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Imitation, Principal Components Analysis and the Effects of Modifications to eSports on Competitive Balance

Pompeu Fabra University - Master of Research - Master's Thesis

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Abstract

I evaluate if the modifications implemented in 2017 and 2019 to League of Legends forced the pro players of the strongest region (Korea) to copy the play style of those of a weaker region (Europe). In turn, I argue that this would have improved the competitive balance between the two regions, which could have increased the broadcasting consumption of the European fanbase. The proposed mechanism is novel in both eSports and traditional sports. The evidence supports it for 2019, displaying that Korean players copied Europeans in four of the five different positions of the game. For 2017, only Korean *jungle* and *adc* players copied Europeans. These results could have strong implications in the eSports industry, since it would point in the direction of a potential disruptive manipulation of the results of the World Cup, as well as towards possible asymmetric knowledge of eSports owners relevant for betting. Regarding the methodology, I propose a novel framework that evaluates if the main characteristics of two groups converge between periods, and if the characteristics of one group move towards imitating the other. The method is based on a hierarchy of metrics involving shifts in the characteristics of each group, that allows to distinguish different imitation scenarios. Additionally, it can integrate dimensionality reduction techniques, such as principal components analysis (PCA) to obtain representative group-specific vectors of latent characteristics. Lastly, this is the first example of using PCA to obtain play styles of League of Legends players, which proves to be very insightful.

Keywords: Principal Components Analysis, eSports, Imitation Analysis.

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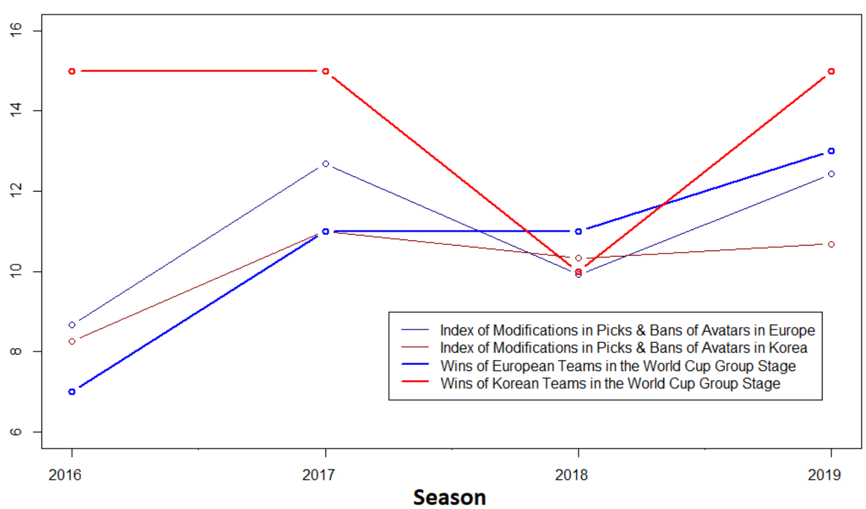
1 Introduction

For the first half of the past decade, the pro *League of Legends* (LoL) teams of Europe and Korea, two of the most skilled regions in competitive LoL, had different accomplishments in the seasonal World Cup[1]. In contrast, during the second half, their international achievements have converged. This might have had positive consequences for the owner of the game, since competitive balance and uncertainty of outcomes in professional eSports drive fans' broadcasting consumption (4), (19). That type of consumption is also driven by the desire of the fans to see their favorite players succeed (14). Therefore, the improvement in competitive balance between Korea and Europe might have boosted LoL's broadcasting consumption from European fans.

Interestingly, in the most recent editions of the World Cup, the seasons in which Europeans have increased their wins are those where there were a larger number of modifications to avatars and new avatars created, namely the 2017 and 2019 seasons (see figure 1[2]). These updates usually target the power and the abilities of the different avatars that players use. With these changes, players can be forced to shift their play style towards one that is better given the new rules.

Figure 1: Modifications of the Game, and Wins in the World Cup Group Stage, By Regions



Motivated by these facts, I evaluate if the modifications made in 2017 and 2019 lead to an improvement of the competitive balance between European and Korean teams in professional LoL. Intuitively, the modifications could have shifted the optimal play styles towards those of the weaker

[1]The equivalent of football's Champions League, but at a worldwide level.

[2]The measure of the modifications displayed in figure 1 weights them according to how much they were used or banned in pro matches. Bans correspond to removing an avatar from being played in a match.

region. Pursuing the new optimal play style, Koreans would have copied Europeans' play styles. In turn, this could have improved competitive balance between Europe and Korea, if adapting a play style has costs proportional to how different it is to the original play style of the region. To the best of my knowledge, this mechanism has never been proposed neither for eSports or traditional sports.

Evidence in favor of this mechanism would raise several dilemmas in the eSports industry. Firstly, regarding a potential disruptive indirect manipulation of the results in the World Cup. And also, if the impact of modifications to the game on the results of the World Cup becomes (or already is) an accurate science, eSports owners could possess relevant asymmetric information in how to predict results, valuable for betting.

The remainder of the paper is structured as follows. In section 2, I develop an identification strategy, summarize principal components analysis (PCA), and develop a novel hierarchy of measures that evaluates if Koreans copied Europeans, integrating PCA. In section 3, I present the features of the dataset and their descriptive statistics, and I explain the aspects of LoL that they capture. Section 4 displays the main results regarding both PCA and the measures. Lastly, section 5 concludes by summarizing the contributions and implications of the paper.

2 Methodology

What are Players' Play Styles in League of Legends?

Before diving into a methodology focused on players play styles, I devote the following paragraph to briefly describe what they are. The following description of LoL is expanded in section 3, which links the main aspects of the game to the performance indicators of the dataset. A conjoint reading of this subsection and section 3 is recommended for readers unfamiliar to the particulars of LoL, before diving into the methodology.

LoL is a *Multiplayer Online Battle Arena* where the winner of the game is the team who destroys the base of the enemy team. Achieving this involves the coordination of five players per team, each of them taking care of specialized tasks. The player of each position is confronted during a large portion of the game to the player in his same position in the other team, but he also confronts the rest of the opponents and coordinates with his teammates. The play styles of the players are a description of how they achieve these tasks, such as how good they are at specific tasks, or how some aspects of the game influence their performance on some tasks. For example, the play style of Paul “sOAZ” Boyer and Heo “Huni” Seung-hoon is characterized by helping their teammates to get resources that make them stronger and by being initiators of scrimmages, while players such as Kang “TheShy” Seung-lok and Soren “Bjergsen” Bjerg focus on gathering resources to be stronger and on dealing as much damage as possible in scrimmages.

2.1 On the Causal Mechanism

Recall that the research question is if the modifications made in 2017 and 2019 lead to an improvement of the competitive balance between European and Korean teams in professional LoL. H1 and H2 propose two cases (see figure 2) in line with verifying this question.

