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The Best Points to Score:

An Econometric Approach to Competitive League of Legends

Abstract: Professional League of Legends is incredibly complex. With 150+ playable characters, 100s of items to buy, and thousands of decisions to make, the possibilities are endless. So how, then are people supposed to consistently win? Many analysts have approached this question, using the at-the-time best options of characters, items, and compositions. In this paper, we approach League of Legends from the constants; the things every game of League has and measure their value to game result. Through models, we find that tower destruction leads over every other factor. We also find that gold advantage plays a large role as well. Map objectives seem to impact game result less but have impactful results on tower destruction and gold advantage, which in turn impact game result. Additionally, we find that early game metrics, such as first blood or first tower, have significant impact on gold advantage, but are insignificant to game result.

Introduction

Professional League of Legends is an experience where thousands of decisions are made between ten players within a single 30-minute match. These decisions can result in a win for one team or mean their team's defeat. Each decision has a measurable impact (Silva et. al.); this impact is directly measurable by in-game statistics. The point of this paper is to use these statistics to measure the best decisions to make, as well as to give ideas on what a casual player should focus on.

To set the stage, a number of things must be discussed; League of Legends is an incredibly complex game. To start, there are decisions that professional players make without thinking before the match even starts: the types of characters they choose to play in which positions. This, among other things, is a choice that professional players have made for years, and no longer give any thought to breaking that mold. Although this taking for granted can cause some ripple effects at the casual level (Donaldson), it is difficult to measure *why* this "meta," as it's called, has been established, and remains relatively unchanging. However, this analysis should prove to be useful even if the way of doing things shifts.

Tim Sevenhuysen, the aggregator of the data used in this paper, has done quite a bit of work regarding the value of different statistics and decisions. In every case, he evaluated these statistics at a professional level, similar to this paper, although his focus was more on specific scenarios and circumstances, like which type of dragon spawns. Many others within the realm of League of Legends have done work to evaluate decisions on a casual level, working to help casual players improve. This paper aims to directly value each objective and decision in a game of League of Legends on an overall basis.

Therefore, the question at hand is what factors most impact the result of a game of League of Legends? To answer that I've gathered data from professional League play for the 2021 season. By collecting this we get the best players playing the best games, and by extension can gather the best data for the question. While numerous analysts have gathered the data, nobody has fully answered what wins games. This is because most analysis of League games are results-based. The question of what will best win games needs to be answered to allow players, teams, and organizations to evaluate performance and modify strategy.

By using multiple regression models, we can see the impact each decision has on game result. Specifically, the smaller decisions that lead into greater decisions, and the impact those greater decisions have on game result.

Data

The data is aggregated Oracle's Elixir, a website ran by Tim Sevenhuysen. The data itself comes from in-season League of Legends games across the competitive regions LCS ("League Championship Series" in North America), LEC (League European Championship), LCK (League Championship Korea), LPL (League of Legends Pro League in China), PCS (Pacific Championship Series), and CBLoL ("Campeonato Brasileiro de League of Legends" in Brazil). This data includes nearly every measurable statistic from professional games in each region. Essentially, the data measures professional players from the six largest and most successful regions in the world.

Win rate is the most important variable we can observe. It's measured by which team destroys the "Nexus" of the other team first. To do that, several objectives must be met, and some others help to facilitate it. A limitation to this variable on its own is that upset wins exist; a team that is losing can take a lucky fight and win the game despite being very behind. These wins are outliers. A fitting correlation would be a basketball game that gives the win to the last team to score, not necessarily the team with the most points.

Due to these limitations, the broad collective of statistics in each game has been separated into four categories, which will be detailed later. Then, I created a model which measured all statistics and their impact on game result, win or loss. After, I created models which measure decisions in specific categories and measure their impact on the most influential statistics.

Additionally, though there is no efficient way to measure how a team might take an objective, the value of that objective, relative to game result, can be measured, which will help teams prioritize their decisions.

The four categories of game statistics or decisions that best describe the overall game state are:

A-type decisions, which are defined by team actions of aggression

B-type decisions, which are defined by team actions of neutrality

C-type decisions, which are defined by solo actions of aggression

D-type decisions, which are defined by solo actions of neutrality

Because a single match of League has hundreds of specific statistics, to avoid confusion they are all collected into these four categories, based on which of the four they most exemplify. Notable examples of each include destroying enemy towers (A-type), capturing map objectives like the Baron (B-type), killing enemy players (C-type), and killing enemy minions (D-type). In short, actions of aggression negatively impact the enemy team, while actions of neutrality positively impact the players' team.

