For Love of the Game:
A Study of Tournament Theory and Intrinsic Motivation in Dota 2

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Abstract

This paper studies the effect of intrinsic motivation on the extrinsic incentives specified by tournament structure in tournament theory in the context of e-sports. It incorporates tournament theory and motivation crowding theory in the same framework, something that past literature have hinted towards but never formally done so. It also uses an e-sports dataset, a type of dataset that few academics in the past have dealt with, but one that offers many interesting potentials. Results weakly show that crowding-in occurs in e-sports, but the effects of tournament structure on performance are inconclusive in the context of this paper. Implications of this paper lie mainly in the possibility for future academics to utilise e-sports data for research.

JEL Classification: J31, J33, J41, M51, M52, Z20

Keywords: Tournament Theory, Motivation Crowding Theory, Incentives, Motivation, e-sports

1. Introduction

On 25th August 2018, OG, a European professional *Dota 2*[1] e-sports team, won USD 11,234,158, 44% of the total prize pool for beating the Chinese PSG.LGD in the Grand Finals of The International 2018 (TI8)[2], an annual *Dota 2* tournament organised by Valve Corporation. With a final scoreline of 3 games to 2, the first-place OG gets 44% of the pool. Second-place PSG.LGD got merely 16% of the pool, of USD 4,085,148. ("The International 2018", 2018).

This highly-skewed distribution of prize money in e-sports is not unique to only *Dota 2*. The Overwatch League[3] has similar prize structures ("Overwatch League – Season 1 Playoffs", 2018). Prize money distribution is slightly less skewed in traditional sports, such as association football, auto racing, golf, and tennis, although the skew is still present.

[1] *Dota 2* is a Multiplayer Online Battle Arena (MOBA) e-sports game developed by Valve Corporation and released in 2013 as a sequel to *Defence of the Ancients*, a mod originally based on Blizzard Entertainment's *Warcraft III*.
[2] The International is an annual *Dota 2* tournament organised by Valve Corporation, usually as the concluding tournament of the Dota Pro Circuit season. It is a double-elimination tournament consisting of 18 teams from six different regions; think of it as the FIFA World Cup for *Dota 2*.
[3] *Overwatch* is a popular first-person shooter (FPS) e-sports game developed by Blizzard Entertainment and released in 2016.

	Traditional Sports			E-sports		
Tournament (Sport / *Game*)	2018 FIFA World Cup Russia[4] (Men's Football)	Wimbledon 2018[5] (Gentlemen's Singles Tennis)	PGA Championship 2018[6] (Men's Golf)	The International 2018 (*Dota 2*)	ESL Pro League Season 8 – Finals[7] (*CS:GO*[8])	Overwatch League – Season 1 Playoffs (*Overwatch*)
Total Prize Pool	USD 400,000,000	GBP 13,039,000	USD 11,000,000	USD 25,532,177	USD 750,000	USD 1,700,000
Rank						
1st Place (*Winner Winnings (% of Pool)*)	France $38,000,000 (9.5%)	Novak Djokovic £2,250,000 (17.3%)	Brooks Koepka $1,980,000 (18.0%)	OG $11,234,158 (44.0%)	Astralis $250,000 (33.3%)	London Spitfire $1,000,000 (58.8%)
2nd Place	Croatia $28,000,000 (7.0%)	Kevin Anderson £1,125,000 (8.6%)	Tiger Woods $1,188,000 (10.8%)	PSG.LGD $4,085,148 (16.0%)	Team Liquid $110,000 (14.7%)	Philadelphia Fusion $400,000 (23.5%)
3rd Place[9]	Belgium $24,000,000 (6.0%)	John Isner & Rafael Nadal £562,000 (4.3%)	Adam Scott $748,000 (6.8%)	Evil Geniuses $2,680,879 (10.5%)	MIBR & mousesports $55,000 (7.3%)	Los Angeles Valiant & New York Excelsior $100,000 (5.9%)
Rest of Winners[10]	$310,000,000 (77.5%)	£295,484,004 (69.8%)	$7,084,000 (64.4%)	$7,531,992 (29.5%)	$335,000 (44.7%)	$200,000 (11.8%)

Table 1
Breakdown of Prize Winnings of selected sports and e-sports tournaments

The presence of this skew in e-sports is posited by Dennis Coates and Petr Parshakov (2016) to be a manifestation of tournament theory, a theory first proposed by Edward Lazear and Sherwin Rosen in 1981. Originally developed as an alternate theory of labour compensation, it postulates that rank order tournaments can be used as optimal labour contracts. It has since become increasingly applied to the study of tournaments in other contexts, such as political appointments, business contracts, and most obviously, sports.

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4 "FIFA World Cup Prize Money", n.d.
5 "2018 Prize Money", n.d.
6 "2018 PGA Championship", 2018
7 "ESL Pro League Season 8", 2018
8 *Counter-Strike: Global Offensive* is a first-person shooter e-sports game developed by Hidden Path Entertainment and Valve Corporation in 2012 as the sequel to *Counter-Strike: Source* in the *Counter-Strike* franchise. It is the most-played FPS e-sport game by professional gamers. ("Top Games Awarding Prize Money", n.d.)
9 When two teams or individuals are listed (separated by "&"), it means that the tournament did not distinguish between 3rd and 4th place; this is usually the result of elimination tournaments with no 3rd place playoff games.
10 Rest of winners' winnings includes all winnings excluding those of the top 3; for tournaments with tied 3rd places, only one share of the 3rd place winnings is excluded.

Tournament theory's extensive application in sports have proven to be robust due to its similarity to tournament structures one often sees in sports. Its application to e-sports, however, has been limited due to the nascent nature of the e-sports industry. Nonetheless, the growth of the burgeoning e-sports industry provides a great context for academics to study tournament theory, given its tournament structure and the amount and types of data available. The accessibility of data pertaining to e-sports, granted by the Internet and the industry's appetite for data, allows academics to examine different factors that predict performance, one of which being motivation.

The ability to study motivation using e-sports data brings about an opportunity to study tournament theory in conjunction with other theories that predict performance. One such theory is motivational crowding theory, formalised by Bruno Frey and Reto Jegen in 2001. It provides and explanation to the odd phenomenon that is not explained by general economics: introducing extrinsic incentives to a task, such as monetary rewards, sometimes results in actors performing worse than when the extrinsic incentive was absent. Works on motivation prior to the formalisation of motivational crowding theory have pointed at the existence of intrinsic motivation, which encourages the performance of actors separately from extrinsic incentives such as prizes. The interaction between intrinsic motivation and extrinsic incentives often lead to the crowding-out effect; the presence of extrinsic incentives "crowd-out" one's intrinsic motivations while performing a task. This can lead the seemingly paradoxical outcomes: one's performance may fall when an extrinsic incentive is introduced because one's intrinsic motivations fell due to the presence of the extrinsic incentive. Motivational crowding theory therefore predicts the opposite of what tournament theory posits, which therefore leads to interesting implications from the perspective of tournaments.

This paper shall attempt to reconcile the seemingly conflicting stories that tournament theory and motivational crowding theory tell us about performance. More specifically, it shall do so by examining the relationship between intrinsic motivation, extrinsic incentives, and performance within the specific context of e-sports. Our question is therefore as follows: Does intrinsic motivation attenuate or promote the effect of extrinsic incentives on performance within the framework of tournament theory? Studying intrinsic motivation and extrinsic incentives them in the context of tournaments, where extrinsic incentives are clearly fleshed out, is something that has curiously never been done. The use of e-sports data in economic research is also a very new phenomenon which we hope to promote further through our paper. Although a common practice among researchers is to explore tournament theory using traditional sports, we have decided to instead examine it via the lenses of e-sports for the following two reasons:

1. E-sport tournaments tend to have larger and convex prize spreads (refer to Table 1), making the effects of prize spreads more apparent.
2. The availability of public e-sports data implies that using e-sports as a testing ground for theories, while time-consuming due to its data structure, is certainly possible; this paper is therefore as much an explorer of new methods as it is an academic venture.

The study will be focused on *Dota 2*, a massive online battle arena (MOBA) game that is the largest e-sport title in terms of tournament prize pool[11] and viewership[12]. These two factors are chosen because a larger tournament prize pool allows for wider dollar prize spreads and high viewership translates to the game's popularity and standing in the e-sports industry. An explanation of the game *Dota 2* is provided in Appendix A; it is suggested that readers unfamiliar with the game read Appendix A prior to the data section.

We will first begin by examining the literature surrounding tournament theory, motivational crowding theory, and the study of e-sports in academic literature. We will then

[11] "Largest Overall Prize Pools in Esports", n.d.
[12] "Most Watched Games on Twitch", 2018

proceed to examine the theoretical underpinnings of tournament theory and motivational crowding theory, before examining our data and empirical methodology. Finally, we will present our results and conclusions on them, and suggest further research directions that should be taken.

2. Literature Review

This section will first independently address the areas of research in tournament theory and motivational crowding theory respectively, before examining the two in conjunction with each other and identify points of synergy between the two theories. There will then be a section dedicated to a brief history of e-sports, the current e-sports industry, and e-sports in academic literature to demonstrate the relevance of e-sports to the two theories and society at large.

2. 1 Tournament Theory

Tournament Theory is a theory proposed by Edward Lazear and Sherwin Rosen in 1981 that envisions a compensation scheme that is pegged to relative ordered performance. Instead of pegging wages directly to the marginal product of labour (MPL) of workers (usually in the form of piece rates), they propose that compensation should be paid according to an individual's ordinal rank in the organisation using specific metrics (such as MPL, sales, or revenue generated). Doing so can induce the same efficient allocation of resources as equating wages with MPL and is especially useful when it is difficult for principals to monitor individual effort levels (Lazear & Rosen, 1981). From the simplest two-player model where the two players are identical, two testable predictions emerge. Firstly, effort levels of players increase with the prize spread. Secondly, it is the difference between the size of the two prizes, rather than the absolute size of the prize itself, that matters to players (Lazear & Rosen, 1981; Knoeber & Thurman, 1994; Connelly, Tihanyi, Crook, & Gangloff, 2014). Barry Nalebuff and Joseph Stiglitz (1983) further expounded on the theory by introducing multi-agent, single principal problems. In the first, the winner of the tournament took all the prize in the pot contributed evenly to by every player. In the second, every participant in the tournament wins a prize based on their ordinal rank. They showed theoretically that a tournament is able to duplicate nonlinear piece rate schemes under specific circumstances, either when the environment factor is not variable or when agents act as if they were risk neutral. Most of the literature built upon tournament theory focus on the two testable implications.

2.1.1 Expansions on original theory

Preliminary expansions on the original theory by Rosen (1986) suggests that the size of the top-ranked prize spurs competition. This finding is corroborated by Ehrenberg and Bognanno (1990a, 1990b), who showed that having a larger prize pool led to higher performances in men's golf. However, this is soon challenged by Becker and Huselid (1992) who used auto racing data to support the second testable implication: tournament prize spread has incentive effects on individual performance and prize distribution less so. Risk aversion also contributes to the optimal rank spread necessary. In the same study, Becker and Huselid (1992) showed that the larger the rank spread is, the more willing players are to take risks in order to win the higher prize; conversely, the more risk averse agents are, the larger the rank spread must be to motivate them to put in more effort. Other researchers soon also started examining risk-taking in the context of tournaments. Knoeber and Thurman (1994) used data from the commercial bidding of broiler chickens and showed that participants who were more skilled took less risks than those who were less skilled. Melton and Zorn (2000b) showed that lower-ranked players in a men's golf tournament take more risks in attempts to catch up in the tournament.