Hypothesis 1 (H1). *The modifications implemented to LoL in seasons 2017 and 2019 induced a convergence in the play styles of European and Korean players. In addition, Koreans shifted their play style towards Europeans more than Europeans towards Koreans and a crossover*[3] *did not occur. In turn, this had a positive effect on competitive balance between them.*

Hypothesis 2 (H2). *The modifications implemented to LoL in seasons 2017 and 2019 induced Koreans to shift their play style towards Europeans, while Europeans did not move towards Koreans. In turn, this had a positive effect on competitive balance between them, even though there was no convergence of play styles.*

Figure 2: Examples of Results Supporting H1 (left) or H2 (right)

Note that, during the paper, I use the term *convergence* to refer to a decrease in the distance between two objects between two periods, in this case vectors of play styles in $\mathbb{R}^K$.

Note that players and teams might take time to adjust their play styles to the new rules. I assume that half season is enough time. Accordingly, I employ data corresponding to the second half of the season, the *Summer Split*.

[3] Defined below. Also, see section figure 5 in section 2.5.2 for a visual representation.

By optimal play style, I refer to a play style located somewhere in the direction towards which both regions are shifting. In line with that abstraction, it only makes sense to consider an optimal play style that is optimal for both regions if both are shifting towards similar directions. This could be interpreted as both regions chasing the optimal play style. Therefore, both hypotheses are built embedding this requirement, the difference being that $H1$ captures imitations of play style when there is convergence of play styles, and $H2$ when there is not.

The *no-crossover* requirement of H1 excludes scenarios in which the play styles have converged and the Koreans have shifted more than Europeans, but the shift in play style has been such that they have crossed (see figure 5 in section 2.5.2). Formally, a crossover takes place when, under convergence of play styles[4], the distance between the new play style of Europe and the old one of Korea is smaller than the distance between the old and the new play styles of Europe. Note though, that the crossover measure[5] is symmetric in terms of regions. The reason for the no-crossover restriction is that these cases do not represent that one of the two regions copied the other, which is what I want to capture.

Assumption 1. *Players choose the play style that maximizes their performance at their regional tournament.*

H1 proposes that, due to the modifications, the optimal play style has shifted away from Koreans towards one closer to Europeans. By assumption 1, Koreans would have shifted towards Europeans by chasing the new optimal play style. In addition, H1 requires that the magnitude of the shift of Koreans towards Europeans would have been greater than any shift of the Europeans. This is necessary to identify if Koreans copied the play styles of Europeans or not. Under convergence, it must be that at least one region has shifted towards the other. Then, if the relative shift of Koreans is greater than that of Europeans, and if a crossover has not occurred, it must be that either Korea is the only region shifting towards the other, or that both are moving towards the other and Korea shifted more. By ruling out confounding mechanisms through which the best teams would copy the play styles of the worst teams without that being caused by modifications to the game, I interpret both cases are representative of Koreans copying Europeans due to the modifications of LoL.

The first alternative confounding scenario is that the shift could be due to the irruption of a new batch of Koreans with a play style similar to Europeans. This is ruled out by the fact that the

[4]Defined in section 2.5.1.

[5]Formal measure defined in 2.5.2.

pool of Korean players has not changed considerably during the analysed period[6]. The second alternative confounding scenario is that the imitation could be due to Europeans (or players from other regions) having learnt how to counter the play style of Koreans. In turn, Koreans would have shifted towards the new best play style, which could have been that of Europeans. This is ruled out by assumption 1, since under it, Koreans do not take into account the effectiveness of their play style against Europeans. This assumption is reasonable in a context of high competition inside regions, which is clearly the case in LoL[7]. Furthermore, the teams have roughly one month to prepare for the World Cup. Therefore, the range of play styles that teams can use to play against teams of other regions is mostly limited to the ones that they develop targeting teams of their regional league.

Assumption 2. *The cost of modifying the play style of a team is proportional to how different its current play style is to that towards which it desires to move.*

The second part of H1, namely that a shift of the play style of a stronger team towards that of a weaker one has a positive effect on the competitive balance between them, is ensured by assumption 2. Accordingly, when faced with a change in the optimal play style leaving it closer to that of the weaker teams, the stronger will adapt worse to it than the weaker if they are farther from it. In turn, this will lead to an increase in the relative performance of the weaker. Additionally, there are more logistic restrictions that reinforce this mechanism, such as the fact that European teams hardly ever import Korean players, and vice versa.

Regarding H2, the modifications would have induced Koreans to copy Europeans, while Europeans would have not shifted its play style towards Koreans. Using the same rationale as for H1, assumption 1 ensures that Koreans would have copied the play styles of Europeans. Assumption 2 ensures that, in turn, this would have had a positive effect on competitive balance, since Koreans had a harder time than Europeans shifting towards the new optimal play style.

The main practical difference between H2 and H1 is that the former implies that the new optimal play style is way farther from Korean's original play style than in the case of H2. Additionally, H2 implies that the new optimal play style is not set between the original play styles of the two regions, and that it is set closer to Europeans. Therefore, the implications of supporting H2 are stronger. With a rationale similar to that of assumption 2, shifts of play styles supporting H2 could represent that the new optimal play style was set to favor Europeans, and also it could have

[6]Source: Gamepedia.com - LoL.

[7]The teams that classify from each region to play the World Cup are different every year

been set such that it was only partially imitable by Koreans due to impossibilities of completely adjusting to it.

2.2 Capturing Play Styles via Performance Indicators

I use per-game and per-minute averages of performance statistics to capture the characteristics of the play styles. By averaging rather than using seasonal totals I capture the way in which a player plays, rather than the amount of games that he plays. This approach has been used for traditional sports such as football (9) and basketball (8), and also for Dota (22), (5), (12), (7), an eSport created by the owner of LoL and highly similar to it. (6), (15) and (23) use metrics of player's movements, which capture a different type of play style characteristics. While that methodology is certainly interesting, it requires a highly developed metric-retrieving technology currently not implemented in LoL.

While previous literature has focused on retrieving play styles that define clusters of players (8), (9), (18), (5), (7), I cluster them by their position and then define the corresponding play style of each position. LoL's positions are Top, Jungle, Mid, Adc and Support. Mid and Adc players are focused on dealing damage, Jungle and Support players assist the previous two, and Top players are somewhere in between, leaning more towards dealing damage. Despite these similarities, the positions have widely different natures. Nevertheless, the performance indicators may fall short in completely capturing that, majorly because they suffer of an inflationary effect caused by the quality of the team. This guides clustering techniques towards separating the players that suffer this inflationary effect more (Tops, Mids and Adcs) by the quality of their team, showcased in tables 1 and 2. While Jungles and Supports are clearly clustered by position in clusters 3 and 4, the other positions get mixed in clusters 1, 2 and 5. In clusters 1 and 2, around two thirds of the players are from teams with a win percentage below 50%, while in cluster 5, around two thirds of the players are from teams with a percentage above 50%.

