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Does the Tendency of Loss Aversion Depend On The Level of Competition? Evidence From Multilevel Esports Tournaments

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DOES THE TENDENCY OF LOSS AVERSION DEPEND ON THE LEVEL OF COMPETITION? EVIDENCE FROM MULTI-LEVEL ESPORTS TOURNAMENTS

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DEDICATION

This dissertation is dedicated to my loving parents, Zhixin and Oujuan, for their unwavering support.

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ABSTRACT

This dissertation investigates the relationships between the level of experience, the magnitude of payoffs, and the significance of loss aversion within the context of esports. In the behavioral economics literature, loss aversion describes why individuals prefer avoiding losses to obtaining equivalent gains depending on a reference point. While previous studies predominantly capitalize on experimental methods to examine how the significance of loss aversion is affected by market experience and payoff magnitude, there is also a growing body of research that examines the behavioral properties of loss aversion outside laboratory environments, with sport being one of the most utilized settings. This is primarily because sporting data are abundant, naturally occurring, and well recorded. As such, the current dissertation is focused on the context of esports, namely, *Dota 2*, which has high-quality data at all levels of competition. Based on well-defined gain and loss domains as well as a risk-averse behavior, survival analysis is employed to analyze whether trailing behind significantly decreases the probability of adopting the less risky solution. The results of this dissertation reveal that individuals have a consistent propensity to avoid losses. Further analysis indicates that experience does not significantly impact the loss aversion tendency, which supports the relevant studies in the literature. However, the magnitude of payoffs has a mitigating effect on the salience of loss aversion, which is radically different from previous findings.

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CHAPTER 1

INTRODUCTION

In the field of sports economics, there is a growing body of literature that incorporates the theories and predictions of behavioral economics into the investigation of the decision biases of stakeholders in the sports industry (Coates & Humphreys, 2018). Particularly, the examination of loss aversion is one of the most frequently discussed topics (Coates, Humphreys, & Zhou, 2014; Humphreys & Pérez, 2019; Pope & Schweitzer, 2011). Researchers are interested in examining loss aversion within the sporting context mostly because the sport industry provides a natural context for behavioral economists to empirically test the related theoretical hypotheses, such as whether ex-ante expectations can function as the reference point (Bartling, Brandes, & Schunk, 2015), and whether goal setting influences individuals' effort adjustment (Allen, Dechow, Pope, & Wu, 2017).

Specifically, loss aversion is a rigorously theorized and widely documented psychological phenomenon that depicts human's systematic and reference-dependent bias regarding risk when making decisions under uncertainty. That is, given a neutral reference point, individuals become more receptive to risk-taking when they foresee losses relative to the reference point, but avoid risky solutions if they anticipate favorable outcomes. The core tenets of loss aversion were originally coined and formalized by Kahneman and Tversky (1979) and Tversky and Kahneman (1991, 1992) in a series of seminal papers developing and expanding prospect theory, which radically converted the landscape of neoclassical economics (Barberis, 2013). To be precise, the rationality principle of neoclassical economics assumes people display stable risk preferences that are immune to any emotional influences, and thus they are always making rational decisions consistent with those preferences. In contrast, prospect theory notes that people exhibit internalized biases that repeatedly lead to inconsistent behaviors in a highly predictable manner because they respond more strongly to losses than to equivalent gains.

Grounded on this unconventional insight into human behaviors, an increasing number of applications of prospect theory help explain some previously puzzling phenomena, such as why investors prefer to sell assets that have increased in value but keep assets that have dropped in value (i.e., the disposition effect, see Shefrin & Statman, 1985; Weber & Camerer, 1998), and why people are inclined to evaluate an owned object higher than the same object when they do not own it (i.e., the endowment effect, see Kahneman, Knetsch, & Thaler, 1990, 1991). Meanwhile, from both laboratory and field settings, researchers have also obtained a plethora of empirical evidence that corroborates the theory's validity in various areas, including consumer utility (Kőszegi & Rabin, 2006, 2007), labor supply (Camerer, Babcock, Loewenstein, & Thaler, 1997; Crawford & Meng, 2011), healthcare (Rice, 2013), as well as sports performance (Brown, 2011; Pope & Schweitzer, 2011).

However, a considerable proportion of research centering around behavioral anomalies predominantly relies on observations from laboratory experiments, which might fail to capture the properties of real markets and thus compromise the credibility of those findings to a great extent (Levitt & List, 2008). For example, choice experiments designed for capturing the tendency or degree of loss aversion typically use either hypothetical payoffs (Erev, Ert, & Yechiam, 2008; Kahneman & Tversky, 1979; Thaler, Tversky, Kahneman, & Schwartz, 1997) or real ones that are small in terms of magnitude (Holt & Laury, 2002), limiting their ability to examine loss aversion with real and/or large stakes. Moreover, researchers cast doubt on the laboratory findings for other reasons as well, such as that the stakes involved do not materially impact the wealth level or circumstances of participants (Gal & Rucker, 2018) and that market experience cannot be quickly accumulated in a laboratory environment (List, 2011). As such, the further examination of loss aversion calls for more attention to real-world observations.

The context of sport, unlike laboratory settings, is often typified by natural experiments, in which individuals make decisions without interference from the investigators (Dunning, 2012). Additionally, this context enables certain conditions that are barely achievable within the laboratory environment, such as real and large prize money of varying sizes awarded to tournament winners (Brown & Minor, 2014; Ehrenberg & Bognanno, 1990), and perceived skill differences or winning probabilities that can be quantified based on pre-game betting odds (Brown, 2011; Ge, 2018). Another important advantage of investigating loss aversion in sports is the wealth and granularity of behavioral data available for large-scale research purposes. For example, Card and Dahl (2011) leveraged domestic violence data from more than 750 police agencies in the US to study sports consumer behavior, and Bartling et al. (2015) used a data set containing over 8,200 professional soccer matches on a minute-by-minute basis in their analysis of athletes and coaches' risk-taking. Hence, there is a burgeoning volume of research that capitalizes on field data in the sports industry to examine the presence and significance of loss aversion amongst sports stakeholders such as athletes, consumers, managers, coaches, and referees, as well as the related hypotheses (Coates & Humphreys, 2018).

Notably, a cohort of researchers is particularly interested in examining whether market experience would attenuate the significance of loss aversion. This line of research starts from List's (2003, 2004) findings based on observing trading patterns about sports card transactions that participants' inclination of loss aversion can be eliminated by their increased market experience. While there is an increasing number of studies replicating List's (2003, 2004) experience results, they are predominantly focused on behaviors associated with financial investment (Dhar & Zhu, 2006; Feng & Seasholes, 2005; Greenwood & Nagel, 2009) and item swapping (Engelmann & Hollard, 2010; Seru, Shumway, & Stoffman, 2010), where individuals are typically assumed to maximize their personal wealth. Sporting performance differs from those areas in the sense that non-economic factors such as win and loss also play an important role in forming the reference point. Therefore, robust empirical evidence beyond economic decision-making can be obtained by examining loss aversion in sport. Interestingly, Pope and Schweitzer (2011) provided counterevidence against List's (2003, 2004) argument and asserted that loss aversion persists even among the most experienced golfers such as Tiger Woods, based on observations from professional golf tournaments. Likewise, Bartling et al. (2015) found evidence supporting that loss aversion prevails among professional soccer players and coaches with field data from the German Bundesliga and the English Premier League.

It is worth noting, however, that studies examining players' on-field loss aversion propensity are overly restricted to observations surrounding top-performing groups of athletes while overlooking those from relatively less competitive groups. Assuming experience is positively correlated with the level of competition (Pope & Schweitzer, 2011), it is still inadequate to assert that increased experience cannot mitigate the significance of loss aversion. If less experienced groups do not display a tendency to avoid potential losses at all, then it would be more proper to state that experience intensifies loss aversion when experienced players are found to be disproportionately averse to losses, or that experience has no significant impact on the tendency of loss aversion when evidence does not support this tendency amongst experienced players. Therefore, a void exists in this research area calling for juxtaposing behavioral observations from different levels of competition in one study. To fill this gap, the current dissertation aims to examine how the degree of loss aversion changes with the level of competition.

Although examining the degree of loss aversion at multiple levels of competition can be conducive to generating insights into the relationship between experience and loss aversion, a potential confounding factor worth attention is the magnitude of payoffs in that highly competitive sports contests are usually characterized by substantial stakes (Pope & Schweitzer, 2011). Interestingly, experimental studies in the behavioral economics literature document the significance of loss aversion increases with the magnitude of payoffs or stakes (Erev et al., 2008; Ert & Erev, 2013; Mukherjee, Sahay, Pammi, & Srinivasan, 2017). Most of the findings in this direction of research indicate loss aversion is only observable at large magnitudes but not at small ones. However, as mentioned above, those experimental studies typically use either hypothetical or real but small payoffs, which might compromise their credibility and generalizability (Levitt & List, 2008). In fact, competitions are so common in daily life that people take part all the time, such as applications for college admissions, promotions, bonuses, elections, as well as sports games. On such occasions, contestants who have different risk preferences and face rewards of varied sizes usually adjust their effort to improve their prospects of favorable outcomes while minimizing the prospects of unintended results (Gill & Prowse, 2012). Therefore, to examine whether loss aversion is magnitude-dependent using data from real-world competitions can help expand the scope of research on this topic.