2.1.2 Empirical testing in the field

Tournament theory has since not only been applied to the labour market, but also to other contexts such as business contracts, political appointments, and unsurprisingly, sports tournaments. Testing of tournament theory in field settings have yielded confirmatory results; we see it being implemented in auto racing (Becker & Huselid, 1992), golf, (Ehrenberg & Bognanno, 1990a; Ehrenberg & Bognanno, 1990b; Melton & Zorn, 2000a; Melton & Zorn, 2000b) commercial bidding (Knoeber & Thurman, 1994), and even in e-sports (Coates & Parshakov, 2016). In their working paper, Coates and Parshakov (2016) found that prize distributions of e-sports tournaments were convex in rank order, suggesting that players were risk averse. They also saw that prizes for team games were more consistent with tournament theory than were individual games, suggesting that from a tournament design perspective, one should take into account whether the game is individual or team-based. While Coates and Parshakov approached e-sports from a tournament structure perspective, we will be examining it from a performance perspective, something no academic has ever done with e-sports data to date. Tournament theory has also been extensively studied in management sciences, with the number of papers written on the subject and citations to Lazear and Rosen (1981) growing almost exponentially (Connelly et al., 2014) since the original paper was published. Most of these papers look at the within-firm labour market in some form, and tournament theory's main idea (prize spread being the main factor in influencing decision-making by agents) has consistently received support and confirmation by subsequent studies. Bloom and Michel (2002) showed that larger dispersions in pay structures within firms correlates to higher turnover rates in personnel, suggesting that agents do take prize spreads into account when making decisions. This is corroborated by Messersmith, Guthrie, Ji, and Lee (2011), whose study not only came to the same conclusion as Bloom's and Michel's study, but went on further to show that one's share of the total prize pool also had an inverse relationship with turnover rate. Carpenter and Sanders (2004) and Frederickson, Davis-Blake, and Sanders (2010) presented the darker side of using pay dispersions as the carrot in labour markets: both studies showed that larger pay gaps among executives led to lower firm performance. This is however disputed by Lee, Lev, and Yeo (2007), whose study showed that increased pay dispersion resulted in improved firm performance. Henderson and Frederickson (2001) presents a more nuanced view: larger prize spreads, while motivating more effort as predicted by tournament theory, also led to less cooperative behaviour. Empirical testing of tournament theory in the field has therefore not only confirmed many of its theoretical underpinnings, but also showed us the dangers of applying it indiscriminately to drive performance.

2.1.3 Limitations of tournament theory

One key weakness that tournament theory struggles with is that it assumes that the prize is the players' main motivation for participation and effort levels. As we have seen from some of the studies mentioned previously, this does not seem to be the case; extrinsic rewards such as the size of the prize and prize spreads can sometimes dissuade individuals from performing, collaborating, or participating in a tournament (Henderson & Frederickson, 2001; Bloom & Michel, 2002; Carpenter & Sanders, 2004;, Frederickson et al., 2010; Messersmith et al., 2011). Connelly et al. (2014) also explicitly warns us about the risk of overemphasising extrinsic rewards to the point where researchers neglect the role that other factors, such as cognitive biases and decision constraints, may play in participation and effort-level decisions by agents. This paper therefore attempts to factor in non-extrinsic rewards to examine their effects on performance. Blind support for tournament theory simply because of the robustness of its main ideas is unwise as it is a theory that only accounts for extrinsic rewards and motivations while completely ignoring non-extrinsic factors that may affect one's motivations for completing a task. In fact, there are many other reasons that may motivate people to perform better at tasks, some of which have nothing to do with the extrinsic rewards presented in tournament theory. Whether it is pride, satisfaction, or any other intangible reward that the player obtains, the field of psychology has a name for them: Intrinsic Motivation. Motivational studies in psychology have long recognised that extrinsic incentives alone were insufficient in predicting performance, and research in this area had culminated in the formalisation of Motivational Crowding Theory, incorporating both intrinsic motivation and extrinsic incentives in predicting performance.

2.2 Motivational Crowding Theory

The study of intrinsic motivation first started in the field of psychology. Robert White (1959) was one of the first psychologists to suggest that motivation can stem from something other than primary drives such as hunger or thirst; animals seem to possess an innate motivation to perform exploratory behaviour that cannot merely be explained by primary drives. Subsequent discussions seem to suggest that this intrinsic motivation to perform tasks can be eroded by the introduction of extrinsic rewards and incentives (Atkinson, 1964; DeCharms, 1968). This was proven empirically a few years later by Deci (1971) who showed that intrinsic motivation decreased when money was introduced and subsequently removed as an external reward to improve task performance. From there, he began to question the effectiveness of piece-rate payments as motivators for employees to work harder (Deci, 1972a; Deci, 1972b). Many empirical studies subsequently followed, all demonstrating that the introduction of extrinsic incentives, such as cash or prizes, “crowds out” intrinsic motivation to compete a task and can reduce task performance (Deci, 1972a; Deci, 1972b; Garbarino, 1975; Anderson, Manoogian, & Reznick, 1976). All this work finally led to the formalisation of Motivational Crowding Theory by Bruno Frey and Reto Jegen (2001), combining the theoretical discussions in economics of the crowding-out effect and the empirical studies in psychology that demonstrates as such.

2.2.1 Empirical studies in psychology

After Deci (1971) conducted perhaps the first field and lab experiments drawing the link between intrinsic motivation and extrinsic incentives, many more were run trying to elicit the relationship between monetary rewards and intrinsic motivation. Studies found that there is a generally inverse relationship between the two. Deci (1972a) went on to show that while the crowding-out effect exists, it is possible for there to be a "crowding-in" effect where introducing extrinsic incentives can boost intrinsic motivation by providing feedback and recognition to one's efforts and competence. The crowding-out effect exists even in children. Garbarino (1975) showed that the promise of a reward to children for completing a task resulted in worse attitudes towards and worse performance on the task, suggesting that the reward had negated any intrinsic motivation to perform. Anderson, Manoogian, and Reznick (1976) showed that introducing external rewards resulted in lowered intrinsic motivation among pre-school children. As more studies were conducted, economists slowly began to understand and formalise what is now known as the crowding-out effect, where the introduction of external incentives can actually lower intrinsic motivation and lead to lower or worse effort levels and performance.

2.2.2 Introduction to economics

The motivation crowding effect, originally an idea from social psychology, was ported into economics in the late 1980s as an explanation to why the direct relationship between price and quantity supplied sometimes was not observed. Economists then began to examine the effects of crowding-out in real world settings. More experiments in the early 2000s then convinced economists that it is an empirically-observed phenomenon; Fehr and Gächter (2000) demonstrated how external incentives can crowd-out reciprocity-based effort elicitation using public good experiments, Frey and Götte (1999) showed that offering financial rewards to volunteers lowered their work efforts although it increased their work time, and Frey and Oberholzer-Gee (1997) showed how offering external incentives to individuals whom are negatively affected by the siting of locally unwanted projects actually became more unwilling to accept the siting when explicit compensation was offered.

2.2.3 Synergy with tournament theory

Literature that encompass both tournament theory and motivation crowding theory are limited. Holmund, in his 2009 working paper about compensation theory, acknowledged that both theories are important to look at when considering compensation policy, but did not offer any formal framework to combine the two. Hvide (2002) discussed the phenomenon where tournament structures lead to lower efforts by players as they took larger risks, known as the risk-lazy "trap", but this too does not mention intrinsic motivation, instead relying on motivation driven by external rewards as an explanation. Vansteenkiste and Deci (2003) did the opposite, showing that in a competitive environment when rewards were present, winners were more intrinsically motivated than losers and losers who received feedback were more intrinsically motivated than those who do not. This however still fails to formally tie together tournament theory with motivational crowding theory. The closest that parts of these theories have been studied together is in Henderson & Frederickson (2001), where they compared a behavioural view (more equal pay between team members will promote collaboration and subsequently firm performance) against an economic view (less equal pay creates a tournament-like structure that encourages effort from individuals). Their conclusion was that both views were useful in predicting firm performance, demonstrating that both incentives proposed by the two theories are at play. In more recent years, Cerasoli, Nicklin, and Ford (2014) conducted a 40-year meta-analysis on previous literature and found that intrinsic motivation was a medium to strong indicator of performance, and that the crowding out effect was more pronounced when incentives were directly performance-related. While extremely comprehensive, they did not examine any effects of extrinsic incentives that were specifically from tournament settings. Thus far, there has been no research that fully ties the knot between tournament theory and motivation crowding theory. We can however see that there should be natural synergy between the two topics;

tournament theory aims to elicit the optimal level of effort from agents via the proper set-up of prizes from tournaments, while motivation crowding theory explains how external incentives from principals can crowd-out intrinsic motivation, resulting in lower levels of effort exerted by their agents. A well-designed tournament may in theory elicit the optimal level of effort according to tournament theory, but in practice fail because the prize incentive crowds out the agent's intrinsic motivation to perform. Or perhaps the incentives are well-aligned, and result in crowding-in, where agents are willing to put in more effort than what was predicted by tournament theory. We therefore hope to fill this gap in the literature and provide insights into how intrinsic motivation from motivational crowding theory plays into tournament theory. From an academic standpoint, the motivation and relevance of this study stems from how understanding the effects of tournament structures on intrinsic motivations can help principals make better decisions on how to best structure rewards to elicit the best response from their agents to maximise payoffs for both parties.

2.3 E-sports

E-sports, also known as professional gaming, is a growing industry that is becoming increasingly mainstream as a form of entertainment[13]. While games often have an element of competition embedded in them, e-sports takes that element and elevates it to a professional level, like that of professional sports. Given that e-sports is still a nascent industry, understanding the mechanics behind tournament structure and their effects on intrinsic motivations can help teams and tournament organisers design optimal tournaments to elicit desirable player behaviours. The abundance of data available in e-sports, courtesy of video game publishers, also provides

[13] In 2018, the global games market was valued at USD134.9 billion, a 10.9% increase from 2017. Within that, the global e-sports market was valued at USD 865 million, a 32.0% increase from the previous year ("Key Numbers", n.d.). To put this in perspective, the estimated size of the global sports industry in 2017 is USD1.3 trillion, a 5.29% increase from the previous year ("Global Sports Industry Revenues", n.d.); the gaming industry is growing at more than double the pace of the sports industry.

researchers with the unique opportunity to play with datasets that do not suffer from missing value problems; a type of observation is either captured or not captured. If it is, every instance of it across every game will be. The growing abundance of e-sports tournaments as a result of the industry's growth allows it to be a great testing ground for tournament theory.