Table 1: Finite Gaussian Mixture for Clustering via EM algorithm[8], Compared By Positions

	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**
TOP	1	14	0	0	98
JUNGLE	24	0	0	92	0
MID	6	62	0	0	45
ADC	10	85	0	0	13
SUPPORT	0	0	107	0	0

[8]Choosen rather than K-means or Hierarchical clustering because it provides an optimal number of clusters (16).

Table 2: Finite Gaussian Mixture for Clustering via EM algorithm, Compared By Win %

	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**
Win % $>$ 50%	13	56	52	46	99
Win % $\leq$ 50%	28	105	55	46	57

2.3 Principal Components Analysis

Assumption 3. *The directions in which $X_1, ..., X_p$ vary the most are the ones associated with the relationship of the data with the target of interest.*

Since the dataset contains several indicators for the main characteristics of each play style, I use principal components analysis (PCA) to retrieve them. PCA summarizes the information of a set of correlated variables into a smaller number of uncorrelated linear combinations of the original variables that represent the directions in which the data varies the most. The suitability of PCA for a specific task relies on assumption 3. Thus, to retrieve the latent components of the play styles via PCA, assumption 4 (see section 2.4) is required. If this assumption holds, by projecting $x_1, ..., x_n$ onto the directions of the first $K < p$ principal components, the data can be represented in a space of a dimensionality lower than p that maintains the core information of the data.

Formally[9], the first principal component of the variables $X_1, ..., X_p$ is defined as

$$Z_1 = \phi_{11}X_1 + ... + \phi_{p1}X_p$$

where $\phi_1 := [\,\phi_{11}, ..., \phi_{p1}]$ is known as the loading vector of the first principal component, which is the normalized p-dimensional direction in which the data shows the highest variability. Normalized stands for $\sum_{j=1}^{p} \phi_{j1}^2 = 1$ for the loadings of all components $Z_1, ..., Z_p$, and is implemented to avoid building principal components with arbitrarily large variances. The first principal component is formally retrieved by solving the following optimization problem via eigen-decomposition[10]:

$$\max_{\phi_{11},...,\phi_{p1}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \left(\sum_{j=1}^{p} \phi_{j1} x_{ij} \right)^2 \right\} \text{ such that } \sum_{j=1}^{p} \phi_{j1}^2 = 1$$

where the objective function is the variance of Z_1. Note that $X_1, ..., X_p$ are standardized to have mean zero and variance one, in order to avoid over-weighting loading coefficients of variables with higher magnitudes.

[9] The following notation mimics that in (10).

[10] For a detailed explanation of eigen-decomposition, see (1).

The second principal component Z_2 yields the linear combination $Z_2 = \phi_{12}X_1 + ... + \phi_{p2}X_p$ with maximal variance that is uncorrelated with Z_1, which is equivalent to constraining ϕ_2 to be orthogonal to ϕ_1 (10). Each subsequent principal component Z_l, where $l \in \{3, ..., p\}$ is built with the constraint of being uncorrelated to all the previous principal components $Z_1, ..., Z_{l-1}$. The goal of imposing these constraints is separating with each component the latent characteristics of the data by relying on assumption 3.

As argued in (10), there is no single answer regarding the criterion for the selection of the number of principal components, from which a researcher should retrieve information from the data. Under assumption 3, the extent to which the first K principal components contain the relevant information of the data regarding its relationship with the target of interest, is determined by the proportion of variability of the data that is explained by those components. Accordingly, one approach when using PCA is selecting the first K components that explain at least a subjectively reasonable percentage of the variability (11), (10), which is inherently ad hoc. A more insightful approach, which again cannot avoid subjectivity, is selecting components in a variability-based descending order until they stop displaying interesting patterns. Once an uninteresting component is found, it is unlikely that further principal components are of interest (10). The results of PCA, detailed in section 4.1, allow to embrace both criteria. Concretely, I select the first five principal components for each position, since the ones beyond those do not retrieve patterns of play styles' characteristics, and also because they account for between 85%-90% of the variation of the data (see figure 8).

2.3.1 Non-linear Principal Components Analysis

The performance of PCA is closely related to the variabilities explained by the first principal components. In that sense, sparse linear PCA performs quite well (see figure 8), which suggests that there is indeed a linear subspace of a lower dimensionality than the original data containing characteristics of the play styles. For completeness, I checked the existence of a potentially more accurate non-linear subspace via two types of non-linear PCA. Firstly, I used kernel non-linear PCA[11] (21), which applies PCA on a feature space instead of the inputs themselves. Out of several kernel functions, the ones that performed the best were the Gaussian and cubic spline. Secondly, I employed non-linear PCA via autoassociative neural networks[12] (13), which computes principal components by minimizing the Euclidean norm of the residual matrix, using a neural network

[11] Computed in R via the library *BKPC*.
[12] Computed in R via the library *pcaMethods*.

with as many end nodes as the number of components that we want to retrieve.

Both methods reported proportions of variability explained by the first few components highly similar to those obtained via the linear PCA. This suggests that a non-linear subspace does not enrich the representation obtained by the linear, and so I use the linear approach.

2.3.2 Sparse Principal Components Analysis

Since each principal component is a linear combination of all the features in the dataset, and obtaining near-zero loading coefficients for many variables has probability zero[13], the interpretation of the components is difficult. We can take care of both by using sparse PCA (25), which adds to the objective function a lasso-type l_1 regularization term that penalizes the magnitude of the loadings coefficients.

The components obtained via sparse PCA[14] explain similar percentages of the variability of the data than those of standard PCA. Due to this and to the fact that the former yields an advantage in terms of interpretability, I perform the analysis using sparse PCA.

It is important to make a remark on the fact that, for PCA, a small number of outliers in the features can drastically change the obtained loadings. This motivated the development of one of the versions of robust PCA (3), which models the data as low rank plus noise. Since the empirical distribution of several performance indicators in the dataset contains a considerable number of outliers, I checked if the loading vectors change significantly using (3)'s robust version[15] of sparse PCA. The resulting loading coefficients for the principal components did not considerably vary from those obtained via the standard sparse PCA.

2.4 Extracting Play Styles using Principal Components Analysis

Assumption 4. *The directions in which the performance indicators of players of a specific position vary the most are the aspects of the game that have more relevance in determining the play style of the players in that position.*

[13] As long as the data generating distribution is continuous.
[14] Computed in R via the library *sparsepca*.
[15] Also computed in R via the library *sparsepca*.