1.1 PRACTICAL BACKGROUND

1.1.1 ESPORTS

Though it is a newly emerging form of activity, esports has gained worldwide popularity, with the 2020 global audience estimated to exceed 485 million in (Gough, 2020). According to Hamari and Sjöblom (2017, p. 213), esports is defined as “a form of sports where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams as well as the output of the eSports system are mediated by human-computer interfaces.” Their definition underscores the enormous reliance of esports gaming on the facilitation of electronic devices (e.g., computers, smartphones, or consoles) for players to exert influence on the game via a constant stream of human inputs. There are multiple categories of esports genres, such as multiplayer online battle arena (MOBA), first-person shooter, and real-time strategy. Based on the total size of prizes in related tournaments (Esports Earnings, 2020), the top five esports games as of 2021 are *Dota 2*, *Counter-Strike: Global Offensive*, *Fortnite*, *League of Legends*, and *StarCraft II*. As noted by Coates and Parshakov (2016), the esports context provides good data for investigating human decision-making in a highly competitive environment.

1.1.2 *Dota 2* GAMEPLAY

Dota 2 is a MOBA-style video game developed and published by Valve Corporation. The gameplay of *Dota 2* occurs when two teams of five players, each in control of a drafted hero (avatar) with different abilities and tactical roles, battle on a specified map consisting of three main lanes and a certain number of neutral areas. Akin to role-playing games, *Dota 2* heroes accumulate Experience Points (XP) and Gold throughout the game by engaging in a series of in-game activities (e.g., farming and killing). While XPs are earned for leveling up through which the heroes' abilities can be unlocked or upgraded, Gold is exchangeable for items that provide different functions. Both enhancements improve the combat ability and tactical flexibility of the heroes. The ultimate objective for winning the game is to destroy the opposing team's main structure (i.e., the "Ancient") located deep in the heart of its home base with the assistance of periodically spawned, automatically controlled, and conditionally reinforced units (e.g., minions or creeps) that march forward along the three set paths.

While *Dota 2* is known as a team competition esports game, its gameplay contains both team and individual decision-making. Specifically, *Dota 2* tournaments, despite the level of competition, typically adopt the so-called Captains Mode[1] for drafting heroes, in which two team captains are responsible for banning unwanted heroes and picking wanted heroes in turn from a random pool. Each captain is given 30 seconds for making a pick and 35 seconds for selecting a ban. Although the term Captains Mode seems to suggest this ban-and-pick procedure is solely undertaken by captains, team members usually participate in selecting heroes both familiar to them and compatible with team strategies. Therefore, the drafting stage essentially represents a team decision-making

[1] https://liquipedia.net/dota2/Game_Modes

process. On the other hand, after the match starts, *Dota 2* players tend to make in-game decisions, such as which items to buy, more on an individual basis considering the fast-paced gameplay. Provided players are allowed to communicate in real-time throughout the match, they typically do so when asking for assistance from teammates or warning about a missing enemy. Purchase decision-making in the game involves mental processes that are more complicated than simply sending signals because players are required to evaluate and predict the trend of the match and then buy items to be most effective in increasing the winning probability. As such, in-game purchases should be considered as individual decision-making.

1.1.3 *Dota 2* TOURNAMENTS

Dota 2 has a considerable number of leagues and tournaments at varying competition levels, with teams and players around the world competing for prize money. According to the esports community[2], *Dota 2* tournaments can be classified into three levels, including Premium (e.g., The International, Epicenter, and DreamLeague), Professional (e.g., LPL Pro and Professional League), and Amateur (e.g., FirstBlood and Epulze.com). The division of *Dota 2* tournaments is primarily based on the total purse. Whereas Premium tournaments usually award no less than 1 million US dollars as prize money and Professional tournaments offer tens to hundreds of thousands of dollars, Amateur tournaments do not necessarily financially compensate participants. Professional and Premium *Dota 2* tournaments typically adopt a convex prize structure, in which rewards increasingly concentrate in the top ranks. For example, The International 9 tournament allocated 45.5%, 13%, 9%, and 6% of the total purse, respectively, to the top four teams. Typically, more talented and experienced players

[2] https://www.dotabuff.com/esports/leagues

attend more competitive and rewarding *Dota 2* tournaments. The current dissertation focuses on the context of *Dota 2* because it provides good data for examining the relationships between experience, stakes, and loss aversion.

1.2 PURPOSE OF DISSERTATION

The purpose of this dissertation is to investigate how the significance of loss aversion changes with the level of experience and the magnitude of payoffs. Considering the availability of relevant data, I first attempt to derive preliminary evidence by examining how the significance of loss aversion changes with the level of competition, which should be positively correlated with the two variables of interest. Particularly, the focus centers on esports and uses players' performance data from esports tournaments of three different levels of competition, including amateur, professional, and premium, as classified by the esports community based on the tournament's prize pool and participants' skills and experience. After modeling typical risk-averse behavior amongst esports players (i.e., the purchase of a key in-game item) based on the standard economic theories concerning risk preferences (Varian, 2014), this dissertation examines how their receptiveness to risks differ in terms of whether they are situated in a gain or loss domain, as well as what personal and in-game factors increase their likelihood of risk-taking. To attain more direct evidence, the number of years spent in a professional career and the total purses of tournaments are used to proxy for observations' experience and the magnitudes of prizes, respectively. Therefore, more direct evidence concerning the relationships between experience, payoff magnitude, and loss aversion is obtained.

1.3 SIGNIFICANCE AND IMPLICATIONS OF DISSERTATION

The investigation of esports players' on-field propensity to avoid losses helps enhance the understanding of loss aversion in relation to two pertinent and widely discussed factors, namely, the level of experience and the magnitude of payoffs, by providing empirical evidence from non-experimental settings. Moreover, examining loss aversion in sport expands the scope of research as the sporting context involves both economic and non-economic considerations, with the latter being given relatively limited attention in the literature.

The current dissertation makes several contributions to the literature of sports economics and behavioral economics. First, while previous research examining loss aversion within the context of sport was predominantly focused on top-performing players (Bartling et al., 2015; Card & Dahl, 2011; Pope & Schweitzer, 2011), this dissertation investigates players at three different levels of competition in one study. In so doing, it helps to extend the scope of research on loss aversion by incorporating relatively less experienced and competitive players and contrasting their "risky" choices with those of top-performing players. Second, this dissertation provides empirical evidence regarding how the significance of loss aversion is affected by players' relevant experience. In particular, unlike previous experimental studies which mainly utilized experience gained in the laboratory environment (Engelmann & Hollard, 2010; List & Haigh, 2010), I leverage real-world esports gaming experience accumulated over a timespan measured by years. Third, this dissertation uses tournament prizes, which can be as large as millions of US dollars, to proxy for the monetary incentives players were facing, which is tremendously different from previous research that primarily relied on either hypothetical or real but small payoffs (Erev et al., 2008; Thaler et al., 1997).

The dissertation also has an important managerial implication for compensation scheme design. According to the framing effect proffered by Tversky and Kahneman (1981), decision-making under uncertainty is greatly shaped by the way information is presented, making economically equivalent payoffs perceptually more or less attractive. That is, choices presented in a way that highlights positive aspects tend to be more favored than the same choices presented in a reverse manner. To avoid potential losses, people usually change the amount or intensity of their effort (Humphreys & Frick, 2019; Lord & Hanges, 1987). If loss aversion is discovered in this dissertation, it could be used as a theoretical basis for esports clubs to utilize customized compensation schemes that frame incentives as a loss instead of a gain for motivational purposes. For example, requiring employees to return money already paid if they fail to meet preset goals (sometimes also known as 'clawback provisions', see Brink & Rankin, 2013) should have the potential to improve employees' effort and performance.

The potential effectiveness of such a payoff design has been supported by empirical evidence from many areas such as consumer behavior (Gamliel & Herstein, 2011), teacher efficacy (Fryer Jr, Levitt, List, & Sadoff, 2012), and health promotion (Patel et al., 2016). In esports, players' risk preferences observed from tournament games are supposed to reflect their attitudes and perceptions toward return and uncertainty, which might be dependent on the magnitude of rewards as well as their experience.

Therefore, when considering compensation contracts for esports players at different competition levels, it would be helpful to take their risk preferences into account to fully solicit effort responses and improve performance. To be more precise, if data from real-world tournament games suggest a consistent inclination of players to avoid losses, esports clubs could assign variable pay contracts, i.e., a non-fixed compensation system contingent on individual or group performance (Merriman & Deckop, 2007), with clawback provisions. Otherwise, if players are not particularly averse to losses, the clubs might as well increase the fraction of guaranteed pay when negotiating with players who are less sensitive in terms of loss aversion.

In addition, this dissertation research extends the understanding of esports game strategies. According to the predictions of loss aversion, individuals change their risk preferences depending on whether they lead or trail relative to the reference point. This is deemed as an irrational human behavior but occurs in highly predictable ways (Asch, 2018). Following the ideas of game theory (Varian, 2014), if players on a *Dota 2* team that is trailing have an internalized urge to take risks, one of the best responsive strategies for the leading team is to redirect resources in favor of the members who control heroes with aptitudes for checking those controlled by the risk-seeking players. At the same time, if the players anticipated to be risk-takers are sufficiently cognizant of the potential responses of the opposing side, they could purposefully manipulate their risk propensity to not only confuse and deplete their opponents but also to create opportunities for a comeback and even reverse the prospects of the match. As a result, larger degrees of counterplay and interaction between the confronting teams would bring in more uncertainties to the game. Furthermore, assuming fans prefer to watch matches whose outcome is less predictable (Rottenberg, 1956), the increased uncertainty of competition would be likely to enhance viewer experience (Benz, Brandes, & Franck, 2009; Rascher, 1999).