2.3.1 Use of e-sports in other academic literature

The use of video or computer games in academic research[14] is, surprisingly, not a relatively new phenomenon. In the early 2000s, academics have used video games as a microcosm of society or systems to study. Examples include Manninen (2001), who used *Counter-Strike* to study team communications, and Wright, Breidenbach, and Boria (2002) who also used *Counter-Strike* to study the creativity displayed by its players in communication. Apart from the above studies which are generally concentrated in the field of cultural anthropology, researchers also used video game traffic to examine networks. Examples include Feng, Chang, Feng, and Wapole (2002) who used a *Counter-Strike* server to analyse network traffic, and Claypool, LaPoint, and Winslow (2003), who examined *Counter-Strike* and *StarCraft*[15] to see how online games impacted the network with their traffic patterns. More recently, Reer and Krämer (2014) examined social capital acquisition from online games by examining *World of Warcraft*[16] and *Counter-Strike*. Most of these papers examined video game titles that were e-sport titles, but non have ventured into the e-sports space as of yet. It was not until 2006 that Wagner (2006) called for the "proper academic treatment of eSports". He argues that e-sports should be viewed as a field of study which allows researchers to use novel and different approaches that can lead to

[14] Here we are referring to instances where video games are used as examples or environments in research, not instances where video games are the subject of research themselves or when video games are used in as tools in experimental methods.
[15] *StarCraft* is a real-time strategy (RTS) game created by Blizzard and first released in 1998. It is often seen as the benchmark for real-time strategy games that has a following up till today.
[16] *World of Warcraft* is a massive multiplayer online role-playing game (MMORPG) first released in 2003 by Blizzard.

insights in areas that are not directly related to computer games. Following Wagner's paper, academics gained interest in the study of e-sports itself, beginning with Rambusch, Jakobsson, and Pargman's (2007) study of *Counter-Strike* competitive gameplay and their cognitive, cultural, economic, and technological aspects. Subsequent studies generally focused on the e-sports market and its cultural impacts (Lee & Schoensteadt, 2011; Seo & Jung, 2014; Hamari & Sjöblom, 2017; Jenny, Manning, Keiper, & Olrich, 2017). In recent years, there have also been papers that analyse e-sports gameplay and performance (Drachen et al., 2014; Schubert, Drachen, & Mahlmann, 2016). These papers are the first to use in-game data such as match scores and player positions to run analyses against performance or skill. As the industry develops and attracts more attention, the amount of research conducted using e-sports data will surely rise.

2.3.2 Use of e-sports in economics

The study of e-sports in economics have been mainly restricted to the realm of marketing and management studies, and the role of e-sports in economic development. Seo (2013) studied value networks in e-sports and argued how multiple stakeholders, such as companies, governments, players, and online communities all have a role to play in curating the experience for e-sports consumption. Liang (2010) and Lokhman, Karashchuk, and Kornilova (2018) examined the development of e-sports as an industry in China and Ukraine respectively and identified factors such as national regulation, media engagement, and support for talents looking to enter the industry as keys to growth for the e-sports industry and the larger economy. While interest about the industry has penetrated into academia, the use of e-sports data in academic work within economics still is a rare phenomenon. In perhaps the first use of e-sports data, Coates and Parshakov (2016)[17] used tournament winnings of e-sport tournaments to show that e-sport

[17] This working paper was first presented at the 85th Annual Meetings of Southern Economic Association in New Orleans, Louisiana, USA on 23rd November 2015.

tournament prize distributions are consistent with tournament theory. Given the current development trajectory of research using e-sports data, this paper will also like to contribute to this trend to encourage more academics, especially those in economics, to do so as well.

3. Theoretical Framework

This section shall individually discuss the two theoretical frameworks that are used in this paper: Tournament Theory and Motivation Crowding Theory.

3.1 Tournament Theory

In this sub-section we will first examine the basic two-player model proposed by Lazear and Rosen (1981). Here we shall distil out the two testable implications of the model mentioned previously: 1. the effort levels of players increase with the prize spread, and 2. it is the difference between the size of the two prizes, and not the absolute size of the prize, that matters to players.

3.1.1 Basic two-player model

In tournament theory, the most basic tournament is a two-player ranked contest where the players are risk-neutral and identical (Lazear & Rosen, 1981; Knoeber & Thurman, 1994). For player *i*, their performance (or output) is modelled as follows:

$$q_i = \mu_i + \varepsilon_i \qquad \text{------ (1)}$$

In this model, q is their lifetime performance (or output), μ is their effort level, and ε is noise (including luck).

Putting in effort is costly, and the associated cost C is a function of the level of effort μ. Here the cost function $C(\mu)$ is identical for both players since the players are identical.

In this ranked contest, the winner (higher performance or output) obtains the prize W_1 and the loser obtains the prize W_2, where $W_1 > W_2$. Let P be the probability of player *i* winning the contest and obtaining the prize W_1. Their expected payoff $E(payoff)$ from the contest is therefore:

$$P(W_1 - C(\mu)) + (1-P)(W_2 - C(\mu)) = P(W_1 - W_2) + W_2 - C(\mu) \qquad \text{------ (2)}$$

To maximise one's expected payoff, one has to vary one's level of effort. To do so, one maximises the probability of winning P with respect to one's level of effort μ. We therefore have the following equations:

First derivative:

$$\frac{\partial P}{\partial \mu_i}(W_1 - W_2) - C'(\mu_i) = 0 \qquad \text{------ (3)}$$

Second derivative:

$$\frac{\partial^2 P}{\partial \mu_i^2}(W_1 - W_2) - C''(\mu_i) < 0 \qquad \text{------ (4)}$$

From Equation (3), we see that the marginal cost of effort for player i is $C'(\mu_i)$, the first derivative of their cost function. If we rearrange the terms, we get:

$$C'(\mu_i) = \frac{\partial P}{\partial \mu_i}(W_1 - W_2) \qquad \text{------ (5)}$$

Equation (5) shows that the marginal cost of effort depends only on the prize spread $(W_1 - W_2)$ of the tournament. This is in line with the two testable implications of tournament theory: effort levels of players increase with the prize spread, and prize size has no bearing on the effort level decision of players. Our final model therefore will be incorporating prize spread as one of our main variables for extrinsic incentives.

3.1.2 Assumptions in the two-player model

Two key assumptions in this simple two-player model are that players are risk-neutral and identical. In a n-player tournament with n rank prizes, having risk-neutral players implies that the prize spread between each rank should be set to be the same, as their risk function is linear. When players are risk-averse, however, the prize spread must be convex (larger prize spread between higher ranks compared to lower ranks) to compensate for the extra risk players are taking in exerting more effort. In a two-player model, this cannot be observed since there is only one prize spread between first and second place, but theoretically the winner must be compensated more than if he were risk neutral. Non-identical players refer to players with different skill levels. More skilled players naturally have an advantage over less skilled players, and therefore their risk-taking behaviour will differ; less skilled players are more likely to take more risk in order to catch up (Knoeber & Thurman, 1994; Melton & Zorn, 2000b). There is therefore a need to control for different skill levels, which we did in our model.

3.2 Motivation Crowding Theory

We shall now examine Frey and Jegen's (2001) motivation crowding theory and explain the interactions of extrinsic incentives and intrinsic motivation as theorised and demonstrated.

3.2.1 Intrinsic motivation

We first begin by defining intrinsic motivation. Deci (1971) defines it very succinctly: it is motivation stemming from "no apparent reward except the activity itself". While the simplicity of the definition makes it easy to understand, it makes it extremely difficult to untangle intrinsic motivation from that stemming from external sources. This has led to older economic literature from treating intrinsic motivation as an exogenous constant or simply disregarded in models (Frey & Jegen, 2001). According to Frey and Jegen (2001), there are two approaches one can take to gauge changes in intrinsic motivation due to the introduction of extrinsic incentives. Firstly, it can be seen as a change in preferences. The introduction of extrinsic incentives changes the amount of intrinsic motivation because with the presence of extrinsic incentives, agents now have their preferences changed, perhaps to one that either favours more extrinsic incentives or less. Secondly, it can be seen as a change in the perceived nature of the task, the task environment, or the actor's self-perception. This view keeps preferences fixed while changing the nature of the task, such that the task now fulfils different purposes and therefore grant different payoffs to the agent. Both these views can help explain the interaction between intrinsic motivation and extrinsic incentives, known as the crowding-out or crowding-in effect depending on their direction.

3.2.2 Crowding-out and crowding-in

In standard economic theory, where there is an "absence" of intrinsic motivation, introduction of extrinsic incentives results in a higher marginal benefit when an agent improves performance. Therefore, any increment in extrinsic incentives, all else held equal, results in increased performance by agents. Increased intrinsic motivation, as defined by Deci (1971), also results in increased performance since agents are more willing to put in more effort. The effect of extrinsic incentives on intrinsic motivation, however, can run both ways. There is the crowding-out effect, where the introduction of extrinsic incentives erodes one's intrinsic motivation. When this happens, the net effect on performance may be either positive or negative, depending on the magnitudes of the individual effects. If the size of the extrinsic incentive is small, it is likely overpowered by the reduction in intrinsic motivation, resulting in lower performance. With a large enough extrinsic incentive, performance may still increase as it overpowers decreases in intrinsic motivation. There is also the crowding-in effect, where the introduction of extrinsic incentives reinforces one's intrinsic motivation, resulting in a larger than predicted increase in performance. Table 2 summarises the effects of the introduction of extrinsic incentives on performance when intrinsic motivation is considered.

Effect	Effect of Extrinsic Incentives on Performance	Effect of Extrinsic Incentives on Intrinsic Motivation	Performance
Crowding-out	▲	▼▼	▼
Crowding-out, but extrinsic incentives dominate	▲▲	▼	▲
Crowding-in	▲	▲	▲▲

Table 2
Summary of effects of crowding-out and crowding-in on performance

Whether crowding-out or crowding-in occurs depends on the psychological processes that occur as a result of the introduction of extrinsic incentives and its interaction with intrinsic motivation. There are two psychological processes in play: changes to self-determination and self-esteem (Frey & Jegen, 2001). Self-determination refers to one's own internal drive to perform in a task. When an extrinsic incentive is introduced, self-determination may be negatively impacted if they feel like they are being pushed towards specific behaviours, or positively impacted if they feel like they are given more freedom to act. Self-esteem refers to one's self-valuation. When an extrinsic incentive is introduced, self-esteem may be negatively impacted if it feels like the introduction is a rejection of one's intrinsic motivation, or positively impacted if it feels like an affirmation of one's efforts. Therefore, whether crowding-out or crowding-in occurs depends on how the agent views the extrinsic incentive. If they view it as controlling, crowding-out occurs, and we may observe a "paradoxically" fall in performance. If they are viewed as supportive, then we may observe a larger-than-expected increase in performance. The interaction effect between extrinsic incentives and intrinsic motivation is therefore a key part of this study, as it can elucidate whether e-sports tournaments crowd-out or crowd-in the intrinsic motivations of e-sports players, and offer a perspective as to whether the prize money is viewed as a positive encouragement or a burden.

4. Data

For the tournaments in question, we chose to use data from the Main Event of The International 2018 (TI8), an annual *Dota 2* tournament that is equivalent to the FIFA World Cup of *Dota 2*. Apart from the reasons explained in the introduction (large prize pool and popularity in the e-sports community), one key reason why The International was chosen specifically over all other *Dota 2* tournaments is that it is the final tournament of the *Dota 2* season. The introduction of the Dota Pro Circuit in the 2017 – 2018 season resulted in the tournaments in a single *Dota 2* season to be non-independent; participation and performance in other tournaments in the Dota Pro Circuit season awarded points to players that can directly influence whether they are invited to participate in The International or must go through qualifiers to do so ("Dota Major Championships", n.d.). Therefore, among all the tournaments in a *Dota 2* season, we can only obtain clear expected payoffs for The International, as it will not influence an individual player's future expected payoffs from other tournaments based on his performance. We will be using data only from TI8 due to its recency and the ability to control for team fixed effects[18]. Due to roster changes that occur at the end of every season, controlling for team fixed effects are impossible if we use data from more than one tournament across different seasons.