I define the play style of the players of a specific position in Europe or Korea and during a specific season, by a vector of medians or means of their scores on the selected principal components retrieved by PCA. Prior research has used PCA to extract the main characteristics of players' play styles using performance indicators in sports (24) and e-Sports (17). Note that other literature in sports has also used PCA to determine play styles in traditional sports, using patterns of players movements (6), (15), (23).

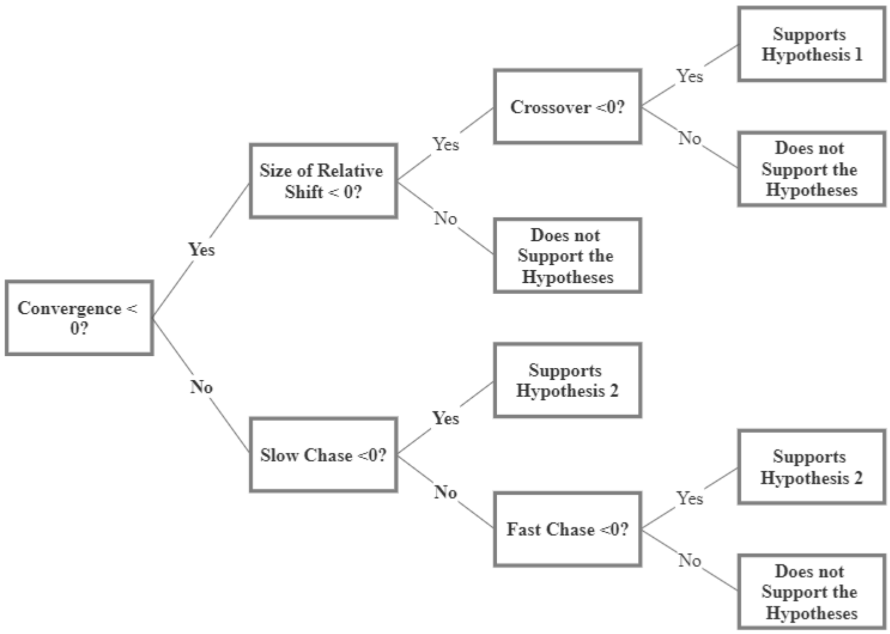
The main motivation behind using PCA to extract play styles is that the dataset of performance indicators in LoL is characterized by having highly correlated variables (see figure 7, section 3) that gather very similar information from a characteristic of the data. If assumption 4 holds, PCA summarizes the play styles with a small number of representative variables of the data, which is key to obtain a representative play style that does not overweight components for which there are several indicators. Additionally, PCA can reveal insightful components of the game that the researcher would have not considered beforehand, which is the case in this paper (see table 5).

2.5 Metrics to Measure the Hypotheses

To evaluate if there is evidence supporting either H1 or H2, I develop a hierarchy of measures, displayed in figure 3. The measures are built such that scores below zero indicate a successful step towards reaching one of the two hypotheses. H1 is only supported if there has been convergence, if the size of the shift in play styles of the Koreans has been greater than that of Europeans, and if there has been no crossover of the play styles. H2 is supported if there has not been convergence and Koreans have shifted either towards the play style of Europeans of the previous year (*slow chase*) or towards the play style of Europeans in the same year (*fast chase*). In the following subsections, I develop the measures and argue why they are sufficient to capture evidence in favor of the hypotheses.

For the five metrics that I develop, all of them based on temporal differences in multi-dimensional distances, I choose the Manhattan distance (i.e. L1 norm) rather than the Euclidean distance. This is because the Euclidean distance gives a higher weight to components of the vector of play styles whose difference between two play styles is higher, and I find no rationale to motivate such weighting criterion. Note though that, while the L1 norm has a neutral weighting, the following measures can be adjusted if it is believed that some characteristics of the game are more relevant than others in defining a play style, by giving more relevance to shifts in those aspects. This would

Figure 3: Results Leading to Evidence in Favor of the Hypotheses



take the form of a coordinate-wise weighted average of the differences in distances. In line with assumption 3 (see section 2.3, 1st paragraph), a non-neutral weighting to the components of the play styles could be inspired in the proportion of the variance that each component explains.

2.5.1 Convergence Metric

The convergence measure captures if the distance between the vector of components of the Korean play styles and the European play styles has decreased from one year to another. Let $u_{it}, v_{it} \in \mathbb{R}^K$ be vectors of play styles corresponding to either Korean (u_{it}) or European (v_{it}) players, for a specific position $i \in \{Top, Jungle, Mid, Adc, Support\}$, and year $t \in \{2016, 2017, 2018, 2019\}$, composed by the medians or means of the $K < p$ principal components scores for that group. Then, the measure of convergence is

$$c_{i,t+1} = \|u_{i,t+1} - v_{i,t+1}\|_1 - \|u_{i,t} - v_{i,t}\|_1$$

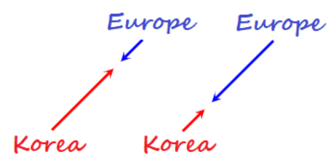
where $\|\cdot\|_1$ is the L1 vector norm operator. Intuitively, the measure captures the difference in the distance between each of the components of the play styles from one year to another.

2.5.2 Size of the Relative Shift, and Crossovers

The relative shift measure captures which region has shifted more between two seasons. Formally,

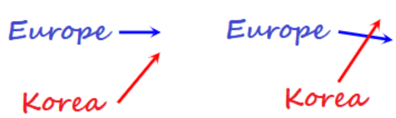
$$r_{i,t+1} = \|v_{i,t+1} - v_{i,t}\|_1 - \|u_{i,t+1} - u_{i,t}\|_1$$

Figure 4: $c, r < 0$ vs $c < 0, r > 0$



This measure is only of interest for the cases in which the play styles have converged, and is a necessary condition for evidence supporting H1. The intuition is that, if Korea and Europe converge, then if Korea shifts more than Europe, it must be that Korea is shifting towards Europe, and in a higher magnitude than the shift of Europe. This identifies that a region copies another one if there is no crossover (defined in the next paragraph). In the case that there is convergence but Europe has shifted more than Korea, this does not support any of the hypotheses since it must be that Europe has shifted towards Korea and in a higher magnitude than Korea towards Europe[16] (see figure 4). In turn, this would capture that Europe would have copied Korea and/or a crossover.