CHAPTER 2

LITERATURE REVIEW

2.1 PROSPECT THEORY

First posed by Kahneman and Tversky (1979) and later refined by Tversky and Kahneman (1991, 1992) in a series of seminal papers, prospect theory is one of the most distinguished and influential behavioral theories of decision-making in the broader social sciences (McDermott, Fowler, & Smirnov, 2008). Through incorporating the highly predictable psychological and emotional factors that shape individuals' economic decision-making, prospect theory radically subverted the dominant position of expected utility (EU) theory, which had been traditionally regarded as "economists' workhorse model of decision making under risk" in the realm of neoclassic economics (Barberis, 2013, p. 173). Prospect theory advanced the economics literature by providing an elegant description of why people's risk preferences under uncertainty differ asymmetrically relative to a neutral reference point, a phenomenon that contradicts the predictions of EU theory but has been widely observed across varied contexts. Specifically, while individuals situated under favorable conditions are more inclined to be risk-averse, those individuals who anticipate potential losses are much more receptive to risk-taking so that they have a chance to avoid unintended outcomes. Such a reference-dependent preference toward risk is coined as "loss aversion."

The theoretical development of prospect theory started from highlighting deviations from the standard economic EU model built on objective probabilities, which was formulated by Von Neumann and Morgenstern (1947) and later improved by Savage (1954) and Samuelson (1952, 1953). Prior to Kahneman and Tversky's (1979) formalization of prospect theory, psychologists Preston and Baratta (1948) and Edwards (1955, 1962) initially attempted to explore the role of subjective considerations in human's decision-making process. Specifically, they capitalized on controlled experiments to examine whether people tend to rely on subjective or objective probabilities when evaluating different outcomes. Meanwhile, in the face of the seemingly paradoxical existence of individuals who spend money simultaneously on lotteries (risk-seeking) and insurance (risk-averse), economists Friedman and Savage (1948) cast doubt on the utility function of the EU model, which is defined as globally concave over the final state of wealth.

To address this problem, Markowitz (1952) suggested using gains or losses relative to the current wealth level as a substitute for the final wealth state when constructing the utility function. Based on those early inquiries surrounding subjective probabilities' influences on the process of decision-making, Kahneman and Tversky (1979) raised and formalized their prospect theory by introducing a probability weighting function that converts objective probabilities into subjective ones measured as decision weights. Moreover, they developed a value function, though similar to the EU model's utility function, with well-defined gain and loss domains. The central tenet of prospect theory, namely, loss aversion, is losses (or disadvantages) have a greater psychological impact on risk preferences than gains (or advantages). In addition to loss aversion, prospect theory introduced several concepts that profoundly influenced the economics and psychology research, such as diminishing sensitivity (i.e., the marginal effect of an increase in value decreases with the distance relative to the reference point) and probability weighting (i.e., people perceive probabilities based on but different from objective probabilities). In their later papers, Tversky and Kahneman (1991, 1992) discussed loss aversion when no risks are involved and when the number of outcomes is no longer limited to two, respectively.

Precisely capturing the behavioral characteristics of decision-makers facing uncertainty, prospect theory has been proven useful to understand phenomena in a variety of areas such as consumer choice (Kőszegi & Rabin, 2006, 2007, 2009; Thaler, 1980, 1985), political science (Druckman 2001; Lau & Redlawsk 2001; McDermott 2004; Quattrone & Tversky 1988), and industrial organization (D'Aveni, 1989; Heidhues & Kőszegi, 2015; Shimizu, 2007). In particular, fields like finance, investment, and insurance, wherein stakeholders' attitudes toward risk play an essential role, are often considered a suitable setting for applying prospect theory and thus are fruitful in producing relevant research findings (Barberis, 2013). For example, Shefrin and Statman (1985) developed the disposition effect to explain a common absurd pattern in financial assets trading. Specifically, given the "momentum" of stock price fluctuations (i.e., stocks that have recently risen in value are more likely, on average, to continue increasing. On the other hand, stocks that have been performing poorly tend to sustain the downward trend.), a rational option for the investor is to consider selling stocks with inferior past performance to prevent further losses. However, actual stock market observations reveal that individual investors and even mutual fund managers are more attuned to selling stocks at prices greater than purchase prices rather than stocks that have shrunk in value. This puzzling phenomenon has been confirmed by a large amount of evidence from stock markets (Frazzini, 2006; Odean, 1998). Shefrin and Statman's (1985) disposition effect, grounded in prospect theory, attempted to explain such a reluctance to dispose of stock shares at losses. That is, if assuming the purchase price serves as the reference point, then an investor whose stock has diminished in value would shift to a loss region, where he/she becomes more risk-seeking and thus leans more toward holding on to the stock even with a relatively smaller probability of appreciating (rebounding) than a rising stock.

Another renowned application of prospect theory is the endowment effect (Kahneman et al., 1990, 1991). Specifically, it is presumed that individuals are more likely to retain a good with ownership than to acquire the same item if they do not own it. Because people tend to view giving up the ownership as a loss from which they suffer emotionally to a greater extent, they would only do so when compensated at prices higher than the fair value (e.g., market price) of the object (Nayakankuppam & Mishra, 2005; Plott & Zeiler, 2005; Reb & Connolly, 2007). For example, Kahneman et al.'s (1990) behavioral experiments showed that participants required approximately twice higher value to compensate for an owned mug than they were willing to pay for acquiring the mug. Similarly, Carmon and Ariely (2000) found that sports fans' hypothetical selling price for NCAA final four tournament tickets were 14 times higher than their hypothetical buying price.

There are four essential components of prospect theory: "1) reference dependence, 2) loss aversion, 3) diminishing sensitivity, and 4) probability weighting" (Barberis, 2013, p. 175). However, for this dissertation as well as the literature review therein, I mainly focus on the first two elements (i.e., reference dependence and loss aversion) as they are most pertinent to the current dissertation, while still trying to incorporate the other two elements into the review of relevant theoretical development.

2.2 REFERENCE-DEPENDENT PREFERENCES

Reference dependence describes individuals' preferences that are subjectively weighted in an asymmetric manner relative to a given reference point (Munro & Sugden, 2003). In other words, people evaluate possible outcomes based on whether they are situated in the gain or loss domain as well as how distant they are away from the point of reference, instead of making decisions according to some absolute scales (e.g., wealth). Akin to time inconsistency (Hoch & Loewenstein, 1991; Loewenstein & Prelec, 1992; Loewenstein, O'Donoghue, Rabin, 2003), reference-dependent preference represents the body of literature focused on human's inconsistent behaviors. Considering that its theoretical evolution is closely aligned with the conceptualization and formalization of prospect theory (Bateman et al., 1997; Farber, 2008), reference-dependent preference applies naturally to decision-making situations that entail risk and uncertainty. Moreover, reference dependence can also be generalized to investigate the behavioral patterns beyond risky choices, such as consumer behavior (Hardie, Johnson, & Fader, 1993; Loomes & Sugden, 2009) and labor supply (Crawford & Meng, 2011; Farber, 2008).

In the relevant literature, it is well established that a properly defined reference point is key to the subsequent analysis of reference-dependent preferences (Barberis, 2013). To begin with, considering that individuals disproportionately cling to the status quo when they display the tendency of loss aversion, a substantial volume of research adopts the status quo as the reference point to account for observed decision-making behaviors, such as healthcare plan choices (Schweitzer, 1995; Sinaiko, Afendulis, &

Frank, 2013; Strombom, Buchmueller, & Feldstein, 2002), retirement saving decisions (Knoll, 2010), and transaction decisions (Kahneman et al., 1991). This phenomenon is typically coined as the “status quo bias” (Samuelson & Zeckhauser, 1988), or sometimes is also known as the “default rules” (Korobkin, 1997). In addition to the status quo, there also exist alternative candidates for the role of the reference point, which is a topic left open by Tversky and Kahneman (1991), who suggested “aspirations, expectations, norms and social comparisons” be given consideration as well (p. 1046).

A noteworthy trend in the related studies is an increasing awareness of how expectations can shape the reference point. Accordingly, there is a growing body of research that studies reference-dependent preferences in the gain and loss domains dichotomized by pre-event expectations (Abeler, Falk, Goette, & Huffman, 2011; Backus, Blake, Masterov, & Tadelis, 2017; Herweg, 2013). Early inquiries in this direction can be traced back to the works conducted by Bell (1985) and Loomes and Sugden (1986). Under the framework of disappointment aversion, the authors posited that participants in a lottery are predisposed to form ex-ante expectations about the possible outcomes, and they experience either thrill or upset based on how the realized outcomes compare to their prior expectations. By the same token, Kőszegi and Rabin (2006, 2007, 2009) justified that a relatively reasonable option for reference point is the rational expectation formed based on events in an individual’s recent past for possible outcomes. Therefore, the authors developed a theoretical model termed as “gain-loss utility” to capture consumer behavior throughout the course of purchase decision-making (e.g., transaction utility, see Thaler, 1985), which is also applicable to other occasions where individuals’ utility is involved.

In addition to the expectation-based reference point, another stream of research argues that the goals can function as the reference point as well, reflecting how people perceive and evaluate possible outcomes following the predictions of prospect theory (Heath, Larrick, & Wu, 1999). Specifically, Camerer et al. (1997) found New York City taxi drivers usually work longer hours when the hourly wages are lower but tend to finish work earlier if the opposite situation occurs. The authors explained their results under the assumption that drivers mentally form daily income targets, against which they compare accumulated earnings and then make decisions about whether to continue working or not. In their behavioral model, earnings below a psychological target are assessed to be a loss, which is unbearable to drivers and thus prompts them to prolong work time while putting forth extra effort to meet their preset targets. The assumption centering around how goal setting impacts daily labor supply has been further examined by following studies and obtained affirmative empirical evidence (Crawford & Meng, 2011; Farber, 2008; Fehr & Goette, 2007). Likewise, researchers also examined whether goals can function as the reference point among marathon runners. For example, Allen et al. (2017) presumed round numbers (e.g., an hour or 30 minutes) to be the target finishing times for marathon runners. Using a large data set of marathon competitions, the authors reported that the finishing times were intensively bunched on the left side of those round numbers, which indicated that foot racers adjust (increase) the amount of effort near the finish line to achieve the predetermined finishing times and thereby avoiding psychological losses relative to their goals.

