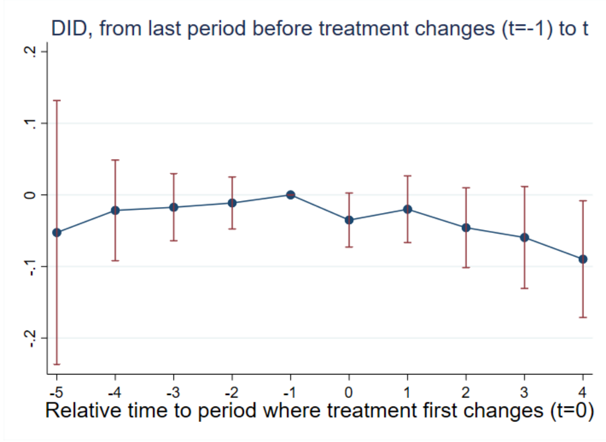
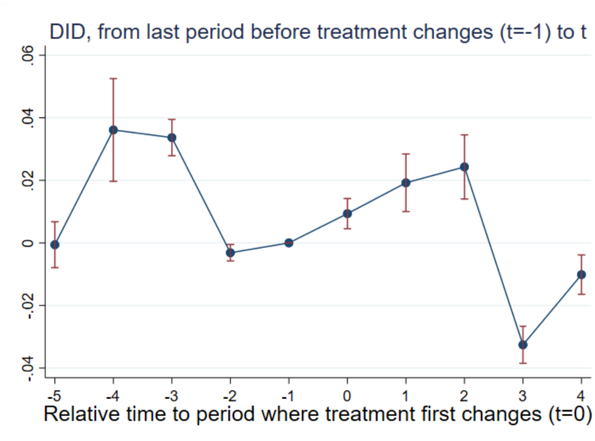
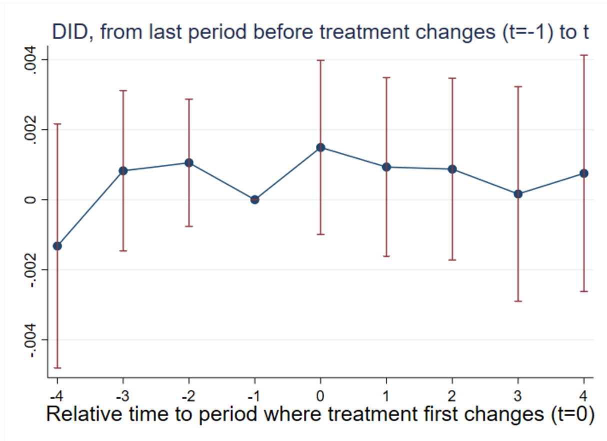


Figure 8: Model 1 Event Study Graph controlling for age
Robustness check of equation 1 by adding the required age into the dataset. Red vertical lines show the upper and lower confidence intervals and the blue line the treatment effect. Standard error are cluster by players.

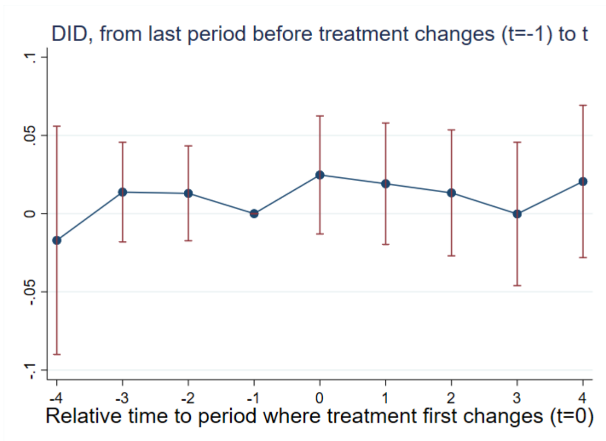
Figure 9: Competitive Balance Robustness Checks



(a) Simple Standard Deviation



(b) Individuals deviation from the mean



(c) Individuals deviation from the mean without controlling for population

Alternative competitive balance estimators. Red vertical lines show the upper and lower confidence intervals and the blue line the treatment effect. Standard error are cluster by players.

C Weight Calculations of the DID estimator

For model 1 I calculated the weights attached to the fixed effect estimator $\hat{\beta_{fe}}$ following de Chaisemartin and D'Haultfœuille [2020]. Under the parallel trends assumption $\hat{\beta_{fe}}$ is a weighted sum of 9337 ATT. Of these 7219 weights are strictly positive, whereas 2118 are strictly negative. If the treatment effect is heterogeneous then $\hat{\beta_{fe}}$ may not reflect the true sign of the treatment effect. Following Collary 1 and using the twowayfeweights package, the negative weights sum up to -0.23 and I obtain the standard deviation $\underline{\sigma_{fe}} = 0.0063$. Since this standard deviation is very small and 22% of the weights are negative β_{fe} may in fact not represent the true treatment effect. Hence, I will use the estimator proposed by [de Chaisemartin and D'Haultfœuille, 2020] to solve this issue.