Figure 5: $c, r < 0$, without (left) and with Crossover (right)



Note that even in the cases that c and r are in line with H1 (i.e. $c, r < 0$), I also capture cases in which there has been a crossover of play styles (figure 5). Interpreting such scenarios as only one of the regions copying the other is not accurate, since both regions are shifting towards the play style of the other in the previous year. Therefore, H1 rules out these scenarios. Nevertheless, as section 4.2 reveals, H1 does not hold for any position even without taking into account the extra restriction of absence of crossover. Thus, I do not report this measure in table 5 since it does not

[16]Note that if there has been convergence and Europe shifted more than Korea, this does not imply that Korea has shifted towards Europe.

change the results. While this implies that for this dataset the measure is irrelevant, I develop it for the sake of a complete methodology:

$$\text{cross}_{i,t+1} = \|v_{i,t+1} - u_{i,t}\|_1 - \|v_{i,t+1} - v_{i,t}\|_1$$

Subject to convergence of play styles, this measure captures if the distance between the new play style of Europe and the old one of Korea is smaller than the distance between the old and the new play styles of Europe. Note that the cross measure is symmetric in terms of regions. If cross < 0, then there has been a crossover.

2.5.3 Chase Measures

Figure 6: Under divergence ($c > 0$), Slow Chase ($sc < 0$) and Fast Chase ($fc < 0$)

Conditioned on divergence of play styles, this measure captures if Korea has shifted towards Europe's play style in the previous year. Formally, the *slow chase* measure is defined as

$$sc_{i,t+1} = \|u_{i,t+1} - v_{i,t}\|_1 - \|u_{i,t} - v_{i,t}\|_1$$

Conditioned on the measure for convergence, the utility of the measure is the following. If there has been divergence but Korea is now closer to the play style of Europe in the previous year, it must be that Korea has shifted towards it, and that Europe has shifted away, since otherwise there would have been convergence. In turn, this would mean that Korea would have copied Europe. If there has not been convergence but Korea is not closer to the play style of Europe in the previous year, there can still be a case where Korea has copied Europe (see figure 6). It could still be that Korea had copied the play style of Europe in the current year, which could have shifted far enough from Europe's play style in the previous year. The *fast chase* measure captures this, formally

$$fc_{i,t+1} = \|u_{i,t+1} - v_{i,t+1}\|_1 - \|u_{i,t} - v_{i,t+1}\|_1$$

Straightforwardly, in the cases that Korea has neither shifted towards Europe's play style of the previous or the current year, Korea cannot have copied Europe.

Note that the hierarchy induces to the slow chase measure nesting the cases in which Korea has shifted towards the play style of Europe in the second year, if the shift is of a magnitude that leads to Korea having also shifted towards the play style of Europe in the previous year. Nevertheless, the goal of the chase measures is to find evidence supporting H2, so in the end it does not matter in which way this evidence appears, as long as it is always captured by the measure, which is the case.

3 Data

The dataset was retrieved from the portal *Games of Legends e-Sports*. It gathers per-game and per minute averages of different aspects of the performance of the players in the Korean or European leagues during the Summer Split of seasons 2016-2019. I intended to include China in the analysis, since it has also experienced an improvement in its performance in the world cup, but there is no available data for several relevant statistics.

Players that played less than 25% of the games were excluded from the analysis, since usually the type of games that they play are not a good representation of pro play styles. Due to the same reason, for players having played in several positions during the same season, only the stats corresponding to when they played in their main position are considered. In addition to these changes, I created a dummy indicating if the player's team had a win rate percentage above or below 50%, used in table 2 and for identifying if any of the principal components retrieved accounts for the quality of the team of the player (see figure 9).

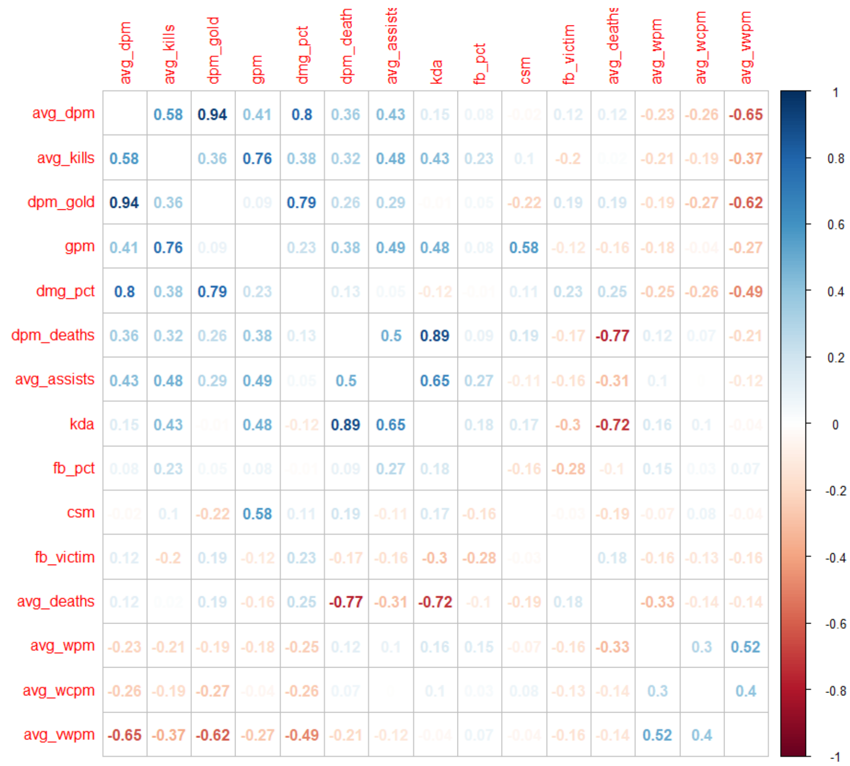
Below I link the main aspects of LoL to the performance indicators of the dataset. Recall that, in order to destroy the enemy's base, the 5 avatars controlled by the players of a LoL team (one per player) gather resources that make them stronger, which increases their chances of overcoming in scrimmages the avatars of the opposite team, who in turn are trying to destroy the base of the former. Some of these fights materialize into killing enemy avatars, which is captured by statistics such as kills, deaths, assists, and a ratio that combines the three called *KDA*. Other fights do not materialize into kills if the amount of damage dealt to an avatar does not exceed the required to kill it; the performance of the players in all fights, regardless of achieving kills in them, is captured by the percentage of the damage of the team dealt, damage per minute, and the ratios of damage to deaths and damage to gold. Gold is the resource that avatar's nourish from to get stronger, and is captured with gold per minute and *creeps* per minute, which are small monsters that grant gold to the avatar that kills them. The scenario where the action happens is characterized by numerous zones where the players do not see who is there until they step on them or put a ward on it, which are items that grant vision of a zone during a determined time. Players take advantage of these vision uncertainty to ambush enemy avatars, and therefore they try to increase their vision of those zones while removing the vision from the other team. The scores that account for this aspect are wards put per minute, wards cleared per minute and vision wards put per minute. Lastly, there is a snowball effect in LoL games that increases the advantages achieved at the earlier stages of the game as the match progresses. Namely, killing an avatar makes the killer and its team stronger, which increases the chances of the player and the team of being victorious in subsequent fights, and so on. This snowball effect is captured by the percentage of first kills of the game in which the player is involved either assisting or killing, and the percentage of first kills of the game in which the player is the victim.