4.1 Game and Player Level Data

Data on the *Dota 2* tournaments and individual players were scraped from Dotabuff and pulled from Steam API, and scraped from OpenDota[19] respectively. Dotabuff is a *Dota 2* statistics website under Elo Entertainment LLC that provides *Dota 2* data[20] ("We Empower

[18] Each The International tournament is broken into two stages: the Group Stage and the Main Event. In the Group Stage, teams are split in to two groups and play every other team in their group in a round-robin format. Their performance decides how they will be seeded in the Main Event, a double elimination tournament. TI8 had 18 teams in the group stage, and the last team in each group was eliminated, leaving 16 teams to proceed to the Main Event.
[19] https://www.opendota.com/
[20] https://www.dotabuff.com/

Players", 2019). The Steam API is a web API provided by Valve Corporation, the publisher of *Dota 2*, for use by web developers to access game data available on Steam[21]. Using the Steam API, data from every single *Dota 2* game ever played on Steam's server, including tournament games, can be accessed. To isolate the games that were played only in the Main Event of TI8, we wrote a web scraper that scraped Match IDs from Dotabuff for every game that was played in the Main Event, and fed that data to the Steam API using a script we wrote ourselves. Data pulled from the Steam API was then stored on an Excel file and formatted manually.

OpenDota is, open source data platform that provides *Dota 2* data. Using a combination of the Steam API and replay parsing of game files, OpenDota extracts and publishes game data for all games not played on private servers. It also collects player-level data, and most competitive players have their game data published and available for perusal. For our paper, we pulled individual data using another web scraper we wrote ourselves that looped through a list of account IDs. Samples of data scraped from OpenDota were cross-checked with those from other *Dota 2* data platforms such as datdota[22] and Dotabuff to verify their accuracy. Minor discrepancies do exist due to the different times each data platform started pulling their data, but they are insufficient to invalidate the accuracy of OpenDota.

4.2 Prize Money Data

Data on tournament prize money are obtained from Esports Earnings[23]. Esports Earnings is a community-driven website that holds tournament data, with a focus on the prize pool, from over hundreds of video games that have professional tournaments; data history goes back to as early as 1998. While there may be a concern about data accuracy given its community-driven

[21] Steam is Valve's game distribution platform through which games like *Dota 2* are played. It also collects game data that occur on its servers.
[22] https://www.datdota.com/ is a *Dota 2* statistics website created in 2013 by Martin Decoud and currently maintained by *Dota 2* analyst Ben "Noxville" Steenhuisen ("datdota – About Us", 2017)
[23] https://www.esportsearnings.com/

nature, prize pool and prize distribution data on The International tournaments are accurate due to the scale and public nature of the information. Cross-referencing the prize amounts shown by Esports Earnings with the official *Dota 2* website[24] and other community-driven websites such as Liquipedia Dota 2[25] confirms their accuracy.

Our dataset has a total of 470 observations, spanning 47 different games, 80 different players, and 16 different teams. While the total number of observations is not very high, it is restricted by the total number of games played in a single TI tournament. Combining multiple datasets from different tournaments, while possible, is not preferred due to the complexity in controlling for time-varying effects of individual players and teams.

5. Empirical Framework

Our empirical framework is largely adapted from Becker and Huselid (1992). We shall first examine their framework, before explaining how we have adapted it.

5.1 Empirical Framework by Becker and Huselid (1992)

In their study that used auto-racing data, Becker and Huselid (1992) regressed adjusted finish position (*ADJUSTED FINISH*)[26] against the prize spread of the race and the percentage of purse awarded to the top *x* finishes (and other control variables) for each driver *i* in each race *k*. For prize spread, they used two different variables: *SPREAD (a,z)*[27] and *PERCENTAGE OF PURSE (a,z)*[28]. Multiple *SPREAD (a,z)* variables were used to account for convexity in prize structures. Control variables *START POSITION*, *LAP LENGTH*, and number of *CAUTION*

[24] https://www.dota2.com/international/overview/
[25] https://liquipedia.net/ is a wiki page created and maintained by e-sports team Team Liquid ("Liquipedia:Mission Statement", 2017).
[26] *ADJUSTED FINISH* is the finishing position times the ratio of the winning speed in that race over the fastest winning speed in all the races. This was done to adjust for changes in performance across races, and to account for the relative speed of the races (Becker & Huselid, 1992).
[27] *SPREAD (a,z)* is the difference in average prize money available per driver in positions *a* to *z* and the average prize money per driver finishing below position *Y*.
[28] *PERCENTAGE OF PURSE (a,z)* is the percentage of the total purse awarded to drivers finishing in positions *a* through *z*.

FLAGS were also included as they would directly affect *ADJUSTED FINISH*; *START POSITION* affects incentives for drivers to improve or prevent declines in their positions, while *LAP LENGTH* and *CAUTION FLAGS* affect the average speed of each race[29]. To account for driver heterogeneity, they included a vector of dummy variables *DR*, one variable for each driver in the sample. Their overall model was as follows:

$$\begin{aligned} &ADJUSTED\ FINISH_{ik} \\ &\quad = a_1 SPREAD(a,z)_k + a_2 START\ POSITION_{ik} \\ &\quad + a_3 LAP\ LENGTH_k + a_4 CAUTION\ FLAGS_k + \sum_{i=1}^{N} DR_i + u_i \end{aligned} \qquad \text{------ (6)}$$

In the above equation, *i* refers to each driver, *k* refers to each race, and *N* is the total number of drivers in the sample.

5.2 Our Empirical Framework

Our empirical framework borrows heavily from that of Becker and Huselid (1992), with two important distinctions: we use a fixed effects logit model and each of our "tournaments" is one game[30] of *Dota 2* in a TI tournament Main Event. Firstly, unlike auto-racing, where each driver has an individual time and rank order, *Dota 2* is a team sport where the outcome of a game is either a win or a loss. While there is a notion of scores in terms of the number of kills each team has, it does not mean that the winning team is the one with the higher score[31]. Therefore, our model is a fixed effect logit model that regresses the outcome of each game (win or loss) against the independent variables. A logit model was chosen over a probit model primarily

[29] Longer tracks have higher average speeds, and every time a caution flag is signalled a caution lap is run where cars run at reduced speeds and overtaking is not allowed (Becker & Huselid, 1992).
[30] To clarify a potential source of confusion terminology: a "match" in *Dota 2* is a series of games that are usually best of 1, best of 3, or best of 5 games. Every individual game played in *Dota 2* can be identified by their (confusingly-named) "Match ID", a term that actually refers to a game rather than a match.
[31] In our dataset of 47 TI8 games, 25 games (12.8%) had the team with the lower kill score winning the game.

because by using a logit model, we are able to convert the coefficients into odds ratios, which allows us to interpret the effect of changes in our variables on win probability. Also, given the skewed nature of our *SPREAD* variable, a logit model with fatter tails better fits our data. Secondly, having each "tournament" as one game allows us to identify exactly the prize spread in the tournament since there are only two prizes; it is almost equivalent to the basic two-player model in Lazear and Rosen (1981).

The general framework of our model is as follows:

$$\begin{aligned} performance &= extrinsic\ incentives + intrinsic\ motivation \\ &+ extrinsic\ incentives * intrinsic\ motivation \\ &+ controls + error \end{aligned} \quad \text{------ (7)}$$

The interaction term accounts for the crowding-out or crowding-in effect that may be present. According to Deci and Ryan (1980), winning in competitions can be experienced as extrinsic to the activity being performed, suggesting that competitions provide extrinsic incentives to participants to perform. While it is possible that there are other sources of extrinsic incentives, they are rare in the context of competitions since the competition itself is the primary source of reward. Therefore, we replace extrinsic incentives with tournament structure itself by using variables such as prize spread and total prize pool as a measure of extrinsic incentives present.

5.2.1 Performance measure

Our performance measure is the binary outcome of each game (win_loss), which can either be a win or a loss. While it being a binary variable implies lower sensitivity to differences in performance across games, using the outcome of each game as a proxy for performance simplifies the process of quantifying performance across different players based on their positions and basic statistics such as kills and assists. Given that one's prize winnings are directly affected by the games that one wins, using game outcome as the depended variable ensures that players are making game decisions that will directly affect their likelihood to win games.

5.2.2 Tournament structure measure

Our measure for tournament structure is $spread\_z_k$ and $total\_pool_k$, both measured on the tournament (game) level. $spread\_z_k$ is the z-score[32] of the difference in the expected payoffs for winning or losing a particular game and $total\_pool\_z_k$ is the z-score of the sum of the expected payoffs for winning and losing a particular game. The situation is complicated by the fact that prizes are given for winning a match, which consists of either 1, 3, or 5 games. While 1-game matches are easy to calculate, it gets complex when we look at multiple-game matches.

5.2.2.1 Probability of winning individual game and match

For each individual game, the probability of a Team A winning in a match-up against Team B is determined by their respective win ratios in the group stage of the tournament. For example, during The International 2018 Group Stage, Team Liquid had a win ratio of 0.8125 (13/16). Team Secret, on the other hand, had a win ratio of 0.5 (8/16). If Team Liquid and Team Secret were to meet during the Main Event, the probability of Team Liquid winning each individual game against Team Secret will be 0.8125 ÷ (0.8125 + 0.5) ≈ 0.619. On the match level, the probability of Team A winning a match against Team B varies in each game in the match series. Let p be the probability that Team A wins each individual game against Team B. Therefore, the probability that Team A wins the match are as follows:

[32] $spread\_z_k = \left(spread_k - avg(spread_k)\right)/avg(spread_k)$. Calculation is similar for $total\_pool\_z_k$. There was a need to convert these two variables into z-scores due to their large magnitudes; odds ratios calculated for these two variables before the conversion were all close to 1 due to the small marginal effect of changing 1 unit of these two variables in any direction.