2.3 REFERENCE DEPENDENCE IN SPORT

The sporting context is inherently suitable for the examination of reference-dependent preferences on the field because there exist many candidates for the reference point, such as betting odds that represent ex-ante expectations. In the behavioral economics literature, a growing body of research suggests that the reference point can be greatly shaped by prior expectations (Gul, 1991; Kőszegi and Rabin, 2006, 2007, 2009; Loomes & Sugden, 1986; Tversky & Kahneman, 1991). Specifically, this line of research often frames loss aversion as a disappointment, assuming that "[t]he higher your expectations, the greater will be your disappointment" (Bell, 1985, p. 1). To set up the stage for empirically examining this topic, albeit "expectations are hard to observe in the field" (Abeler et al., 2011, p. 470), Bartling et al. (2015) capitalized on pre-game betting odds and actual scores to construct a loss domain if a professional soccer team is behind the predicted match outcome, and a gain domain if it performs better than the expectation.

When it comes to motorsports racing (e.g., NASCAR), a racer's current position ranked in the tournament is regarded as the reference point (Bothner, Kang, & Stuart, 2007), which can be naturally extended to other racing sports or competitions adopting a tournament format. Technically speaking, such a kind of reference point resembles its most common type, i.e., status quo, in the broader literature of reference dependence (Ritov & Baron, 1992; Schweitzer, 1995; Sugden, 2003; Tversky & Kahneman, 1991). The frequent usage of the status quo reference point is theoretically underpinned by a well-defined psychological bias that people prefer the current state and thus try to avoid changes that make them depart from the state, i.e., the proclivity to stay in a comfort zone (Bridges, 2001; Brown, 2008). Like the endowment effect (Kahneman et al., 1990, 1991), when participating in sports that have a ranking system, players tend to feel comfortable with their current positions if they are not falling short of their previous achievements to a great extent. Meanwhile, even though surpassing a superior competitor can generate a certain degree of pleasure, such a psychological gratification would be significantly overshadowed by the displeasure of losing the current rank to competitors from lower positions, i.e., underdogs (Bothner et al., 2007; Boudreau, Lacetera, & Lakhani, 2011; Kilduff, Elfenbein, & Staw, 2010). Given that the alterations of relative standings in rank order are readily measurable (i.e., a certain number of positions up or down), it is easier and more straightforward to contrast contestants' reactions to equivalent positional changes that occur in the gain and loss domains, respectively.

On top of considering the expectation-based and status quo reference points in sport, researchers have also proposed and empirically examined goals as the reference point. For example, both Allen et al. (2017) and Markle et al. (2018) leveraged large-scale field data from marathon runners and test whether goals are pertinent to runners' psychological formation of the reference point. Their findings revealed marathon runners are accustomed to internalizing round numbers (e.g., four hours) in their valuation of performance and outcome. Put differently, how well marathon runners are satisfied with their performance is critically determined by the gap between the preset and actual finishing times. The reference dependency here indicates that runners disproportionately exert an increased level of effort when falling short of their preset goals, which would be tremendously less observed if they feel confident to finish the race in time. In the same vein, the goal-setting literature has documented improved performance in both physical and cognitive tasks (Latham & Locke, 1991; Mento, Steel, & Karren, 1987; Tubbs, 1986).

For the sake of catering to the unique properties of the sports that are used for analytical purposes, researchers in this field have also developed many customized reference points specifically for entailed sports. For example, in the game of golf, the par when attempting putts is often treated as the reference point in that “golfers may be influenced by the salient, but normatively irrelevant, reference point of par when they attempt putts” (Pope & Schweitzer, 2011, p. 130). Contingent on “under par” (e.g., shoot a “birdie” putt that would earn a score one stroke under par or shoot an “eagle” putt that would earn a score two strokes under par) or “over par” (e.g., shoot a “bogey” putt that would earn a score one stroke over par or shoot a “double bogey” putt that would earn a score two strokes over par), golfers might react differently in terms of risk-taking. Therefore, the current positional relations to the par could arguably influence their on-field performance (i.e., putting accuracy).

In addition to on-field performance, research on reference dependence analyzes the behaviors of sports consumers. Specifically, Card and Dahl (2011) are considered some of the first authors who apply Kőszegi and Rabin’s (2006, 2007) “gain-loss utility” scheme into the investigation of sports consumer behavior. In their analysis, they used betting odds on NFL match outcomes organized through Las Vegas bookmakers to proxy for sport consumers’ pre-game expectations. That is, if an NFL team that is anticipated to win the game turns out losing it, then such a type of loss is structured as an upset loss or unexpected loss, which is assumed to be associated with a surge in the likelihood of sports fans’ negative behaviors, such as domestic violence. Conversely, upset wins or unexpected wins are formulated if the reverse situation occurs, and they are probably to lower the chance of unfavorable behaviors taking place in the wake of broadcast football games. Notably, Card and Dahl (2011) utilized halftime scores to test whether sports consumers' reference point is updated as per the most recent on-field news, following the idea of Bayesian updating that combine both subjective and observational information in the evaluation of probabilities. Likewise, based on Card and Dahl's (2011) work, Coates et al. (2014) and Ge (2018) employed pre-game betting odds and post-game outcomes to frame sport consumers' emotional gain and loss domains, and investigated their related behaviors within the contexts of MLB and NBA, respectively. Both papers obtained affirmative empirical evidence that points to the prevalence of loss aversion among sports consumers.

Like studies that probe sports consumer behavior under the "gain-loss utility" framework, Brown and Hartzell (2001) portrayed sports consumers as financial investors who are responsible for making decisions about whether to continue holding or trade the stock shares of publicly listed sports franchises depending on their on-field success. It is well recognized in the sports literature that fans holding the stock shares of a sports team should not be viewed as typical investors whose top priority is to maximize financial returns (Curatola et al, 2016; Gallagher & O'Sullivan, 2011). Instead, they tend to attach disproportionate weight to the symbolic values of possessing a small fraction of the sports team they want to be associated with (e.g., the community owners of the Green Bay Packers, see Mulder, 2015). In fact, the way that Brown and Hartzell (2001) used bookmakers' point spreads and sporting outcomes to respectively quantify pre-game expectations and fan sentiments is not uncommon in the finance literature. That is, if the efficient market hypothesis (Fama, 1970) holds true, then the agents in the stock market must have collected every piece of publicly available information and factored it into their assessment of the financial assets in question. Notably, Stadtmann (2006) extended this influential finance theory into sport and established the so-called "news model," with the main idea being that it is the expectation errors (i.e., the difference between the expected and realized components) rather than the game outcomes per se that explain the price fluctuations of the listed sports franchises' stocks.

While reference dependence describes how individuals evaluate outcomes and reveal preferences relative to a neutral reference point in a general sense, loss aversion is a specific example of reference dependence with the focus on risk decision-making under uncertainty. My dissertation research will advance the knowledge of reference dependence by providing non-experimental evidence for how people's reference-dependent preferences are affected by their relevant experience and the magnitude of payoffs they face.

2.4 RISK-TAKING AND LOSS AVERSION IN SPORT

Loss aversion assumes people dislike losses to a greater extent than commensurate gains, and thus they tend to opt for risky choices in the loss domain which they would not accept if anticipating favorable outcomes (Kahneman & Tversky, 1979). With a psychologically salient reference point being properly defined, the subsequent gain and loss domains can be framed by locating the current state relative to the reference point (Barberis, 2013). The following analytical task of loss aversion is to contrast certain measurable behavioral indicators (i.e., the frequency of risk-taking conducts) respectively observed in the two opposite domains. As such, in addition to defining the reference point, the examination of loss aversion also calls for identifying and quantifying risky choices or behaviors in the sport that is treated as the context.

In particular, how to select suitable risk-taking behaviors depends on the type of sport, in which the related rules, strategies, tactics, and styles of play can be drastically different. For instance, Bartling et al. (2015) employed cards assigned by referees and offensive substitutions implemented by coaches to represent risk-taking behaviors in professional soccer games. As another example, historical records of crashes in NASCAR are utilized to analyze risk-taking by drivers in professional motorsport (Bothner et al., 2007). In the case of professional golf, risk-related strategies are focused on how players attempt putts (Pope & Schweitzer, 2011). Specifically, when a golfer's current score is under par, risk-averse players prefer to set up easy follow-on putts by placing the ball on the left side[3] of the hole, and try to putt in the following stroke with higher assurance. On the contrary, risk-seeking golfers who decide to attempt finishing the hole with a single stroke are likely to place the ball on the right (far) side of the hole if they miss the putt. From the above examples, it can be seen that ad hoc risk-taking behaviors are selected or identified for examining loss aversion in different types of sports.

Generally, there are two directions for investigating loss aversion within the sport setting, with one centering on athletes' on-field performance and the other revolving around sports consumers' utility. Both directions of research capitalize on the behavioral observations about athletes or sports consumers to infer and contrast their emotional states between the gain and loss domains, through which knowledge of their decision-making under uncertainty can be obtained. Specifically, studies concerning athletes' on-field performance usually attach considerable importance to the aforementioned risk-taking behaviors, including attempting to finish putts with one stroke instead of two or

[3] The left side here means the same direction as the player relative to the hole.

more in golf (Pope & Schweitzer, 2011), switching to more aggressive actions and strategies in soccer (Bartling et al., 2015), and driving in a riskier manner in order to prevent displacement by lower-ranked contestants in motorsport (Bothner et al., 2007). In relatively riskless sports (e.g., marathon), however, players try to evade unwanted losses primarily through adjusting the amount or intensity of effort (Allen et al., 2017). On the other hand, studies aimed at anatomizing sports consumers' utility associated with loss aversion are mostly interested in observing and quantifying consumer behavior induced by consuming sports products, typically a sports match. In particular, this collection of related consumer behavior involves the propensity to abuse domestic violence (Card & Dahl, 2011), the likelihood to tip at rates above the norm (Ge, 2018), and buy and sell the sports team's stock shares if they are publicly traded (Brown & Hartzell, 2001).