Table 3: Descriptive Statistics of the Performance Indicators, Pool of all Positions

	Mean	**Median**	**St. Dev.**	**Min**	**Max**
kda	3.66	3.30	1.60	1.10	13.00
avg_kills	2.23	2.20	1.11	0.10	5.80
avg_deaths	2.27	2.20	0.64	0.70	6.00
avg_assists	5.30	5.00	1.60	2.00	12.40
csm	6.50	8.00	3.09	0.70	10.90
gpm	354.30	371.00	64.61	199.00	490.00
dmg_pct	19.93	22.20	7.92	5.00	34.60
avg_dpm	359.67	386.00	150.42	72.00	712.00
avg_wpm	0.71	0.52	0.41	0.26	1.87
avg_wcpm	0.30	0.28	0.13	0.07	0.72
avg_vwpm	0.24	0.20	0.14	0.02	0.67
fb_pct	0.25	0.24	0.12	0.00	0.67
fb_victim	0.10	0.09	0.07	0.00	0.46
dpm_deaths	177.18	162.59	103.91	25.29	737.14
dpm_gold	0.97	1.01	0.29	0.33	1.76

Table 3 provides descriptive statistics for the pool of all the positions during all the seasons. Due to the widely different ranges of the metrics, I standardize them to have mean zero and variance one, since the performance and interpretation of PCA is highly sensitive to that. Figure 7 displays the correlation matrix for one of the positions. As already mentioned, the features are highly correlated for all the positions, with some variables giving highly similar information of certain aspects of the game.

Figure 7: Correlations' Heatmap of Performance Indicators for Mid Players



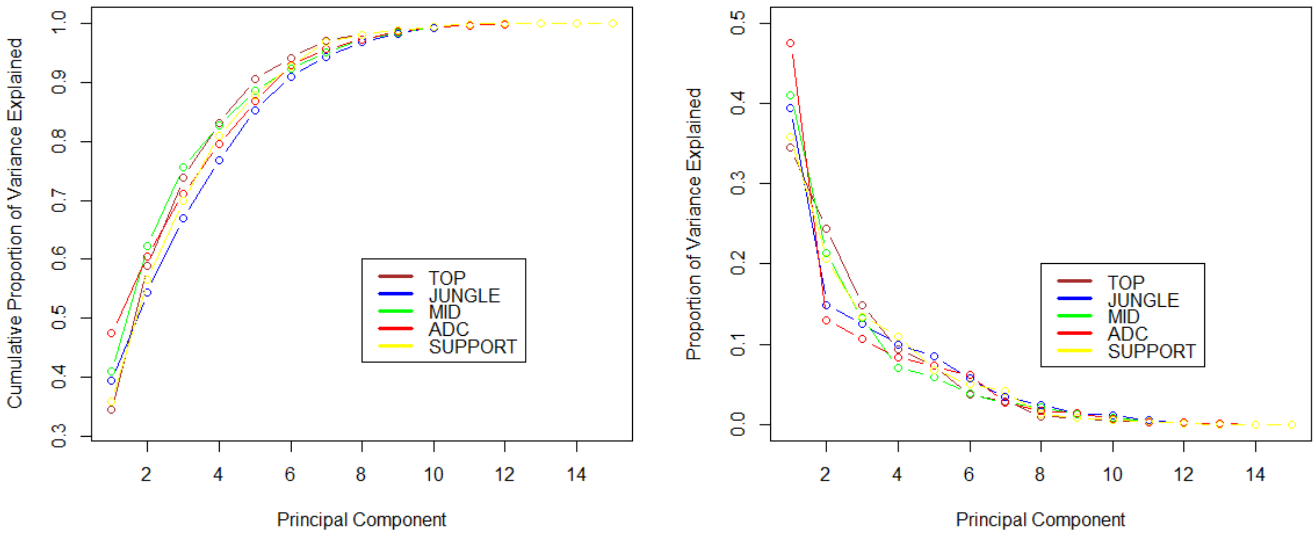
4 Results

4.1 Principal Components

As already mentioned, the first five principal components retrieved by PCA explain between 85%-90% of the variability observed in the data (see figure 8) for each position. Additionally, the remaining components beyond the fifth do not identify any strong pattern regarding characteristics of the play styles of the game. Due to this, I select the first five principal components for each of the positions to compute the measures developed in section 2.5.

Table 4 displays the characteristics of the play style that each of the components capture, for each of the positions. For each component, I focus on the indicators with the largest loadings. This is inherently ad-hoc (2), and therefore more sophisticated methods have been developed aiming at a more rigorous interpretation, such as Monte Carlo resampling to obtain an optimal hyperplane that maximizes the amount of information of the relevant variables (20). Nevertheless, almost in all cases, the loading vectors displayed clear cutoffs between the magnitudes of the coefficients of

Figure 8: Variability Explained by the Sparse Principal Components



the variables included in the interpretation and of those that are not, which is the main advantage of using sparse PCA. Therefore, I proceeded with the cutoffs yielded by sparse PCA.

To illustrate that methodology, I give an explicit example to see how the interpretations of the principal components (table 4) are built. The six variables with the six largest loading for the first principal component of top players are, in order of absolute size, {*fb victim, avg deaths, kda, dpm deaths, fb pct, avg assists*}, with the corresponding loadings $\{0.83, 0.39, -0.27, -0.17, -0.14, -0.13\}$. This principal component displays about 2-3 large coefficients, corresponding to deaths in the early game, deaths in the whole game, and a ratio that has deaths in the denominator. Additionally, the 4th, 5th and 6th variables with largest loadings are also related with deaths. Namely, *dpm deaths* is a ratio with deaths in the denominator, *fb pct* is negatively correlated with *fb victim* since it is the percentage of times that the player is involved in successful first kills of the game, and *avg assists* is negatively correlated with deaths. Out of these six variables, the sign of their loading is positive for *fb victim* and *avg deaths*, which are increasing in deaths, and the sign is reversed for *kda, dpm deaths, fb pct, avg assists*, which are either decreasing in deaths or negatively correlated with them. Therefore, this principal component gathers the ability of top players to not die, either in the early game or during the whole game.