Score before current game is played (Team A – Team B)	Probability that Team A wins a Best-of-3 match series	Probability that Team A wins a Best-of-5 match series
2 – 2		p
2 – 1		$p + (1 - p) * p = 2p - p^2$
1 – 2		p^2
2 – 0		$p + (1 - p) * p + (1 - p)^2 * p = 3p - 3p^2 + p^3$
0 – 2		p^3
1 – 1	p	$p^2 + 2 * p^2 * (1 - p) = 3p^2 - 2p^3$
1 – 0	$p + (1 - p) * p = 2p - p^2$	$p^2 + 2 * p^2 * (1 - p) + 3 * p^2 * (1 - p)^2$ $= 6p^2 - 8p^3 + 3p^4$
0 – 1	p^2	$p^3 + 3 * p^3 * (1 - p) = 4p^3 - 3p^4$
0 – 0	$p^2 + 2 * p^2 * (1 - p) = 3p^2 - 2p^3$	$p^3 + 3 * p^3 * (1 - p) + 6 * p^3 * (1 - p)^2$ $= 10p^3 - 15p^4 + 6p^5$

Table 3
Probability that Team A wins match given current match score

The expected payoff for Team A from winning (and losing) in each game is therefore the prize for winning (or losing) that particular match (can be an expected value) times the probability that Team A wins (loses) the match series given the current match score

5.2.2.2 Expected payoff of a game and match

The expected payoff of a game is calculated using three components: the prize for winning the particular match, the probability of winning the match in each particular game, and the probability of winning that individual game against one's opponent. The prize for winning a particular match is calculated using expected payoffs in subsequent rounds. In the calculation of the expected payoff of winning and losing a match, we use the win ratio of each team in the group stage of the tournament and transform it into the probability that the team will win the next match given that the score is 0 – 0. For example, during The International 2018 Group Stage, PSG.LGD had a win ratio of p = 0.6875 (11/16). Their expected payoff from winning the Lower

Bracket Finals is therefore $payoff_w$ = $(10p^3 - 15p^4 + 6p^5)$ * <First Prize> + $(1 - 10p^3 + 15p^4 - 6p^5)$ * <Second Prize> since the next game is a Best of 5 game, and expected payoff from losing is $payoff_l$ = <Third Prize>. On the game level, the expected payoff from winning Game 1 in the Lower Bracket Finals is their expected payoff from playing Game 2 given that the score becomes 1 – 0 (they win Game 1) calculated using their win probability against their opponent, Evil Geniuses: $(2p_{ab} - p_{ab}^2)$ * $payoff_w$+ $(1 - 2p_{ab} + p_{ab}^2)$*$payoff_l$, and the expected payoff from losing Game 1 is their expected payoff from playing Game 2 given that the score becomes 0 – 1 (they lose Game 1): p_{ab}^2* $payoff_w$+ $(1 - p_{ab}^2)$* $payoff_l$.

The Main Event of The International has a double-elimination bracket. Therefore, we worked backwards from the Grand Finals of the game and using the rank prize for each match, determined the expected payoff in each game based on the expected payoff of the subsequent games that are going to be played. A detailed breakdown this calculation is in Appendix B.

5.2.3 Intrinsic motivation measure

Our measure for intrinsic motivation is $ratio\_noncomp_i$, measured on the player level, which is defined as the ratio of non-competitive games played over the total number of games played by each player, measured from the first recorded match on their account to matches occurring on the last day of the TI8 tournament[33]. The rationale behind this variable is that more intrinsically-motivated players are more likely to play non-practice games outside of tournaments. Such games do not increase one's probability of winning a tournament, and therefore can be construed to be the manifestation of the player's genuine interest in the game. This measure also excludes any games that are held on private lobbies such as practice games, so

[33] In an ideal situation, $ratio\_noncomp_i$ should be measured at the end of each game, but due to the lack of granularity on the data available, a compromise had to be made. Given that the professional players in our sample have played an average of 5958 games and an average of 1190 tournament games (both up to the last day of TI8), a difference of up to 5 or 6 games will not affect the ratio much.

it does not include games that can count towards training sessions, which are games that does increase one's probability of winning future games.

We acknowledge that there may be a few concerns that arise due to the use of $ratio\_noncomp_i$ as a measure of intrinsic motivation, and we shall address some of them. Firstly, with the advent of video game broadcasting and streaming websites such as Twitch, non-competitive games are still able to generate revenue for a player who is building his personal brand and image via streaming his non-competitive games. However, that is outside of the scope of a tournament; we are measuring extrinsic incentives in the context of winnings in a tournament. Therefore, such payoffs are not considered payoffs resulting from tournaments in our context, and those games are not considered responses to extrinsic incentives in a tournament. Another concern is our assumption that non-competitive games that are not practice games do not contribute to one's probability of winning a tournament. One might argue that playing these non-competitive games may constitute as some form of practice that may make one better at the game. Therefore, it may be seen as a response to the extrinsic incentives offered by the tournament winnings. While this may be true for amateur players, it does not apply to players at the professional level. Similar to an NBA player playing pickup basketball, there is little training value to these games at the professional level. Lastly, a player may use one account for his competitive games and another for his non-competitive games. If that is the case, then this variable will not be able to capture a player's intrinsic motivation. We find this to rarely, if ever, to be the case as professionals have incentives to stick to the same account. Firstly, matchmaking is based on one's account details and history, and using another account will interfere with that process and create sub-par gaming experiences since one will likely be paired with people not in one's skill bracket. Secondly, personal branding is a large part of the life of e-sports professionals and sticking to one account allows them to keep that association with their fans, which is in their interest so as to maximise long-run payoffs.

5.2.3 Controls

Two controls are included in our model, one tournament level control and another player level control, to account for two factors known to affect win rates: map imbalance and skill.

5.2.3.1 Map imbalance

We included a tournament level control variable: $as\_radiant_{ik}$. $as\_radiant_{ik}$ is a dummy variable that has a value of 1 if player *i* is playing on the Radiant faction[34] in game *k*. Unlike most team sports between two opposing teams where the arena is symmetrical, the map in *Dota 2* is not perfectly symmetrical along any axis. This results in teams playing as Radiant having a slight advantage over the team playing as Dire, a well-documented disparity that is generally known by *Dota 2* players. In our dataset of 47 games, 25 out of 47 games (53.2%)[35] were won by the Radiant faction. While not statistically significant given our small sample size, we have decided to still account for the faction each player played as in each game given that this anomaly is extremely well-documented in the game literature.

5.2.3.2 Skill

We also included a player level control variable as a proxy for skill: $years\_pro_{it}$, the number of years a player has played professionally, starting from his first professional tournament game up to the point in which he plays in the current tournament. Controlling for skill levels among players is important because there is a positive correlation between skill level and one's likelihood of winning, all else being equal. The most common skill measure used in

[34] Like two sides of a tennis court, the *Dota 2* map is divided into two halves, each associated with a faction. The Radiant faction is on the bottom-left side of the map, while the Dire faction is on the top-right side of the map. For more information on factions please refer to Appendix A.
[35] *p-value* = 0.385 using binomial test $P(X \geq 25)$

Dota 2 is a player's individual Matchmaking Rating (MMR), a measure that uses the Elo rating system like what is done in chess. This paper has chosen not to use MMR as a proxy for skill due to the lack of MMR data for players that are accessible, both cross-sectional and over time. Therefore, we chose to use another proxy for skill that is much more accessible for our use.

5.2.4 Fixed effects variable

Lastly, we include a vector of dummy variables DT, where each variable is a dummy variable for each team in our sample. The team dummy variable controls for any unobserved differences that result from players being in a different team: different resources available, team culture, team roster, etc. Since we are using data from a single TI, the team composition remains constant over all the games played. In theory, controlling for player heterogeneity using player dummy variables is necessary to account for multiple variables that remain fixed for a player such as position played and nationality. However, using player dummy variables to run our model resulted in every player dummy variable having extremely large coefficients; being a specific player highly influences one's win rate. This offers little to our analysis. A compromise was therefore made, and team dummy variables were used instead, resulting in much more manageable coefficients that did not take away too much from the rest of our analysis.

6. Hypotheses and Models

Our paper aims to explore the relationship between performance, extrinsic incentives, and intrinsic motivation within the context of an e-sports tournament. Based on knowledge from existing literature and understanding of the e-sports industry, we crafted three specific hypotheses we would be testing using four different models.

6.1 Hypotheses

Our hypotheses are as follows:

H1: Both extrinsic incentives and intrinsic motivation have a positive effect on probability of winning in a tournament, all else being equal

H2: Crowding-in effect occurs in e-sports tournaments

H3: Lower skilled players are more risk-seeking than higher skilled players

Hypothesis 1 is essentially the summary of tournament theory and motivational studies. When considered individually, increases in extrinsic incentives or intrinsic motivation makes one more willing to exert effort to perform, thereby increasing one's probability of winning.

Hypothesis 2 is the opposite of what readers might have expected. While most observations of crowding effects have been those of crowding-out, we believe that in the context of e-sports, given its nascency, crowding-in is more likely to occur. Current e-sport athletes could not have possibly imagined that their "hobby" of playing video games becoming an actual career path, and are more likely to see tournament winnings as better enabling them to pursue their interests, resulting in crowding-in. As the industry develops and the career paths of e-sport athletes become more mainstream, there may be a shift in mindsets of these athletes to think of it simply as another job, and we may see a shift towards crowding-out instead.

Hypothesis 3, while not directly related to intrinsic motivation per se, acts like a check against different levels of risk-taking due to different skill levels among players. Previous research has shown that lower skilled players are more likely to take risks than higher skilled players and respond to larger prize spreads more (Knoeber & Thurman, 1994; Melton & Zorn, 2000b). Hypothesis 3 therefore tests this claim again.

6.2 Models

A total of four models were run, each with and without the team fixed effects[36]. For models run with team fixed effects, no constant was prescribed. In all our models, the subscripts *i* refers to each player, *k* refers to each game, and *N* refers to the total number of players in the sample.

Our base model (Model I) is as follows:

$$win\_loss_{ik} = \beta_1 spread\_z_k + \beta_2 total\_pool\_z_k + \beta_3 ratio\_noncomp_i + \beta_4 is\_radiant_{ik}$$

$$+ \beta_5 years\_pro_i + (\beta_0\ OR \sum_{i=1}^{N} TP_i) + error$$

Extrinsic incentives in the tournament is captured by $spread_k$ and $total\_pool_k$. Intrinsic motivation is captured by $ratio\_noncomp_i$. Controls $is\_radiant_{ik}$ and $years\_pro_i$ account for map imbalance and skill respectively. Depending on whether we are running fixed effects, the constant is either removed or included. This model allows us to examine Hypothesis I at face value, before introducing any interaction variables in the subsequent models.

Building upon our base model, we developed Model II, where we accounted for tournament structure (extrinsic incentives provided by tournament) by adding an interaction variable between $spread_k$ and $total\_pool_k$. Model II is as follows:

$$win\_loss_{ik} = \beta_1 spread\_z_k + \beta_2 total\_pool\_z_k + \beta_3 ratio\_noncomp_i + \beta_4 is\_radiant_{ik}$$

$$+ \beta_5 years\_pro_i + \beta_6 spread\_z_k * total\_pool\_z_k + (\beta_0\ OR \sum_{i=1}^{N} TP_i) + error$$

By including the interaction between $spread\_z_k$ and $total\_pool\_z_k$, we account for the possibility that the interaction between prize spread and total prize pool affects players'

[36] Running a model using team fixed effects caused 20 observations to be dropped, as they perfectly predict win_loss_{ik}. These observations are from the 20 players from 4 teams who only played a single game in the TI8 main event and lost in Lower Bracket Round 1.

incentives for tournament structure. As we will see in the next section, including this interaction variable increases the goodness of fit of our model.