With empirical examinations based on both considerably large samples and rigorous methods attuned to the specific sport in question, the observed field evidence across an extensive variety of sports has pointed to the prevalence of loss aversion in the sports industry (Coates & Humphreys, 2018). Of those studies surrounding on-field performance, for example, Bartling et al. (2015) combined pre-game betting odds and minute-by-minute actual in-game goal differences of more than 8,200 soccer matches in the German Bundesliga and English Premier League over 12 seasons. They found that the risk-taking behaviors of both athletes and coaches are significantly more probable to occur when their teams fall behind the expected game outcome, which is consistent with the predictions of loss aversion. By the same token, Pope and Schweitzer (2011) derived robust evidence that supports the presence of loss aversion among the highest performing and most experienced athletes (e.g., Tiger Woods) based on a statistical analysis of over

2.5 million putts recorded by precise laser measurements. Their results showed that golfers finish their par putts approximately 2 percentage points more often than they make comparable birdie putts. Such an increase in putting accuracy indicates that golfers are more sensitive to losses than equivalent gains because they devote a greater degree of attention and effort when attempting to putt for par than for birdie.

Similarly, the other strand that is concerned with sport consumers has provided abundant evidence suggestive of loss aversion as well. For instance, Card and Dahl (2011) formulated a loss-of-control model grounded in the consumer utility theory to examine the relationship between the likelihood of domestic violence and visceral triggers associated with upsets resulted from professional football match outcomes. Their statistical results that are drawn from over 750 city and county police agencies revealed a 10% increase in reported family violence rate ensuing surprising losses of NFL matches. As a result of falsification check, they further found that the estimated effects of predicted losses and unexpected wins dwarf in comparison to that of upset losses in terms of magnitude and significance. That is, loss aversion among sport viewing audiences takes the form of losses relative to the reference point being asymmetrically more pronounced than gains. Another relevant study focused on sport consumer behavior is the work of Coates et al. (2014), who incorporated reference-dependent preference and loss aversion into the depiction of consumers' decision-making regarding live game attendance. Through conducting a comprehensive review of previous research and supplementing with additional data from MLB, the authors argued that the reference dependence-founded model has stronger explanatory power in elucidating sports fans' preference for uncertainty than Rottenberg (1956)'s uncertainty of outcome hypothesis

(UOH). Notably, their paper is considered the first to interpret UOH through the lens of loss aversion, which has fundamentally changed the landscape of this field of research.

2.5 EXPERIENCE AND LOSS AVERSION

Inquiries into how market experience influences the stability of loss aversion stemmed from a pair of field experiments. Specifically, List (2003, 2004) found that traders in autonomously occurring markets for commodities such as sports cards and sports memorabilia exhibited fewer behavioral clues indicative of loss aversion as they became more experienced in trading, which is in concert with the predictions of neoclassical economics theories. From there, that market experience would attenuate behavioral anomalies has been widely replicated and supported by subsequent empirical examinations from both laboratory and field settings (Choe & Eom, 2009; Dhar & Zhu, 2006; Engelmann & Hollard, 2010; Feng & Seasholes, 2005; Seru et al., 2010). For example, Feng and Seasholes (2005) leveraged account-level data of stock investors, which had documented the history of their transactions and stock holdings, to investigate how stock market experience impacts investment decision-making. It was found that the reluctance to realize losses as well as the propensity to realize gains (i.e., the disposition effect grounded in loss aversion) turned out to be mitigated by accumulated trading experience though did not disappear entirely. In the same vein, Engelmann and Hollard (2010) proposed that why the endowment effect is muted by increased experience can be explained by its ability to reduce trade uncertainty, that is, individuals hesitate to trade due to their overestimation of the cost or risk aligned with transactions. The experiments where the two treatments were exposed to different levels of trade uncertainty helped substantiate their conjecture.

Provided that List's (2003, 2004) mark on experience has been supported by a sizable corpus of research, skeptical voices also emerged to challenge this argument (e.g., Bokhari & Geltner, 2011; Erev et al., 2008; Mrkva et al., 2020). Interestingly, List himself was among those who observed counterevidence against the claim that market experience can attenuate the behavioral anomaly. Specifically, List and Haigh (2010) compared and contrasted the trading patterns of professional traders recruited from the Chicago Board of Trade and undergraduate students. The comparison results showed that professional traders display a greater level of myopic loss aversion even than college students. Likewise, using sales data from the housing market including both asking prices and realized transaction prices, Bokhari and Geltner (2011) found loss aversion behavior persists among sophisticated and experienced property investors.

It should be noted, however, field evidence reveals the linkage between market experience and loss aversion comes disproportionately from the contexts of financial investments and exchange experiments, restricting its generalizability and applicability to the broader discussion of human psychology and behavior. Considering this research void, Pope and Schweitzer (2011) shifted attention to the on-field performance of professional golfers as well as how they react to risky choices therein. The authors probed into a dataset containing over 2.5 million golf putts with precise laser measurements of both starting and ending ball locations, and found that golfer became more accurate (i.e., increased attention and effort) when they attempted putts for par than when they attempted birdie putts, with even some of the highest performing and most experienced athletes, such as Tiger Woods, exhibiting this behavioral tendency. The fact that experience and expertise do not necessarily eliminate the presence of loss aversion broadens and enriches the relevant research with a robust empirical examination. Moreover, it is also suggested that sports performance could be hypothetically improved and additional prize money could be earned if players are able to overcome and consciously manage such risk preferences. Inspired by the work of Pope and Schweitzer (2011), there is a growing line of research in the sport literature that attempts to study loss aversion and the related behaviors (e.g., Bartling et al., 2015; Card & Dahl, 2011). Generally, the field evidence from the sporting context supports the salience of loss aversion among professional athletes as well as other stakeholders.

Whereas it is indeed a remarkable innovation to use the sport context for empirically examining loss aversion, this line of research still fails to explain, in a panoramic view, how the degree of loss aversion varies with the level of experience. This is because the investigated population to date has been confined to solely professional athletes, partially due to the relative ease with which related data can be obtained. Accordingly, the lack of attention to less experienced groups has left a research void, which calls for juxtaposing players of varied experience in one study to investigate how the significance of loss aversion responds to participants' experience. In the sport literature, previous research has employed players' age, professional years, or the number of games played to proxy for their experience (Ashworth & Heyndels, 2007; Kuethe & Motamed, 2010; Lucifora & Simmons, 2003; Simmons & Berri, 2011). Meanwhile, researchers also capitalize on different levels of competition as an inference of players' experience. For example, Teeselink et al. (2020) analyzed the extent to which players of varied experience are susceptible to choking under pressure, using performance data of professional, amateur, and youth darts players. As such, the following hypothesis is proposed:

H1: The significance of loss aversion is attenuated by increased experience.

2.6 PAYOFF MAGNITUDE AND LOSS AVERSION

In addition to the contestants' experience, the level of competition is also closely aligned with the magnitude of payoffs. In the behavioral economics literature, there is a cohort of researchers focused on how the magnitude of payoffs or stakes impacts the degree of individuals' risk preferences and loss aversion, which is termed as "relative risk aversion" (Holt & Laury, 2002) or "the peanuts effect" (Weber & Chapman, 2005). One of the early inquiries into how risk preference responds to payoff size was conducted by Binswanger (1980), who observed farmers' decision-making in an experimental gamble and concluded that they became increasingly risk-averse when the payoffs increased. Particularly, to ensure that the participants perceived the potential return of truly high values, the author raised the maximum payoff to the extent that exceeded the monthly incomes of participants. In the same vein, Kachelmeier and Shehata (1992) carried out a sequence of dichotomous lottery experiments to infer risk preferences based on the certainty-equivalent method in the context of the People's Republic of China, where the authors were able to offer relatively large monetary incentives in comparison to the subjects' living costs. Their results showed the level of monetary payoffs significantly impacts the revealed risk preferences in the sense that increased prize value mitigates risk-seeking behaviors. To improve the validity of the hypothetical high stakes widely used in laboratory settings, Holt and Laury (2002) investigated the relationship between payoff size and risk preference in the use of real and hypothetical monetary incentives for lottery-choice experiments. They found the larger the size of stakes, the stronger inclination to avoid risks. Furthermore, the erratic behaviors observed in their study when the stakes were hypothetically high suggested that the subjects facing hypothetical options might not be able to imagine what they would do under real conditions. Therefore, the perceptions toward monetary payoffs and stakes in terms of magnitude pertain largely to participants' risk preferences and behavioral choices.

To further investigate the linkage between the significance of loss aversion and payoff size, Erev et al. (2008) recruited students to participate in experiments characterized by payoffs drawn from distributions with different means and standard deviations, while the means were treated as the reference point and the standard deviations as risks. They found that small-sized nominal payoffs tend to eliminate clues indicative of diminishing sensitivity, which is one of the core theoretical tenets of loss aversion. Furthermore, Harinck et al. (2007)'s findings based on experiments using questionnaires showed that loss aversion became reversed, that is, risk-taking behaviors occurred more frequently in gains than in losses, when the participants were provided small monetary amounts. The authors interpreted this abnormal reversal with two assumptions: a) people have an innate motivation to maximize gain while minimizing pain (i.e., the hedonic principle); and b) a small loss is easier to be cognitively discounted than a large loss. Similarly, Ert and Erev (2013) detected a reversed loss aversion propensity when individuals were presented with nominal payoffs of small magnitude. For the sake of determining whether the anomaly of loss aversion related to small outcomes should be attributed to the affective judgments or measurement errors, Mukherjee et al. (2017) capitalized on measurement scales to quantify people's affective perceptions of losses and gains, thereby eliminating noises due to measurement errors. Their experimental results were consistent with the previous findings that the salience of loss aversion depends on the magnitude of payoffs.