The first highlight of the results of PCA is that the quality of the team is a strong source of differences in play styles. Such characteristic appears in the first component for all of the positions except top, for which it is the second. This can be clearly seen in figure 9, which plots jungle players as an example. For all the positions, for such component the loading corresponding to *kda*, which is a ratio of kills plus assists divided by deaths, has a considerably high magnitude, which does not occur for any of the other components. Particularly, kda is one of the statistics that depend more on the quality of the team rather than on the performance of a player. This poses a concern, since it might be the case that such component captures the inflating effect of the quality of the team on performance indicators rather than the way in which the quality of the team shapes a play style. Since there is no conclusive reason to firmly support that this principal component is not relevant in defining play styles, but at the same time this is not highly unlikely, in section 4.2 I report the results for the metrics including that component and excluding it, to check if it changes the results.

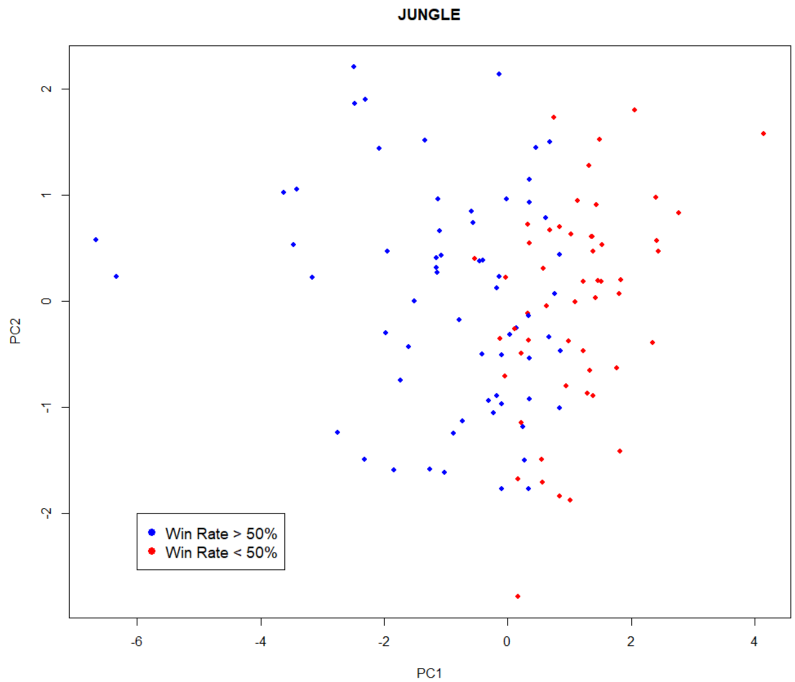
Table 4: Interpretation of Principal Components

Position	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**
TOP	Ability to not die either early or late in the game.	Team's quality.	Relation between a positive early game[17] and the results of scrimmages.	Relation between a positive early game and assists and damage dealt.	Relation between early game and damage dealt plus gold generated.
JUNGLE	Team's quality.	Relation between vision granted and removed with success rate of early game ambushes.	Successful in early game ambushes.	Deaths in early game ambushes.	Relation between vision removed and damage dealt.
MID	Team's quality.	Damage dealt.	Relation between a negative early game and the results of scrimmages.	Relation between a positive early game and the results of scrimmages.	Relation between a negative early game and the ability of converting gold generated into damage and kills.
ADC	Team's quality.	Relation between a positive early game and the results of scrimmages.	Vision granted and removed.	Relation between a positive early game on damage dealt.	Relation between a negative early game and kills.
SUPPORT	Team's quality.	Assists and deaths.	Relation between a positive early game and vision granted plus removed.	Relation between a positive early game and proactive plays generated.	Relation between the degree of involvement in early game scrimmages and vision granted.

For the remaining components up to the fifth, PCA yields a rich and powerful identification of characteristics defining the play styles associated to each position. For tops, mids and adcs, which

[17] Early game stands for the earlier stages of the game, i.e. the first minutes of the game.

Figure 9: Jungles' Play Styles Clustered by Team's Quality by the First PC



are the positions usually in charge of dealing damage, the retrieved principal components separate their play styles by the way in which their contribution to the game is shaped by their early game advantages or disadvantages. This allows distinguishing the play style of players that waste early advantages from those who actually leverage them, and players that come back victoriously from early deficits from players for which a negative early game condemns the rest of their game. For positions devoted to tasks that are not directly dealing damage, which are jungles and supports, PCA displays other specialized abilities of the players.

Despite the above-mentioned similarities, the interpretation of the principal components has particular variations between positions. The play style of tops differs in their ability to not die either early or late in the game, as well as in their ability to convert early advantages or disadvantages into contributions to scrimmages. Jungles differ in how successful they are in early-game ambushes, and in their ability to control the vision and to convert vision advantages into favorable scrimmages. Mids differ in their ability to deal damage, and in how they convert early advantages into contributions to scrimmages. Besides the differences displayed by the play styles of Mids, Adcs play styles also differ in their ability to grant and clear vision. And lastly, supports differ in their ability to contribute to scrimmages without dying, in how they convert early advantages and disadvantages in clearing and granting vision, and in how they use these advantages to proactively create offensive ambushes.

Note the ability to clearly distinguish between the relation amidst a positive or negative early game and several outcomes of the game. This is possible since the dataset gathers a variable for each of the two aspects, which allows to identify which is the main driver of a characteristic captured by a principal component, since the magnitude of their loadings is considerably different.

4.2 Hierarchical Measures

Table 5 contains the results for c, r, sc, and fc. No position showcases evidence supporting H1 neither for 2017 nor 2019. H2 is supported in 2017 for Jungles and Adcs via a fast chase, and in 2019 it is supported for Tops, Mids and Supports via a slow chase, and for Adcs via a fast chase. This suggests that the modifications to LoL shifted the play styles of both regions in a way that improved the competitive balance between them in 2019, since H2 holds for four of the five positions. In 2017, there is only clear evidence for two positions, while the other three displayed divergence in play styles, with each region shifting its play style towards different directions. This poses strong evidence of the mechanism proposed by H2 for 2019, and inconclusive, rather weak evidence for 2017. Despite the weak evidence for 2017, an interesting highlight retrieved from 2017 is that Jungles displayed the largest fast chase measure of all the positions, and the changes in 2017 targeted mainly avatars that were only played by Jungles[18]. This could mean that the modifications in 2017 aimed at shifting only the optimal style of jungles.

As argued, H2 has strong implications. Evidence supporting H2 means that the new optimal play style was not only closer to that of Europeans, but considerably far away from that of Koreans, rather than somewhere between the original play style of the two (as H1 proposes, which does not hold for any case). Finding that the modifications to the game drove the optimal play style to shift not only towards that of weaker teams but also very far from the stronger ones, is in favor (though far from being conclusive) of hypothesising that this phenomenon was deliberate.