Building upon Model II, Model III includes an interaction between our tournament structure variable $spread_k$ and our intrinsic motivation variable $ratio\_noncomp_i$. This tells us which crowding effect (out or in) is in play. Model III is as follows:

$$\begin{aligned} win\_loss_{ik} = {} & \beta_1 spread\_z_k + \beta_2 total\_pool\_z_k + \beta_3 ratio\_noncomp_i + \beta_4 is\_radiant_{ik} \\ & + \beta_5 years\_pro_i + \beta_6 spread\_z_k * total\_pool\_z_k + \beta_7 spread\_z_k \\ & * ratio\_noncomp_i + (\beta_0\ OR \sum_{i=1}^{N} TP_i) + error \end{aligned}$$

We chose not to include an interaction between our other tournament structure variable, $total\_pool\_z_k$, for two reasons. Firstly, tournament theory's original model clearly specifies that it is the spread between the rank prizes that motivates agents to perform and not the size of the prizes themselves. To stay true to that model, we picked $spread\_z_k$ over $total\_pool\_z_k$ Secondly, running a model with both interaction terms ($spread\_z_k * ratio\_noncomp_i$ and $total\_pool\_z_k * ratio\_noncomp_i$) causes the correlation coefficient between the main variables and interaction variables to become exceedingly high (absolute value over 0.8). To minimise collinearity, we therefore chose to only run the interaction between $spread_k$ and $ratio\_noncomp_i$. This model allows us to examine Hypothesis 2.

Model IV includes an interaction between $spread_k$ and $years\_pro_i$, our measure of skill. This allows us to examine and isolate the effects of different risk appetites among players. Model IV is as follows:

$$win\_loss_{ik} = \beta_1 spread\_z_k + \beta_2 total\_pool\_z_k + \beta_3 ratio\_noncomp_i + \beta_4 is\_radiant_{ik} + \beta_5 years\_pro_i + \beta_6 spread\_z_k * total\_pool\_z_k + \beta_7 spread\_z_k * ratio\_noncomp_i + \beta_8 spread\_z_k * years\_pro_i + (\beta_0 \ OR \sum_{i=1}^{N} TP_i) + error$$

The inclusion of this interaction variable not only allows us to examine Hypothesis 3, but also allows us to control for different risk appetites among players of different skills.

7. Results and Discussion

Results of the regressions are shown below. More information about the regressions, such as summary statistics of the variables and predicted effects, are included in Appendix C.

Below are the regression results for the first two models. All coefficients reported have already been converted to odds ratios for easier interpretation.

Variables	**(1) Model I no FE**	**(2) Model I FE**	**(3) Model II: Extrinsic Incentives Interaction no FE**	**(4) Model II: Extrinsic Incentives Interaction FE**
$spread\_z_k$	0.7183*	0.6135***	0.9901	0.4336*
	(0.1232)	(0.1144)	(0.2315)	(0.1432)
$total\_pool\_z_k$	1.8000***	0.3525***	1.5867	0.3314***
	(0.3298)	(0.1158)	(0.3040)	(0.1077)
$ratio\_noncomp_i$	1.0964	1.0000	1.1231	1.0000
	(0.3873)	(0.4008)	(0.3986)	(0.4026)
$is\_radiant_{ik}$	1.2358	1.4095	1.2561	1.4404*
	(0.2318)	(0.3008)	(0.2369)	(0.3090)
$years\_pro_i$	1.0509	1.0000	1.0272	1.0000
	(0.1147)	(0.1334)	(0.1133)	(0.1329)
$spread\_z_k$	[N/A]	[N/A]	0.6552**	1.5132
$* total\_pool\_z_k$	[N/A]	[N/A]	(0.1400)	(0.4862)
$spread\_z_k$	[N/A]	[N/A]	[N/A]	[N/A]
$* ratio\_noncomp_i$	[N/A]	[N/A]	[N/A]	[N/A]
$spread\_z_k$	[N/A]	[N/A]	[N/A]	[N/A]
$* years\_pro_i$	[N/A]	[N/A]	[N/A]	[N/A]
$constant$	0.6553	[N/A]	0.8406	[N/A]
	(0.4638)	[N/A]	(0.6066)	[N/A]
Team Fixed Effects	No	Yes	No	Yes
Observations	470	450	470	450
Pseudo R^2	0.0204	[N/A]	0.0265	[N/A]
χ^2 statistic (df)	13.27 (5)	45.72 (17)	17.29 (6)	46.10 (18)
p-value	0.0210	0.0002	0.0083	0.0003
Log Likelihood	-319.14	-282.79	-317.14	-281.96

Standard Errors in Parentheses
*** p<0.01, ** p<0.05, *p<0.1

Table 4
Regressions Results for Models I and II

7.1 Model I

One of our first observations of regressions (1) and (2) is that, contrary to what tournament theory prescribes, the odds ratio for $spread\_z_k$ are less than 1. This implies that as the prize spread of the tournament increased, performance in these tournaments decreased. Both these coefficients are statistically significant in the opposite direction as we would expect them to have, with the coefficient in the fixed effects model statistically significant at 1% level of significance. The fact that including team fixed effects resulted in the odds ratio for $spread\_z_k$ to fall and also become more significant suggests that there may be omitted variables in Model I whose effects are being captured by the inclusion of team fixed effects. The inclusion of team fixed effects also lowers the p-value of the model, suggesting a better fit[37]. There are a couple of reasons why this is the case. Firstly, it may be due to the lack of a variable that captures skill level well enough. We had to use $years\_pro_i$, an easily obtainable statistic, as a proxy for skill level due to MMR being unavailable. It is extremely likely that $years\_pro_i$ does not fully capture the skill level of a player, leaving much to be captured by team fixed effects. Secondly, it may simply be a case of insufficient data points. Because of the specifications of our model, our dataset is restricted to 470 maximum observations from a single TI tournament. This is an unfortunate reality that cannot be overcome unless the whole model is re-specified.

The second observation we make is that the odds ratio for $total\_pool\_z_k$ are > 1 in the model with no fixed effects and <1 in the model with fixed effects. Before examining the direction and magnitude of this odds ratio, one key thing to note is that in both models, the odds ratio is statistically significantly different from 1 at 1% level of significance. This is at odds with what tournament theory prescribes, which is that the size of the prizes should not have an impact

[37] Due to the fixed effects models having no constant (the FE themselves act as constants), there is no pseudo R^2 value for models running fixed effects. We therefore compare models' goodness of fit using their χ^2 statistic.

on agents' decisions to perform. However, as we have seen from past literature, the point on whether total prize pool affects agents' decision-making is contentious, with academics arguing both for (Rosen, 1986; Ehrenberg & Bognanno, 1990a; Ehrenberg & Bognanno; 1990b) and against (Lazear & Rosen, 1981; Becker & Huselid, 1992; Knoeber & Thurman, 1994; Connelly, Tihanyi, Crook, & Gangloff, 2014). Our results therefore suggest that perhaps total prize pool is not as inconsequential as previously thought. We also see that the odds ratio for $total\_pool\_z_k$ changes from >1 to <1 when team fixed effects are included. It suggests that when controlling for teams, players are more likely to lose when the total prize pool is higher. The total prize pool is generally higher in later stages of the tournament, where one is more likely to meet a more skilled team or players. Therefore, one may be more likely to lose when the total prize pool is higher simply because it is more likely that one's opponent is more skilled in a later round. In the absence of the team fixed effects, the odds ratio for $total\_pool\_z_k$ does suggest that having a larger prize pool results in agents performing better, in line with the incentive effects that tournaments are supposed to provide. However, caution must be exercised when interpreting this result, as there is a high possibility that these results suffer from the omitted variable bias.

The odds ratios of rest of the variables in Model I ($ratio\_noncomp_i$, $is\_radiant_{ik}$, and $years\_pro_i$) are all within expectation in terms of direction, although none of them are statistically significant. Again, this can be attributed to insufficient data points available. In the team fixed effects model, both the odds ratios for $ratio\_noncomp_i$ and $years\_pro_i$ are 1.0000, suggesting that they both have little to no bearing on win probability. The combination of a low sample size and imperfect skill proxy is likely still the culprits. This speaks to one of the key issues of using e-sports data in research: when there is missing data (in our case, a skill proxy like MMR), the whole column will be missing, and one has to resort to imperfect proxies.

7.2 Model II

The inclusion of an interaction variable between $spread\_z_k$ and $total\_pool\_z_k$ significantly improves the goodness of fit for Model II over Model I; the p-value for the regression in the case of no fixed effects falls from 0.0210 to 0.0083. The odds ratio for $spread\_z_k * total\_pool\_z_k$ is <1 (statistically significant at 5% level of significance) in the no fixed effects model, implying that the effect of $total\_pool\_z_k$ on performance is lower when $spread\_z_k$ is higher. This seems to suggest that $spread\_z_k$ is still the first thing players consider when thinking about tournament extrinsic incentives. It is only when $spread\_z_k$ is low that players consider $total\_pool\_z_k$ more.

What is harder to explain is the <1 odds ratio of $spread\_z_k$. In the fixed effects model, the odds ratio of $spread_z_k$is 0.4336, significant at 10% level of significance. This is further suggestion that there is an omitted variable in Models I and II which is causing $spread\_z_k$ to fall and become more significant when team fixed effects are introduced.

Similar to Model I, the odds ratio for $total\_pool\_z_k$ flips from >1 to <1 upon the introduction of team fixed effects. We can therefore draw similar conclusions from this as we have done with Model I. Other similarities Models I and II share are that the rest of the variables all have odds ratios that are within expectations in terms of direction, and that the odds ratios for $ratio\_noncomp_i$ and $years\_pro_i$ are 1.0000 in the fixed effects model. Again this points to the problem of having too small a sample size and imperfect proxies for skill, further highlighting some of the potential challenges in using an e-sports dataset where few researchers have experiences with.

Thus far, we are unable to reject the null hypothesis of Hypothesis 1. Models I and II have thus far been inconclusive on the effects of tournament extrinsic incentives and intrinsic motivation, although the direction of the odds ratios does at least suggest that intrinsic motivation is positively correlated with performance in a tournament.

Variables	(5) **Model III: Crowding Effect Interaction No FE**	(6) **Model III: Crowding Effect Interaction FE**	(7) **Model IV: Skill Interaction no FE**	(8) **Model IV: Skill Interaction FE**
$spread\_z_k$	0.8813 (0.3420)	0.4022** (0.1803)	1.2965 (1.1822)	0.4601 (0.4391)
$total\_pool\_z_k$	1.5835** (0.3037)	0.3142*** (0.1080)	1.5757** (0.3028)	0.3143*** (0.1081)
$ratio\_noncomp_i$	1.1280 (0.4004)	0.9970 (0.4018)	1.1256 (0.3999)	0.9995 (0.4032)
$is\_radiant_{ik}$	1.2579 (0.2373)	1.439* (0.3087)	1.2573 (0.2373)	1.4386 (0.3086)
$years\_pro_i$	1.0291 (0.1136)	1.0014 (0.1332)	1.0321 (0.1143)	1.0053 (0.1359)
$spread\_z_k * total\_pool\_z_k$	0.6488** (0.1398)	1.4990 (0.4851)	0.6468** (0.1397)	1.4959 (0.4846)
$spread\_z_k * ratio\_noncomp_i$	1.1865 (0.5367)	1.1208 (0.5125)	1.0719 (0.5381)	1.0829 (0.5470)
$spread\_z_k * years\_pro_i$	[N/A] [N/A]	[N/A] [N/A]	0.9414 (0.1214)	0.9791 (0.1291)
$constant$	0.8315 (0.6003)	[N/A] [N/A]	0.8236 (0.5957)	[N/A] [N/A]
Team Fixed Effects	No	Yes	No	Yes
Observations	470	450	470	450
Pseudo R^2	0.0268	[N/A]	0.0271	[N/A]
χ^2 statistic (df)	17.43 (7)	46.16 (19)	17.65 (8)	46.17 (20)
p-value	0.0148	0.0005	0.0240	0.0008
Log Likelihood	-317.06	-281.93	-316.95	-281.92
Standard Errors in Parentheses *** p<0.01, ** p<0.05, *p<0.1				

Table 5
Regressions Results for Models III and IV

7.3 Model III

From both regressions (5) and (6), we see that the odds ratio for $spread\_z_k * ratio\_noncomp_i$, the crowding interaction variable, is >1. This implies the crowding-in effect; increases in $spread\_z_k$ results in a more than proportionate increase in one's likelihood of winning given one's intrinsic motivation. While not statistically significant, their directionality weakly supports Hypothesis 2.