Provided the empirical evidence from laboratory settings generally supports the magnitude effect of payoffs on loss aversion, there is a growing voice that points out inadequacies of those findings. For example, Holt and Laury (2002) emphasized that risk preferences are "ultimately an empirical issue, and additional laboratory experiments can produce useful evidence that complements field observations by providing careful controls of probabilities and payoffs" (p. 1644). In the same manner, researchers have also proposed that how the magnitude effects on loss aversion are dependent on whether the stakes materially impact the wealth or circumstances of participants (e.g., Gal & Rucker, 2018). As such, field observations outside laboratory settings are in need to enlarge the understanding of the magnitude effects of payoffs on loss aversion. Thus, the following hypothesis is proposed:

H2: The significance of loss aversion increases with the magnitude of payoffs.

2.7 ESPORTS BUSINESS

The empirical setting of esports is particularly appropriate for examining the relationship between the competition level and the salience of loss aversion, not only because it has multiple candidates for the reference point and risk-taking behaviors, but also due to the well-documented game statistics at all levels of competition provided that esports matches occur entirely in connection with electronic devices. To date, researchers have investigated the esports ecosystem from different perspectives, including business, media, sociology, law, and informatics (Reitman, Anderson-Coto, Wu, Lee, & Steinkuehler, 2020).

The esports business literature typically revolves around topics such as the motivations for esports consumption, different entities in the esports industry, and esports business models (Hamari & Sjöblom, 2017; Lee & Schoenstedt, 2011; Seo & Jung, 2016; Weiss, 2011). It is worth noting that esports consumers and their related behaviors are at the center of research interest. Particularly, based on the established understandings of traditional sports, there is an increasing number of studies that seek to investigate esports viewership. For example, Hamari and Sjöblom (2017) and Qian, Zhang, Wang, and Hulland (2019) applied the Motivation Scale for Sports Consumption (MSSC) scale, one of the most widely adopted tools in the research of sports consumption, to measure the incentives for esports spectators, and found that escapism, knowledge acquirement, and novelty are important predictors of esports viewing frequency. While early inquiries into esports consumers' motivations primarily focused on what elements within esports games prompt continuous use and engagement (e.g., competition, challenge, and hedonic gratification; see Weiss & Schiele, 2013), Seo and Jung (2016) underscored the multifaceted roles of esports consumers beyond solitary play and conceptualized esports consumption as "assemblage of consumption practices, where consumers actualize and sustain the eSports phenomenon through their engagement with the interconnected nexuses of playing, watching and governing of eSports" (p. 637).

As a relatively emergent industry, the esports ecosystem is often described as a value network co-created by a multitude of stakeholders, including consumers, players, game developers and publishers, communities, and organizations (Reitman et al., 2020;

Seo, 2013). While esports consumers are the most researched subjects in the discussion of esports business, the scope of the relevant studies has been extended to entities other than the consumer group. For instance, Parshakov and Zavertiaeva (2018) explored the relationship between players' success in esports tournament competitions, as measured by the aggregated amount of prize earnings, and their home nations' key economic indices such as GDP per capita. According to their regression results, esports achievements at the country level are largely determined by economic strength and mode. That is, a 1% increase in GDP per capita is associated with a 2.2% increase in prize money per unit of population, and people living in planned or post-planned economies appear to be more interested in esports-related activities. In addition, Jenny et al. (2018) investigated the status of venues for hosting esports events and looked toward the future of esports-specific facilities. Interestingly, with the burgeoning popularity of user-generated content in the esports realm, researchers have also paid attention to a cohort of users who act as esports consumers and providers concurrently, with the main focus on the creation, trading, pricing, and permission strategies (i.e., copy, modify, and transfer) of virtual goods and services within video games like *Second Life* or *Minecraft* (Ba, Ke, Stallaert, & Zhang, 2010; Ke, Ba, Stallaert, & Zhang, 2012; Niemeyer & Gerber, 2015).

At the same time, a growing line of research aims to describe the business models of the thriving esports industry. Notably, the so-called free-to-play business model has been widely adopted by many game developers and publishers (Macey & Hamari, 2018; Rosell Llorens, 2017; Weiss & Schiele, 2013). Under the free-to-play model, game users can access the basic functionality without any charges but are usually monetized through expenditures on virtual goods, such as characters, items (weapons and armor), skins (clothing), currencies, and tokens, that serve the purpose of facilitating gameplay and enriching gaming experiences within the game environment (Frank, Salo, & Toivakka, 2015; Hamari & Lehdonvirta, 2010). In other words, the preliminary and general content of a game (i.e., the core service) is aimed purposefully at enlarging the fan base, with the premium content (e.g., virtual goods) being designed to generate substantial revenue streams, which coincides with the descriptions of the “Like” economy (Van Dijck, 2009). Selling virtual goods has formed a multi-billion-dollar market, especially for popular esports game titles such as *League of Legends*, *Dota 2*, *Counter Strike: Global Offense*, and *Fortnite* (Bonder, 2017).

2.8 ESPORTS MEDIA

Communication and media studies inquire into the esports phenomenon primarily through the lens of live-stream platforms in the interest of why esports consumers watch video game streaming as well as how they interact with streamers if permitted (Burroughs & Rama, 2015; Hamilton, Garretson, & Kerne, 2014; Qian et al., 2019). Notably, the exponential growth of the esports market has been accompanied by a proliferation of video game titles and user-generated content surrounding them, which provides additional products for esports fans. Along with this sweeping trend, many esports streaming platforms, such as Twitch, YouTube Gaming, and Steam TV, have established a considerable base of users comprising both committed and occasional viewers. In contrast to the previous communication mode that large corporations and organizations monopolize the production of media content, the esports streaming industry is mainly constituted by smaller entities and individuals (Cha et al., 2007), a remarkable shift in the media landscape termed as “the democratized process of content creation” (Sjöblom, Törhönen, Hamari, & Macey, 2017, p. 161).

In search of why people watch esports streaming content, Hamari and Sjöblom (2017) proposed to incorporate the uses and gratification (UGT) theory into the analysis, which is frequently adopted in the communication and media literature (West & Turner, 2010). Specifically, the UGT theory aims to shed light on the psychological motivations that stimulate people to choose a certain type of media and what leads to a set of specific media-use behaviors that can gratify their intrinsic needs (Rubin, 1994). Following this idea, Sjöblom et al. (2017) examined how viewer gratification is affected by video game genres and content types of streaming channels. Based on a cross-reference between the well-established classification of game genres (Lee et al., 2014) and manual observations of the top 50 popular games on Twitch, the authors selected a list of game genres including action, collectible card games (CCG), fighting, first-person shooter (FPS), massively multiplayer online (MMO), multiplayer online battle area (MOBA), etc. Furthermore, they categorized streaming channels, according to the structure and content, into multiple types, such as Competitive, Let’s Play, and Casual. The results of their analysis revealed the content topic serves as a more significant factor in contributing to spectator gratification than the video game genre.

Additionally, attention has been given to the online behaviors of streamers and viewers on live-stream platforms. For example, Lessel, Mauderer, Wolff, and Krüger (2017) conducted two case studies about Twitch to explore the link between participation rates and the contents that are been streamed. In both cases, the viewers were presented with participatory options, including a chat room and an opinion poll, which allowed them to exert personal influences throughout the course of streaming. The authors found that the options encouraging the audience to get involved are highly appreciated and regarded as an essential component of the spectating experience. Another interesting study from Matsui, Sapienza, and Ferrara (2019) examined whether streaming gameplay (i.e., double-tasking) boosts or deteriorates a streamer's in-game performance. Through merging data from both *League of Legends* matches and Twitch streams and using a mixed-effect model, the authors detected a significant undermining effect of streaming on in-game performance, which should be attributed to the extra tasks imposed on streamers when producing commentary for viewers synchronously with focusing on in-game activities. Moreover, the authors also found that live streaming is highly probable to increase streamers' engagement, keeping them in longer gaming time than non-streaming circumstances.

2.9 ESPORTS SOCIOLOGY & LEGAL ISSUES

Extant investigations into the esports community in the sociology literature are sparsely distributed across several research topics, such as gender differences, social support, and social diversity. Among these topics, gender differences in esports seem to have received the most academic attention. Specifically, sociological studies of gender-related issues in esports mainly focused on whether the rampancy of under- or misrepresented female characters in video games leads to distorted social beliefs and attitudes toward women, as well as whether such social stereotypes deter women from pursuing esports careers and foster self-doubt on their abilities (Breuer, Kowert, Festl, & Quandt, 2015; Kim, 2017; Ruvalcaba et al., 2018). For example, Bègue et al. (2017) executed a large-scale survey to empirically examine the association between exposure to video games containing sexist content and the likelihood of cultivating sexist attitudes, and they noted supporting evidence of this relationship. In the same vein, Kaye and Pennington's (2016) experimental study indicated that stereotype-plagued female gamers tended to be outcompeted, with regard to in-game tasks, by their male counterparts in the control group, though such performance decrements can be eliminated by directional social identity interventions.

In addition to gender differences, sociologists have been concerned with social interactions and diversity within the esports community. For example, Hilvert-Bruce, Neill, Sjöblom, and Hamari (2018) utilized a collection of social motivations, such as social interaction, sense of community, meeting new people, information seeking, and entertainment, to explicate why viewers engage in esports streaming. The results pointed to a greater social and community dependence of live-stream viewership than mass media. Furthermore, Parshakov, Coates, and Zavertiaeva (2018) assessed the impacts of three types of diversity, namely, the diversity of culture, the diversity of language, and the diversity of skill, on esports teams' performance. Their regression outcomes implied that while the language diversity might thwart players' instantaneous communications and in-game cooperation, the diversity in cultural background is remarkably constructive to strengthen team performance.