Most of the measures are sensitive to the choice of the mean or the median as aggregation measures of the play style components for each specific group. Nevertheless, this choice is not critical in determining if there is evidence supporting H1 or H2. In all of the above mentioned cases that display evidence in favor of H2, only the slow chase of Korean Tops displays a sign-dependence on the measure chosen. For that specific case, I choose the results for the median because it adjusts

[18]Source: LoL Fandom - Wiki.

Table 5: Convergence, Relative Shift and Chase Measures

C (**$C < 0$ implies convergence**)

	Median				**Mean**			
	7-6 (K=5)	**7-6 (K=4)**	**9-8 (K=5)**	**9-8 (K=4)**	**7-6 (K=5)**	**7-6 (K=4)**	**9-8 (K=5)**	**9-8 (K=4)**
TOP	0,10	-0,01	0,27	0,37	0,13	0,01	-0,17	-0,05
JUNGLE	0,01	0,06	-0,12	-0,10	0,16	0,14	-0,12	-0,05
MID	0,01	0,04	0.43	0,26	0,12	0,11	0,20	0,20
ADC	0,00	0,13	0.30	0,08	0,07	0,14	0,13	0,08
SUPPORT	-0,14	-0,02	0,01	0,00	0,02	0,16	0,00	0,06

R (**$R < 0$ implies that Korea shifted more than EU**)

	Median				**Mean**			
	7-6 (K=5)	**7-6 (K=4)**	**9-8 (K=5)**	**9-8 (K=4)**	**7-6 (K=5)**	**7-6 (K=4)**	**9-8 (K=5)**	**9-8 (K=4)**
TOP	0,00	0,03	-0,04	-0,14	-0,01	0,02	0,10	0,07
JUNGLE	0,03	0,09	0,09	0,07	-0,08	-0,07	0,10	0,08
MID	-0,24	-0,38	0,41	0,39	-0,26	-0,31	0,28	0,31
ADC	0,09	-0,02	0,33	0,11	-0,05	0,12	0,06	-0,01
SUPPORT	0,15	0,04	-0,04	0,00	0,14	0,05	0,02	0,04

SC (**$C < 0$ and $SC < 0$ implies that Korea shifted towards EU's play style of the previous year**)

	Median				**Mean**			
	7-6 (K=5)	**7-6 (K=4)**	**9-8 (K=5)**	**9-8 (K=4)**	**7-6 (K=5)**	**7-6 (K=4)**	**9-8 (K=5)**	**9-8 (K=4)**
TOP	0,15	0,11	-0,09	-0,01	0,11	0,06	-0,38	-0,42
JUNGLE	0,27	0,40	0,03	0,06	0,25	0,35	0,03	0,08
MID	0,16	0,17	-0,06	-0,16	0,26	0,29	-0,13	-0,05
ADC	0,31	0,40	-0,02	0,00	0,31	0,35	0,06	0,09
SUPPORT	0,11	0,11	-0,16	-0,29	0,12	0,15	-0,27	-0,30

FC (**$C < 0$ and $FC < 0$ implies that Korea shifted towards EU's play style of the current year**)

	Median				**Mean**			
	7-6 (K=5)	**7-6 (K=4)**	**9-8 (K=5)**	**9-8 (K=4)**	**7-6 (K=5)**	**7-6 (K=4)**	**9-8 (K=5)**	**9-8 (K=4)**
TOP	0,01	-0,06	0,16	0,11	0,05	-0,05	-0,10	0,50
JUNGLE	-0,41	-0,44	0,00	-0,02	-0,11	-0,26	-0,04	-0,07
MID	0,06	0,10	-0,05	-0,14	0,02	0,00	-0,05	0,07
ADC	-0,05	-0,07	-0,11	-0,12	-0,04	-0,09	-0,12	0,17
SUPPORT	-0,22	-0,30	-0,19	-0,16	-0,02	-0,02	-0,19	0,18

for outliers, which are highly present in the dataset.

The measures are also sensitive to choosing the first four or five principal components. Despite this, most of the measures do not display a sign-dependence on K, with the only notable exception being fc for 2019 when using the mean. This exception is only relevant in determining if Korean Adcs fastly chased Europeans; to solve this, I choose the results of the median due to the same reasons argued above. Interestingly, the sign-independence of the measures on K suggests that the principal component corresponding to the quality of the team moves in the same direction as the aggregation of the others. If the true components of the play style move more or less jointly towards the same direction when the play style shifts, the results would suggest that this principal component captures relevant characteristics of the play style, rather than just having an inflationary effect in the indicators. If such assumptions holds, including the principal component is more accurate than excluding it.

5 Conclusions

This paper posed a research question novel to the field of both sports and eSports. The evidence suggests that, at least in 2019, the modifications implemented to the most popular eSport of all time, yielded an improvement in competitive balance favoring one of the regions with a higher fan base. Explicitly, broadcasting consumption in the once weaker region could have improved due to this. These results have potentially strong implications, even though they are not completely conclusive.

Further research focused on evaluating similar hypotheses for different eSports would shed light on the relevance of modifications to eSports in general as a tool to modify play styles. If eSports owners in fact use modifications as a tool to adjust competitive balance, this raises several dilemmas that concern the eSports industry. This has an obvious effect on international eSports competitions, regarding which the team owners, players, fans and sponsors would have something to say. In addition, consider a case in which the performances in the world cup of the teams of the different regions could be influenced with a high precision by the modifications, and therefore become somewhat predictable. In such case, eSports owners would possess asymmetric information very valuable for eSports betting.

Besides the contributions of the paper through the nature of the research question, I also contribute to the literature with a novel methodology that I develop to evaluate it, which can also be applied other fields. I have proposed a methodological framework that evaluates if the main characteristics of two groups converge between two periods, and if the characteristics of one group move towards imitating the other. The method is based on a hierarchy of metrics involving shifts in the characteristics of each group, that allows to distinguish different imitation scenarios. Additionally, it can integrate dimensionality reduction techniques such as PCA to obtain group-specific vectors of latent characteristics.

Also, it is the first time that PCA is used to retrieve the main characteristics of play styles of League of Legends players. This contributes to the not very extensive literature using PCA in traditional sports and e-Sports. PCA proves to be successful in retrieving insightful components by using per-game and per-minute averages.

This paper faces two main limitations. Firstly, China has been excluded from the analysis due to absence of data, even though its performance in the World Cup has evolved similarly to that of Europe (and even more successfully). A complete analysis including Chinese players would shed light on the validity of the mechanism proposed by H2, since it could show if the new optimal play styles are between the original ones of Europe and China, and very far from Korea. Secondly, the degree of representativeness of the principal components relies on the validity of assumption 4, which is a common problem of analysis relying on PCA. If it does not hold, the metrics developed in section 2.5 display shifts in the variables that vary the most, rather than shifts in the components of the play style, which would invalidate the analysis.

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