Methods

There are a few models that will be used in this paper. First is a model that accounts for all four categories and measures their impact on win rate. However, there are two types of decisions represented here: team and solo. To accurately determine the value of a singular player's skill and a team's cohesion, two more models will help to evaluate each.

The dependent variable in models 2 and 3 are based on the results from model 1. The first model showed that tower destruction and gold advantage hold the greatest impact on game result, and that other variables have a lesser direct impact on game result. To accurately determine the value of these other variables, models 2 and 3 measure accordingly.

First, the overall model:

$$\begin{aligned}(game\ result) = ß_0 + ß_1(A - Type\ Decisions) + ß_2(B - Type\ Decisions) \\ + ß_3(C - Type\ Decisions) + ß_4(D - Type\ Decisions) + u\end{aligned}$$

Second, the model for tower destruction:

$$\begin{aligned}&(Towers\ Destroyed) \\ &\quad = ß_0 + ß_1(A - Type\ Decisions\ [except\ towers]) + ß_2(B - Type\ Decisions) \\ &\quad + ß_3(C - Type\ Decisions) + ß_4(D - Type\ Decisions) + u\end{aligned}$$

Finally, the model for gold advantage:

$$\begin{aligned}&(gold\ difference\ per\ minute\ [in\ hundreds]) \\ &\quad = ß_0 + ß_1(A - Type\ Decisions) + ß_2(B - Type\ Decisions) \\ &\quad + ß_3(C - Type\ Decisions) + ß_4(D - Type\ Decisions) + u\end{aligned}$$

Gold difference refers to earned gold: this excludes starting gold and passively earned gold. Many variables are per minute: this helps to mitigate the variance caused by game time.

Here we reach a limitation with modelling League stats: most decisions in a game of League *facilitate* advantages, rather than directly causing them. Another example of note is wave management. Professional-level players can manipulate the minions in a lane to their advantage, making it harder for the enemy team to gain creep score, to gank (team up and try to kill the player), and in some cases to destroy that lane's towers. This is a skill that has no direct measurability but impacts games all the same. A portion of this can be explained through the missing R-squared, but it is also arguable that wave management can be seen through the final stats. The Rift Herald is also a great example of these facilitating decisions: It only grants 25 gold to the killer, and provides no numerical buffs, but it is a vital piece of teams' tower destruction, as shown by the data.

Another significant limitation to this analysis is its relevance. Each year, around November, Riot Games (the developer of League of Legends) introduces their preseason changes. These changes are significant and massively impact the state of the game. For example, some preseason changes of recent years implemented turret plating and dragon souls, both of which have shown to be impactful to game results (Models 1 and 2). With a new batch of preseason changes already implemented, these statistics are dated. Fortunately, this only means that there are more ways to win, not that the current data is irrelevant Despite their age, these models show a general idea of what decisions are impactful in a game of League.

The models and results are shown on the next two pages.

VARIABLES	(1) result
Gold Difference [in 100s]	0.0572***
A-Type Decisions	(0.00323)
Destroyed 5-8 Towers	0.288***
	(0.0173)
Destroyed 9-11 Towers	0.414***
	(0.0236)
Destroyed the First Mid Tower	-0.0219*
	(0.0128)
First Team to Three Towers	-0.0199
	(0.0138)
Inhibitors Destroyed	0.0644***
B-Type Decisions	(0.00730)
Elemental Drakes Slain	0.0109**
	(0.00529)
Team with Dragon Soul	0.0341**
	(0.0152)
Barons Slain	0.0151*
	(0.00911)
Elder Dragons Slain	0.0182
	(0.0186)
Heralds Slain	0.00896
C-Type Decisions	(0.00709)
Kills per Minute	-0.147***
	(0.0490)
Assists per Minute	0.106***
	(0.0201)
Turret Plates Destroyed	-0.00789***
	(0.00200)
First Blood	-0.00693
	(0.00905)
First Tower Destroyed	-0.0163
	(0.0110)
Double kills	0.00994**
	(0.00460)
triple kills	0.00932
	(0.0100)
Quadra kills	0.00198
	(0.0248)
Penta kills	-0.0563
D-Type Decisions	(0.0580)
Creep Score per Minute	0.00501**
	(0.00235)
Vision Score per Minute	-0.0305***
	(0.00476)
Constant	0.252***
	(0.0885)
Observations	2,152
R-squared	0.848