On the other hand, with the rapid growth of the esports industry in recent years, economic tensions among interested entities in this thriving business have been intensified and escalated. Accordingly, there is an increasing body of literature that forges a path to the legal aspects of esports, covering numerous areas of litigation such as intellectual property, gambling, corruption, antitrust, doping, and employment (Holden, Kaburakis, & Rodenberg, 2017). Although still focusing on the different stakeholders in the esports industry as the business literature does, this line of study in law tends to attach disproportionate weight to the legal bonds between those entities, such as licensed and contractual relationships as well as the related rights and liabilities entitled by the legal status (Chao, 2017). Notably, who owns the intellectual property rights of video game titles is one of the most discussed issues in the legal sphere of esports due to its fundamental role in maintaining the ecosystem's stability and vitality. That is, intellectual property rights (i.e., the exclusive right to distribute and publicly display a game) grant the game owner unparalleled controls over the esports business's major revenue streams from sponsorships, live events, and merchandises (Brickell, 2017; Karhulahti, 2017; Martinelli, 2019). Accordingly, game developers and publishers authorize, via license agreements, the selected tournament organizers and content distributors to exercise their exclusive rights protected by the copyright law in return for royalties and fees. Such a highly centralized structure of powers in the esports industry has further led to several antitrust concerns (Arin, 2019; Miroff, 2018), especially considering the game developers and publishers' uncontested control and the professional players' restricted mobility owing to their specialized talents and skills that are barely transferrable to other game genres, both of which prompt to form and reinforce a monopolistic labor market (Bayliss, 2016; Heggem, 2016).

Another prominent legal issue surrounding esports is gambling, which mainly takes two forms: direct betting on the outcomes of esports matches and selling loot boxes. Specifically, the former is widely considered a secondary market created by industry luminaries to further exploit esports consumers' willingness-to-pay (Dobill, 2016). This form of wagering in esports bears a striking resemblance to fantasy sports, which has been a heated topic in gambling law discussions. In spite of the ongoing debates over esports' identity as a sport, the similarity between esports and traditional sports in terms of betting on game outcomes is much less questionable (Peter et al., 2019). In addition, a substantial proportion of legal research focused on gambling activities in esports has cast light on a newly emergent betting mechanism called the "loot box." This term originates from gaming jargons and refers to in-game sealed containers purchasable with real-world money, which once opened release randomized virtual items in the form of weapons, armor, abilities, or cosmetic artifacts that can only be used within the game environment (Abarbanel, 2018; Griffiths, 2018; Nielsen &; Zendle & Cairns, 2019). Moreover, it has multiple equivalents, such as loot crates, loot cases, loot chests, and card packs (Griffiths, 2018; Li, Mills, & Nower, 2019). According to a recent large-scale survey undertaken by Zendle and Cairns (2018), 78 percent of video game users across the world are reported to have spent money on loot boxes. Given loot boxes' enormous popularity and supreme ability to generate revenues in the esports business, severe criticisms have been increasingly put forth toward their high potentials to induce gambling problems, such as underage gambling, addiction, gaming disorders, and public stigma (Brooks & Clark, 2019; Drummond & Sauer, 2018; Griffiths, 2018; Li et al., 2019; Peter et al., 2018; Nielsen & Grabarczyk, 2018; Zendle, & Cairns, 2019).

2.10 ESPORTS ANALYTICS

Esports analytics is a newly emergent field focused on identifying and evaluating successful gameplay and strategies (Schubert et al., 2016), along with the rapid development of sports analytics. Similar to statistics and computer science research, esports analytics requires collecting secondary data generated in non-experimental matches via application programming interface (API) and implementing machine learning or data mining algorithms on the datasets for detection or prediction purposes. Therefore, it is usually informatics researchers that are active in this sphere, investigating topics such as team formation and strategies, as well as player interactions and dynamics.

Notably, one of the most heated research questions for esports analytics is what game-related factors can increase win probabilities (Maymin, 2018). To achieve this goal, relevant match statistics occurring throughout different game stages have been frequently employed to uncover or verify variables of interest. Specifically, several pioneering studies applied machine learning classifiers, such as Logistic Regression and Decision Tree, to analyze the strategic decision-making during the drafting phase of the esports game *Dota 2* (Makarov Savostyanov, Litvyakov, & Ignatov, 2017; Semenov et al., 2016). It was found that, out of a randomly shuffled hero pool, which characters the team members are most proficient at playing, which roles the opposing team is good at, as well as what heroes are the most dominant and sought-after ones in the current game version (i.e., metagame; see Summerville, Cook, & Steenhuisen, 2016), are key considerations at the drafting stage, though the drafting process is complicated to some extent by the pattern that the right to pick alternates between the two competing teams (Gourdeau & Archambault, 2020). In addition, the role-division mechanism in MOBA games (e.g., Attack Damage Carry, and Support), whose core objective is to optimize the accumulation and distribution of in-game economy, also plays a crucial role in the drafting phase. Accordingly, a couple of researchers, driven by precise role identification and classification, endeavored to devise recommendation systems for hero line-ups

(Demediuk et al., 2019; Eggert, Herrlich, Smeddinck, & Malaka, 2015; Hanke & Chaimowicz, 2017). The analytical results in this sphere are basically consistent with Kim, Keegan, Park, and Oh's (2016) prediction that team performance (i.e., win probability) is positively associated with the familiarity with assigned roles as well as the complementarities among roles, while the latter factor produces a more significant effect.

Another lineage of research in esports analytics is carried out following the idea of Bayesian updating, one of the most popular statistical methods in the field of artificial intelligence (AI). In Bayesian statistics, a prior distribution is usually assigned based on pre-event speculations on possible outcomes, and actual data recorded during or after the event are incorporated to derive a posterior distribution as an updated belief. Under this Bayesian framework, Yang, Qin, and Lei (2016) developed a statistical learning model to predict the winning side before a match starts based on prior features (e.g., a player's historically averaged performance and ranking information) and improved the model's prediction accuracy by absorbing real-time gameplay features (e.g., the KDA ratio) as the match proceeds. Other similar studies dedicated to predicting the winner, though built on traditional regression methods, have also developed novel tools for feature engineering (i.e., crafting new independent variables out of existing information) when specifying the model. For example, Schubert et al. (2016) capitalized on a specialized data parser to extract spatio-temporal coordinates of *Dota 2* matches at a highly granular level from game replay files. In this study, while temporal coordinates were measured as segments in a 128*128 game map grid, the time unit of recording information occurred at a 30Hz tick rate (i.e., 30 times per second). Due to their ability to obtain those precise spatio-temporal data, the authors defined an in-depth analytical component that is termed as "encounters," which are formed if the distance between players from both sides reaches a predetermined threshold, to facilitate the tasks of team performance evaluations and win predictions. Likewise, Maymin (2018) started from extracting fundamental *League of Legends* match statistics (e.g., kills and deaths) via the game publisher's (Riot Games) API, and then he leveraged this comprehensive data to construct more advanced metrics to address questions interesting to esports players and coaches, such as whether a kill is a smart one in the sense that it adds up to the team's likelihood of winning rather than merely varnishing an individual's statistics. Furthermore, the author also devised a couple of visualization tools as a means to display his analytical results in more user-friendly interfaces, which is a fairly popular practice in esports analytics (Block et al., 2018; Li et al; 2016; Li et al., 2018).

In particular, the context of esports is appropriate for empirically examining the relationship between the level of competition and the significance of loss aversion. For example, multiple candidates in esports can be used for constructing the reference point, such as pre-game betting odds (Bartling et al., 2015; Card & Dahl, 2011) and in-game leading and trailing situations, which will be discussed in the following methodology section. Moreover, many esports games have well-documented match statistics at all levels of competition, largely facilitating the analysis of players' in-game behaviors and choices (Maymin, 2018; Schubert et al., 2016).

CHAPTER 3

METHODOLOGY

This chapter first frames the gain and loss domains where decision-making under uncertainty is directly contrasted. Then, a risk-averse behavior in the context of *Dota 2* is identified in compliance with the standard economic approach of modeling risk preferences (Kimball, 1993). The main statistical model used for this dissertation is survival analysis, with each observation being a player's in-game risky choice updated on a tournament-match-minute basis. Furthermore, to handle time-varying covariates, a modified Cox proportional-hazard model is employed for data analysis. Lastly, the data collection process and alternative specifications are also discussed in this chapter.

3.1 FRAMING THE VARIABLE OF INTEREST

The data analysis for the dissertation begins with the conceptualization of loss aversion in the esports game *Dota 2* by applying the standard economic approach defining risk preferences to gameplay mechanisms. Specifically, two critical problems – how to frame the in-game gain and loss domains (i.e., the reference point) and how to select an in-game risk-taking behavior – need to be addressed in this section for identifying potential loss aversion (Bartling et al., 2015; Bothner et al., 2007; Pope & Schweitzer, 2011) within the context of esports.

3.1.1 DEFINING GAIN AND LOSS DOMAINS

First, gain and loss domains are naturally embedded in head-to-head competitions that involve two confronting sides. That is, if the party in question is outperformed by its opponent in terms of those major statistics (e.g., points scored), then it should be classified as being in the loss domain. Alternatively, the gain domain is assigned when the reverse situation occurs. In other words, the gain domain corresponds to the side that maintains the leading position while the loss domain is aligned with the side that trails behind. Accordingly, I split the duration of a *Dota 2* match into three exclusive situational categories: leading, trailing, and mixture, using the most prominent measures indicative of in-game relative positions, including team net worth advantage, team experience points advantage, and team kill differential. More specifically, one side is classified as leading (i.e., IG Lead) if those measures are simultaneously greater than zero (41.28%) and trailing (i.e., IG Lag) when they are all negative (41.28%). Following the approach Bartling et al. (2015) used to frame the gain and loss domains, this dissertation directly contrasts players' risk-seeking tendency when they were trailing and leading in the game, by using the latter condition as the reference category, to empirically examine the significance of loss aversion. Therefore, it can be seen whether players' risk preference became stronger in the loss domain compared to the situation in the gain domain. The leftover conditions without clear-cut relative advantages (17.44%) are labelled as mixture and excluded in the data analysis.