We still observe that $spread\_z_k$.has an odds ratio of <1, and that the directionality of $total\_pool\_z_k$ flips when team fixed effects are introduced. This again highlights the potential challenges with using e-sports data; the lack of precedence of papers that use e-sports data makes it extremely challenging for researchers to know which variables to control for.

Odds ratios of the other three main effects ($ratio\_noncomp_i$, $is\_radiant_{ik}$, and $years\_pro_i$) are still within expectations in terms of direction, with the exception of $ratio\_noncomp_i$ in the fixed effects model. The introduction of the crowding interaction variable implies that when taken as a whole, intrinsic motivation still has a positive effect on performance. The high standard error on that odds ratio, which is extremely close to 1, also suggests that we should not interpret that odds ratio too strictly.

7.4 Model IV

Model IV weakly supports Hypothesis 3; the <1 odds ratio on the $spread\_z_k * years\_pro_i$ implies that the effect of spread increases on performance is bigger for players who have played for less years professionally. Given that $years\_pro_i$ is our skill measure, this implies that players with lower skills are more motivated by spread increases, suggesting that they are more risk-seeking than higher skilled players. Caution is suggested when interpreting this; previous discussions on $years\_pro_i$ have suggested that it may not be a good skill proxy.

Regression (7) is the only model where $spread\_z_k$ has an odds ratio >1. However, given its large standard error, we are hesitant to draw any conclusions from it. Although $total\_pool\_z_k$ has statistically significant odds ratios in both regressions (7) and (8), the drastic swing in direction when team fixed effects are introduced strongly suggests that it is extremely biased due to omitted variables. Despite having more variable odds ratios that agree with theory, Model IV is not necessarily a better model than Models II and III; its p-value for the regressions is higher than both Models II and III. The introduction of new interaction variables, while necessary for testing our hypotheses, did not improve the goodness of fit.

To summarise our results and conclude: our results are inconclusive over all three hypotheses, although there are weak suggestions that Hypotheses 2 and 3 may hold.

8. Conclusion and Future Directions

This paper attempted to elucidate the relationship between tournament structure as extrinsic incentives and intrinsic motivation using an e-sports dataset. While the results are inconclusive, the methodology used suggests that future research using e-sports datasets are certainly possible and should be encouraged.

Our results weakly suggest that crowding-in occurs in e-sports. This is not surprising; most professional players enjoyed playing the game before they were offered contracts to pursue their hobby professionally. Since crowding-in occurs when the extrinsic incentive is seen as supportive, the case for crowding-in in e-sports can certainly be made.

Extrapolating the weakly conclusive findings of this paper to the broader labour market, if one is able to identify labour markets that are organised as tournaments, then depending on the nature of the work, different types of extrinsic incentives should be offered depending on whether the industry will view it as controlling or supportive. In the context of e-sports, tournament prize money triggers the crowding-in effect due the entertaining nature of games; perhaps it is similar in other entertainment industries such as sports and film. Therefore, if one were a principle in such an industry, it may prove wise to use extrinsic incentives such as bonuses or promotions to motivate one’s employees. On the other hand, if one were a principle in an industry where extrinsic incentives are viewed as controlling, care should be exercised when using extrinsic incentives to motivate employees, as they may backfire.

Within the specific realm of e-sports, this paper has demonstrated that while predicting performance is still a monumental task, the amount and type of data available in e-sports to do so is plentiful. Over time, there will be more of a need for performance measurement and player valuation. Early academic pioneers in e-sports will therefore not only be contributing to their academic fields but also dictate the industry methodology. As more e-sports data become available, the possibilities of using e-sports data to study different problems broaden as well.

Given that the findings of this paper are inconclusive, more work should be done to determine the relationship between tournament theory and motivation crowding theory. We offer two ways we believe our work can be improved on. Firstly, the sample size used can be enlarged to better capture the variation in the available data and make better use of the huge dataset. One can either run the exact same models separately on different TIs or consolidate all observations and run the observations together. The latter may require a change in model specifications; generating a model that places less restrictions on the scale and type of e-sports data that can be used will also contribute to the methodology within the field. Secondly, other variables for intrinsic motivation can be tested to see if they are better proxies for it. Related data such as number of streaming hours on the internet, while less accessible, can also provide insights into the motivations of gamers that are not available purely from game data.

Our hope for this paper's contribution is less of it being a paper with strong theoretical underpinnings but more of it demonstrating the possibilities of using e-sports data in academic research. This paper has exclusively focused on tournament games due to the research question at hand. Future research that does not require a tournament setting can make use of non-tournament games, which broadens the number of games that one can analyse by many factors. With the growth of the e-sports industry and the availability of data, we certainly hope that research using e-sports data becomes a more common phenomenon.

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APPENDIX A – Basic introduction to *Dota 2*

Dota 2 is a massive online battle arena (MOBA) game developed and published by Valve Corporation on their Steam platform. Examples of MOBAs apart from *Dota 2* include *League of Legends*, *Heroes of the Storm*, and *Heroes of Newerth*.

Dota 2 (and MOBA games in general) is characterised by two opposing teams of five players each who wins a game by destroying a structure in their opponents' team's base known as the Ancient. To do so, each player controls a character called a "hero", each with their unique set of abilities and base stats.[38] The bases are located in the top right (Radiant Faction) and bottom left corner (Dire Faction) of a square map; an annotated copy of the map is shown at the end of Appendix A. Three lanes connect the two bases together: a middle lane, a safe lane (Radiant bottom or Dire top) and an offlane (Radiant top or Dire bottom). Running diagonally across the map from the top left to the bottom right is the river that connects the midpoint of all three lanes together. On each faction, each lane has three tiers of "towers", immobile structures that shoots projectiles at enemy forces, dealing damage. There are two extra towers in front of each faction's Ancient. In order to destroy the Ancient, players have to destroy the towers in succession of their tiers before being able to destroy the Ancient. Every 30 seconds, non-player-controlled lane creeps spawn in front of the Tier 3 towers of each lane and move towards the enemy base. These lane creeps attack any non-friendly unit they encounter in their path and killing them grants heroes experience (used to level up and learn new abilities) and gold (used to purchase items to improve stats or gain extra abilities). This process of killing creeps in order to secure experience and gold is known as "farming".

[38] As of the 7.20c patch on 24th November 2018, *Dota 2* has a total of 116 heroes, all of which are allowed in Captain's Mode, the mode that most tournaments use.

Just like in professional sports, there exists a notion of positions, or roles, among the five players. This not only affects their play style in the game but also the potential heroes that they pick to play in a game, since different heroes are suited to different roles. Positions are ranked according to their farm priority. In general, the five positions can be summarised as follows:

Position 1 (Carry): also known as the hard carry, positions 1s are the main damage dealers in the late game and require high amounts of experience and gold

Position 2 (Mid): called "Mid" mainly because this role requires the player to play alone in the mid lane early on in the game (solo-mid), position 2s generally require large amounts of both experience and gold quickly and early in the game

Position 3 (Offlaner / Ganker): positions 3s require less resources than position 2s, and is more experience-dependent than gold-dependent. They are also sometimes known as the "ganker" because their role is to hunt for vulnerable opponents,

Position 4 (Roaming Support): Heroes suited for position 4 are those that have very powerful abilities independent of items. They also frequently join position 3 in ganks.

Position 5 (Lane Support): position 5s is often in charge of purchasing utility items for their team so that their team is able to control as much of the map as possible.

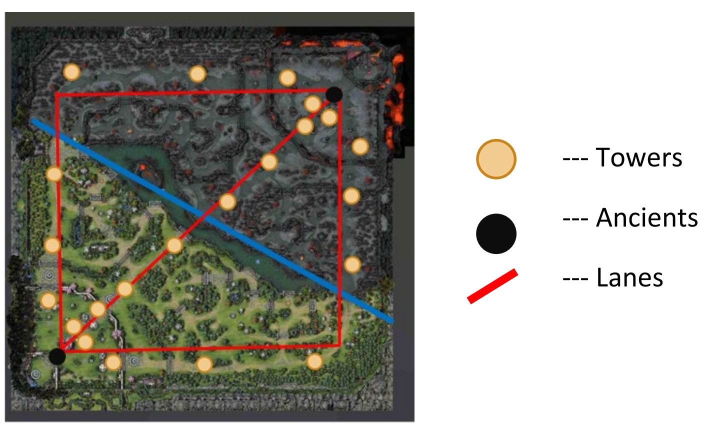


Diagram A1
Annotated map of *Dota 2*

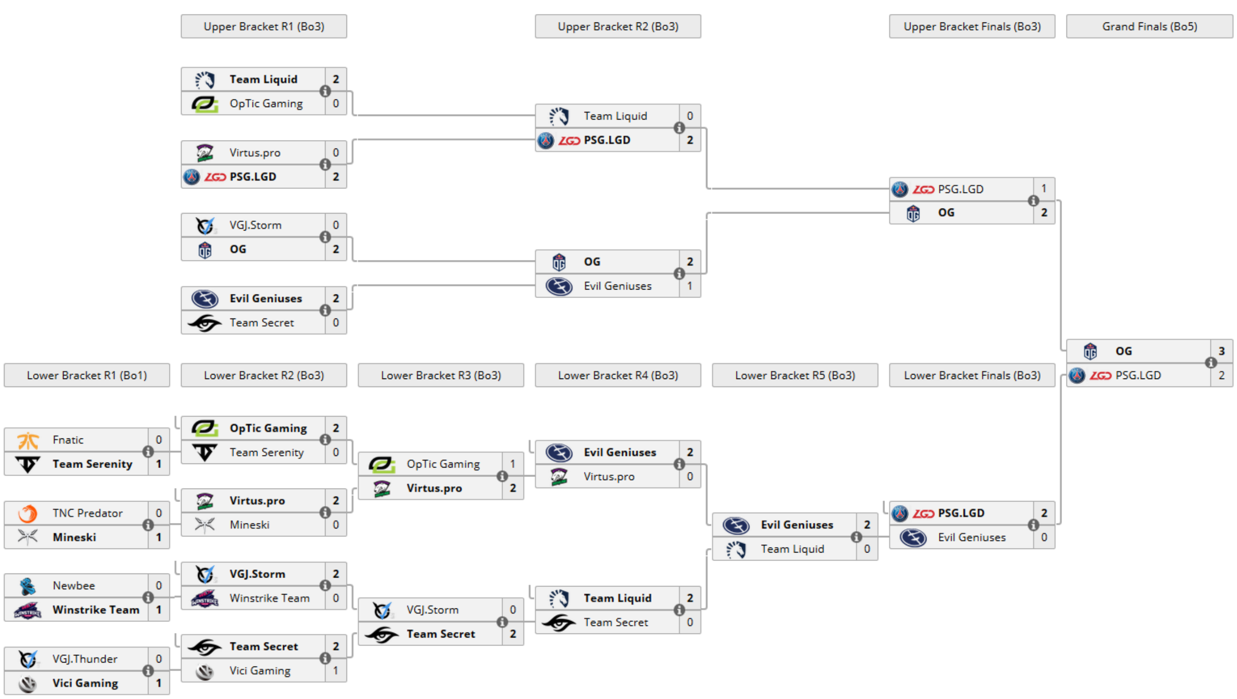
APPENDIX B – Calculation of Expected Payoffs

To further illustrate our process in calculating the expected payoff in each stage of the tournament, we shall demonstrate the process using games from the Grand Finals, Lower Bracket Finals, and Lower Bracket Round 5 of The International 2018:

Place	Prize Amount
1^{st}	$11,234,158
2^{nd}	$4,085,148
3^{rd}	$2,680,879
4^{th}	$1,787,252
5^{th} – 6^{th}	$1,148,948
7^{th} – 8^{th}	$638,304
9^{th} – 12^{th}	$382,983
13^{th} – 16^{th}	$127,661
17^{th} – 18^{th}	$63,830
Total	**$25,532,177**

Table B1
Rank Prize Breakdown for TI8

All other rounds follow the same formula, by working backwards using the expected payoffs from the match that will be played after. The bracket for TI8 is shown below.