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(2) towers	(3) Gold Difference [in 100s]
B-Type Decisions		
Heralds Slain		0.255***
		(0.0499)
Dragons Slain		0.223***
		(0.0288)
Barons Slain	0.379***	1.129***
C-Type Decisions	(0.0818)	(0.0559)
Kills per Minute		4.908***
		(0.348)
Assists per Minute		1.532***
		(0.145)
Turret Plates	0.173***	0.0822***
	(0.0145)	(0.0147)
First Blood		0.216***
		(0.0669)
First Tower	0.436***	0.532***
	(0.0820)	(0.0793)
double kills		-0.0562*
		(0.0341)
triple kills		0.0452
		(0.0743)
Quadra kills		0.157
		(0.184)
Penta kills		-0.453
D-Type Decisions		(0.432)
Creep Score per Minute		0.440***
		(0.0144)
Vision Score per Minute	0.389***	0.275***
A-Type Decisions	(0.0314)	(0.0343)
inhibitors	1.742***	
B-Type Decisions	(0.0431)	
First Herald Slain	-0.0299	
	(0.0993)	
Second Herald Slain	0.622***	
	(0.0961)	
Both Heralds Slain	0.383***	
	(0.0946)	
First Baron Slain	1.798***	
	(0.108)	
Constant	-0.754***	-21.76***
	(0.225)	(0.456)
Observations	2,152	2,152
R-squared	0.827	0.843

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results

Overall, the data overwhelmingly favors the team decisions, such as tower destruction and objective taking, over the micro decisions a singular player makes. This is consistent with the idea that a *team* game requires *teamwork*. Though gold difference does show a significant impact in win rate (increasing win rate by 7% per 100 gold a team has over the other), the decisions that impact gold difference the most are team-based actions: barons, kills per minute, and early tower destruction.

A point of note from Model (3) is the measuring of multi-kills. These, while satisfying to watch and certainly impactful on the game's viewership, do not grant any extra gold, and therefore are statistically insignificant. In short, three kills acquired safely are worth just as much as risking it all for a flashy triple kill. It can be argued that multi kills are valuable as they mean that the same player acquired multiple kills in the succession, though there is no added value beyond multiple kills going to a single player.

Additionally, in Model (2), the first herald shows as statistically insignificant to tower destruction. This could be because the first herald is often taken at a time when turret plating is still present, drastically reducing its effectiveness.

Ultimately, this all helps to answer the question: what factors most impact win rate in a game of professional League of Legends? Towers. Destroying towers have an immense impact on game result, mostly because they are required to win. The more towers a team destroys, the more likely they will win the game. Gold advantage is also incredibly valuable, as shown in both model (1) and (3).

Some stats in these models show as not statistically significant, detrimental to win rate, or only slightly beneficial, but it is simple to explain why. Barons, for example, have a very small impact on game result in Model (1), but are widely regarding in-game as the most important objective. The explanation for this is threefold: First, it grants 1500 gold spread across the team. That gold gain translates to an increase in win rate. It also empowers any minions near players, making them harder to kill and making them do more damage, especially to turrets. When we look at the impact barons have on turrets, the first baron tends to facilitate nearly four towers being destroyed (combining the coefficients of per-baron and first baron variables). Each baron after that facilitates another 1.5 towers. We can see these impacts in Models (1) and (2).

Conclusion

Ultimately, League of Legends is an incredibly complex game. It is not feasible to include every possible option (let alone combinations of options) in a simple game and measure their effectiveness. To account for this, I've taken every statistic I can that represents win-positive decisions being made (acquiring gold, killing the enemy team, etc.). There are also parts of professional games which have a harder time being measured at this scale. One in particular is the Ban and Pick phase, a draft-style team-by-team selection system for players to choose who they will play. Champions can be banned and picked, and their power in the current season varies constantly. Because of this, measuring the impact of specific picks or bans are not feasible in these models.

Despite these limitations, this is a suitable analysis for the most impactful decisions a team or a player can make in a game of League of Legends, both at the professional level and at the casual one. Certainly, there is more research to be done and insights to be found in this regard. We need to look no further than most professional sports, where they have in depth analysis that fans and analysts of League of Legends have yet to crack.

As far as the question, "what wins a game of League of Legends?" we can arguably say that tower destruction has the greatest impact on win rate. Feeding into that, capturing Baron and destroying inhibitors have the greatest impact on tower destruction. League players and organizations should take this into account when analyzing performance, and should prioritize Baron, inhibitors, and towers in their gameplay.

Further research can be done in future seasons, as each season has new ways for teams to gain an advantage. Most notably in the 2022 season are objective bounties, a way for a team that is behind to gain extra gold, which would hypothetically increase the value of those objectives, and of gold advantage. Additionally, research can be done regarding the Pick and Ban phase, and side selection (determining who picks and bans first), helping to show if a team has an advantage from the start of the game.

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