B1.1 Grand Finals (GF) – OG vs PSG.LGD

Win Payoff = $payoff_w(GF)$ = 11234158

Lose Payoff = $payoff_l(GF)$ = 4085148

Team	**Win Ratio**	**P(wins opponent)**
OG	9/16 = 0.5625 = p	0.5625/(0.5625+0.6875) = 0.45 = p_{ab}
PSG.LGD	11/16 = 0.6875 = q	0.6875/(0.5625+0.6875) = 0.55 = q_{ba}

Game No.	Prior Round Score (OG – PSG.LGD)	OG		PSG.LGD	
		Win Expected Payoff	Lose Expected Payoff	Win Expected Payoff	Lose Expected Payoff
5	2 – 2	$payoff_w$ = 11,234,158	$payoff_l$ = 4,085,148	$payoff_w$ = 11,234,158	$payoff_l$ = 4,085,148
4	1 – 2	p_{ab}*$payoff_w$ + (1-p_{ab})* $payoff_l$ = 7302202.5	$payoff_l$ = 4,085,148	$payoff_w$ = 11,234,158	q_{ba}*$payoff_w$ + (1-q_{ba}) *$payoff_l$ = 8017103.5
3	1 – 1	$(2p_{ab} - p_{ab}^2) * payoff_w + (1 - 2p_{ab} + p_{ab}^2) * payoff_l$ = 9071582.475	$p_{ab}^2 * payoff_w + (1 - p_{ab}^2) * payoff_l$ = 1447675.525	$(2q_{ba} - q_{ba}^2) * payoff_w + (1 - 2q_{ba} + q_{ba}^2) * payoff_l$ = 9786483.475	$q_{ba}^2 * payoff_w + (1 - q_{ba}^2) * payoff_l$ = 6247723.525
2	1 – 0	$(3p_{ab} - 3p_{ab}^2 + p_{ab}^3) * payoff_w + (1 - 3p_{ab} + 3p_{ab}^2 - p_{ab}^3) * payoff_l$ = 10044741.46	$(3p_{ab}^2 - 2p_{ab}^3) * payoff_w + (1 - 3p_{ab}^2 + 2p_{ab}^3) * payoff_l$ = 7125264.503	$(3q_{ba}^2 - 2q_{ba}^3) * payoff_w + (1 - 3q_{ba}^2 + 2q_{ba}^3) * payoff_l$ = 10044741.46	$(3q_{ba} - 3q_{ba}^2 + q_{ba}^3) * payoff_w + (1 - 3q_{ba} - 3q_{ba}^2 + q_{ba}^3) * payoff_l$ = 7125264.503
1	0 – 0	$(6p_{ab}^2 - 8p_{ab}^3 + 3p_{ab}^4) * payoff_w + (1 - 6p_{ab}^2 + 8p_{ab}^3 - 3p_{ab}^4) * payoff_l$ = 8439029.134	$(4p_{ab}^3 - 3p_{ab}^4) * payoff_w + (1 - 4p_{ab}^3 + 3p_{ab}^4) * payoff_l$ = 5811499.871	$(6q_{ba}^2 - 8q_{ba}^3 + 3q_{ba}^4) * payoff_w + (1 - 6q_{ba}^2 + 8q_{ba}^3 - 3q_{ba}^4) * payoff_l$ = 9507806.129	$(4q_{ba}^3 - 3q_{ba}^4) * payoff_w + (1 - 4q_{ba}^3 + 3q_{ba}^4) * payoff_l$ = 6880276.866

Expected payoffs are calculated by assuming that the team wins / loses the current game. For example, the Win Expected Payoff for OG in Game 4 is calculated using the win and lose payoffs for the Grand Finals and the probability that he will win the match given the score is 2 – 2 (we assume OG wins this current game). Formulas for the probability that a team will win the current match given the current score is shown in Table 3 of the page 29.

B1.2 Lower Bracket Final (LBF) – PSG.LGD vs Evil Geniuses

Win Payoff = $payoff_w(LBF)$ = $(10p^3 - 15p^4 + 6p^5)* payoff_w(GF)$

$+ (1 - 10p^3 + 15p^4 - 6p^5)* payoff_l(GF)$

Lose Payoff = $payoff_l(LBF)$ = 2680879

Team	Win Ratio	P(wins opponent)
PSG.LGD	11/16 = 0.6875 = p	0.6875/(0.6875+0.8125) = 0.4584 = p_{ab}
Evil Geniuses	13/16 = 0.8125 = q	0.8125/(0.6875+0.8125) = 0.5417 = q_{ba}

Game No.	Prior Round Score (PSG.LGD – Evil Geniuses)	PSG.LGD		Evil Geniuses	
		Win Expected Payoff	Lose Expected Payoff	Win Expected Payoff	Lose Expected Payoff
2	1 – 0	$payoff_w$ = 7103716.931	p_{ab} $* payoff_w$ $+ (1 - p_{ab})$ $* payoff_l$ = 4708013.052	q_{ba} $* payoff_w$ $+ (1 - q_{ba})$ $* payoff_l$ = 5678846.954	$payoff_l$ =2680879
1	0 – 0	$(2p_{ab} - p_{ab}^2)$ * $payoff_w$ $+ (1 - 2p_{ab} + p_{ab}^2)$ $payoff_l$ = 5806043.996	$p_{ab}^2 * payoff_w$ $+ (1 - p_{ab}^2)$ $* payoff_l$ = 3609982.107	$(2q_{ba} - q_{ba}^2)$ * $payoff_w$ $+ (1 - 2q_{ba} + q_{ba}^2)$ $payoff_l$ = 7052915.6	$q_{ba}^2 * payoff_w$ $+ (1 - q_{ba}^2)$ $* payoff_l$ = 4304778.308

B1.3 Lower Bracket Round 5 (LBR5) – Evil Geniuses vs Team Liquid

Win Payoff = $payoff_w(LBR5)$ = $(3p^2 - 2p^3)* payoff_w(LBF)$

$+ (1 - 3p^2 + 2p^3)* payoff_l(LBF)$

Lose Payoff = $payoff_l(LBR5)$ = 1787252

Team	Win Ratio	P(wins opponent)
Evil Geniuses	13/16 = 0.8125 = p	0.8125/(0.8125+0.8125) = 0.5 = p_{ab}
Team Liquid	13/16 = 0.8125 = q	0.8125/(0.8125+0.8125) = 0.5 = q_{ba}

Game No.	Prior Round Score (PSG.LGD – Evil Geniuses)	Evil Geniuses		Team Liquid	
		Win Expected Payoff	Lose Expected Payoff	Win Expected Payoff	Lose Expected Payoff
2	1 – 0	$payoff_w$ = 5170266	p_{ab} $* payoff_w$ $+ (1 - p_{ab})$ $* payoff_l$ = 3478759	q_{ba} $* payoff_w$ $+ (1 - q_{ba})$ $* payoff_l$ = 3478759	$payoff_l$ = 1787252
1	0 – 0	$(2p_{ab} - p_{ab}^2)$ * $payoff_w$ $+ (1 - 2p_{ab} + p_{ab}^2)$ $payoff_l$ = 4324512.5	$p_{ab}^2 * payoff_w$ $+ (1 - p_{ab}^2)$ $* payoff_l$ = 2633005.5	$(2q_{ba} - q_{ba}^2)$ * $payoff_w$ $+ (1 - 2q_{ba} + q_{ba}^2)$ $payoff_l$ = 4324512.5	$q_{ba}^2 * payoff_w$ $+ (1 - q_{ba}^2)$ $* payoff_l$ = 2633005.5

The win and lose payoff for each match is calculated using the payoffs in the subsequent rounds.

APPENDIX C –Summary Tables

Category	Count
Observations (n)	470
Games (k)	47
Players (i)	80
Teams	16

Table C1
Breakdown of Total Observations

Variable	Expected Direction	Hypothesis
$spread\_z_k$	>1	Larger prize spread encourages performance
$total\_pool\_z_k$	≥1	Prize pool should have zero effect on performance; if there is an effect it should be positive
$ratio\_noncomp_i$	>1	Players with higher levels of intrinsic motivation should perform better
$is\_radiant$	>1	Playing on the Radiant faction increases odds of winning
$years\_pro$	>1	Higher skill / experience increases odds of winning
$spread\_z_k * total\_pool_k$	≤1	Prize pool should have zero effect on performance; if there is an effect it should weaken the effect of prize spread
$spread\_z_k * ratio\_noncomp_i$	>1	Crowding-in effect
$spread\_z_k * years\_pro_i$	<1	Lower skilled players should prefer higher spread to compensate for risk-taking

Table C2
Predicted Effects

Variable	N	mean	sd	min	max
win_loss_{ik}	470	0.5	0.5005	0	1
$spread\_z_k$	470	-0.1450 (median)	0.7602	-0.9497	3.3205
$total\_pool\_z_k$	470	-0.1392 (median)	0.7205	-0.8717	1.8907
$ratio\_noncomp_i$	470	0.6812	0.2893	0.0279	0.9601
$is\_radiant_{ik}$	470	0.5	0.5005	0	1
$years\_pro_i$	470	5.1638	0.9400	3	6

Table C3
Summary Statistics of Variables

	$spread\_z_k$	$total\_pool\_z_k$	$ratio\_noncomp_i$	$is\_radiant_{ik}$	$years\_pro_i$
$spread\_z_k$	1.0000				
$total\_pool\_z_k$	0.6826	1.0000			
$ratio\_noncomp_i$	0.0314	0.0604	1.0000		
$is\_radiant_{ik}$	0.0338	0.0761	0.0016	1.0000	
$years\_pro_i$	0.0575	0.0646	-0.3911	0.0159	1.0000

Table C4
Correlation Matrix of Main Effects