3.1.2 IDENTIFYING RISK-TAKING BEHAVIOR

Next, to identify a risk-taking behavior in the game of *Dota 2*, I focus on the purchase decision-making concerning a core item within the game setting, which is supposed to reveal the controlling player's perception and attitude toward in-game risks under uncertainty. In particular, the Black King Bar (BKB) is one of the most distinctive and representative items in *Dota 2* that epitomize the designer's conceptions about how the game should be played. BKB serves as a core defensive equipment that is categorized as armor but works peculiarly. As opposed to providing any defensive benefits, BKB in fact fortifies the hero's attack damage with a relatively low benefit-cost efficiency. That is, with the comparable cost of gold, there are other options, such as the Monkey King Bar (MKB), that can supplement stronger offensive enhancements. However, the tactical function of BKB rests on its ability to empower any hero who has activated it to be shielded from almost all disabling spells and magic attacks from opponents over a short period. As a result, this feature ensures the hero can deal damage to the opponents rather than being paralyzed (disabled) and destroyed (nuked) at the beginning of encounters and battles, in which case minimal or even negative contributions are made to winning the game.

Given such a superior tactical benefit, the opportunity cost of BKB is also sizable, measured as the hypothetical enhancement of combat ability typically represented by attack damage or armor that could have otherwise been acquired with the commensurate amount of gold. For example, Table 3.1 provides a numeric comparison in terms of the situational returns of investing in BKB and MKB. These two items are comparable with respect to the expense, which cost 4,050 and 4,175 gold, respectively. Based on hypothetical numbers for clarification, opting for MKB has a 50% chance to deal 10,000 damage and 50% to exert none. On the other hand, buying BKB guarantees the hero to exert 5,000 damage. According to the standard economic theory that models individuals' risk preferences (Neumann & Oskar Morgenstern, 1944), the risk-averse utility function is realized by a concave curve, whereas a convex curve indicates the propensity to seek risks. Figure 3.1 shows the utility/value functions associated with the different types of risk preferences.

Following this standard economic approach of modeling risk preferences, the adoption of BKB sacrifices higher yet contingent combat ability enforcement for a significant reduction of uncertainty in the contributions a hero can make in encounters and battles, a trade-off between a certain payoff with relatively small returns and an uncertain payoff with more extreme values in favorable and unfavorable outcomes. Therefore, it is believed that the decision-making on BKB in different situations reflects a *Dota 2* player's preference for risks. In sum, with the well-defined gain and loss domains as well as the measurable risky choice at hand, loss aversion in the game *Dota 2* can be defined as a higher frequency of BKB purchase (i.e., a risk-averse behavior) when observations lead the game in comparison to situations when they trail behind.

3.2 SELECTING CONTROL VARIABLES

In addition to constructing the variable of interest, this dissertation incorporates a list of gameplay and player-specific control variables that are pertinent to *Dota 2* players' risky choices.

3.2.1 GAMEPLAY-RELATED FACTORS

The first control variable I am concerned with is the position. Specifically, the position is an important notion that typifies the in-game economy and the associated gameplay strategies of *Dota 2*, which serve as critical determinants of the match outcome because the economy can be translated into equipment and combat advantages and thus relate profoundly to the probability of winning. As such, how to distribute the farming and killing opportunities to players, or how to prioritize a player's access to gold and experience points earning is a vital question of team strategic planning.

Within the *Dota 2* community, the concept of position has been conventionally structured as a 1-to-5 system in which the lower number denotes the higher priority a hero has on procuring gold and experience points. The positions are typically assigned before a match starts, and players usually engage in the same positions throughout a tournament. More specifically, the position assignments can be illustrated with the contrasting tactical roles of Carry and Support. Whereas a Carry relies heavily on the in-game economy and equipment to reach the full potential and "carry" the team at the late stage, a Support is characterized by abilities less dependent on the economy, enabling it to contribute to the team starting at an early stage but offering limited help in the late game. Accordingly, the Carry is usually assigned a lower position (higher priority) number than the Support character. In general, any decision-making related to the in-game economy or gold, such as buying BKB as well as other items, is not independent of position. Therefore, I use the rankings of net worth[4], a major in-game economy statistic of *Dota 2*, to proxy for position assignments.

Another set of control variables associated with gameplay are the threats imposed by the opponent's disabling spell and magic attack, as well as the hero's ability to endure and dodge damages. Since the tactical function of BKB is to grant spell immunity and 100% magic damage resistance, the strengths of the rival's disabling and magic spells are presumed to increase the likelihood of opting for BKB. Therefore, I include the disabler and nuker scores of opponents to control for such effects. Moreover, I add one binary

[4] https://www.dotabuff.com/matches/5126886697. For the difference between net worth and gold, see https://tinyurl.com/uz6fumt.

variable to indicate whether the hero is classified as the durable type and another for identifying escape heroes. This is because durable heroes are characterized by relatively high health points that increase their chance of surviving mighty magic attacks, whereas escape heroes feature abilities that facilitate them to evade damages by retreating or repositioning during team fights. As a result, these two factors would theoretically reduce the reliance on BKB.

3.2.2 PLAYER AND YEAR-SPECIFIC FACTORS

To account for the potential that risky choices are more attributable to a player's habitual inclination than the reference-dependent preference, I add player-fixed effects to the main specification by creating a sequence of dummy variables. This approach only applies to players who have repeated observations in the sample more than a certain number of times. Similarly, year-fixed effects are incorporated to control for factors such as the game version, which typically undergoes major upgrades on a yearly basis.

3.3 SURVIVAL ANALYSIS MODEL

3.3.1 MODEL SPECIFICATION

Survival analysis is a statistical method for analyzing the expected duration of time until one or more events take place, such as a death in biological organisms and a failure in mechanical systems. With defining the in-game purchase of BKB as the event of interest, which occurs at most one time in a single game on an individual basis, I use a survival analysis model to conduct data analysis in the current dissertation. Furthermore, to deal with both time-independent and time-varying covariates, a modified Cox proportional-hazard model powered by lifelines[5], an open-source Python library, is adopted for this dissertation.

[5] https://lifelines.readthedocs.io/en/latest/Survival%20Regression.html

$$h(t|x) = \overbrace{b_0(t)}^{baseline} \underbrace{\exp\left(\overbrace{\sum_{i=1,k=1}^{m,n} \alpha_i x_i + \beta_k(x_k(t) - \overline{x_k})}^{log-partial\ hazard}\right)}_{partial\ hazard} \tag{1}$$

Equation 1 shows the model specification. On the left side is the hazard rate $h(t|x)$, which is determined by two components on the right side. The first component, $b_0(t)$, measures the underlying baseline hazard, namely, how the risk of event per time unit changes over time at baseline levels when the values of covariates are set to be zeros. The second component accounts for the partial hazard contributed by a group of covariates, the effects of which on the hazard rate are assumed to respond exponentially. Furthermore, I denote time-independent variables as x_i's, and time-varying variables as $x_k(t)$'s, with α_i's and β_k's being the respective parameters.

While survival analysis does allow the event for each subject to repeat, such as a cancer patient in remission possibly facing a recurrence, I need to clarify that the defined event in the dissertation is a one-shot activity that will not be observed again after its first occurrence. Even though it is indeed allowed in the game to buy BKB more than once, doing so provides limited material gains that increase winning probability because same items share cooldowns so that they cannot be activated neither simultaneously nor sequentially. Therefore, the model specification in this dissertation falls into the common category of survival analysis with non-repeated events.

3.3.2 MODEL PARAMETER INTERPRETATION

Loss aversion means that individuals are more receptive to risk-taking when they anticipate unfavorable outcomes. Accordingly, *Dota 2* players trailing their opponents are less likely to buy BKB (i.e., a risk-averse behavior) than those players in the lead, ceteris paribus. In other words, the hazard rate is predicted to be lower in the loss domain than in the gain domain. Although it seems to be counterintuitive, the defined event in this dissertation captures risk-averse preferences and thus a higher hazard is aligned with a less risky solution. When it comes to interpreting estimation results from the Cox model, a positive coefficient (i.e., the exponential being greater than 1) is equivalent to a higher hazard rate that the event of interest happens. On the contrary, if an estimated coefficient is negative, then it follows that the associated factor tends to stimulate players to act in a more audacious manner since a decreased hazard rate means that they prefer to postpone or circumvent buying an item that provides secured benefits for the purpose of chasing a chance of even higher returns. The estimated results will be reported separately based on the level of competition, which can provide preliminary evidence for Hypotheses 1 and 2 under the assumption that the level of competition is positively correlated with the level of experience and the magnitude of payoffs. In the alternative specifications, more precise evidence is obtained by replacing the level of competition with more direct variables, i.e., the number of years in professional play and the total purse of the tournament. But the sample size will be smaller as data for these two variables are not available for many observations, particularly those not at the top-performing level.

3.3.3 THE CENSORING ISSUE

Censoring is a form of missing data issue common in survival analysis. It occurs when the time to the event is not observed for reasons such as the termination of the study or the subject dropping out prior to experiencing the event, also known as right-censoring. For dealing with this problem, I adopt the usual practice that substitutes the likelihood of right-censored observations with the probabilities of time being greater than the duration of the investigation to form the likelihood function (Equation 2). In this dissertation, the only source of the right-censoring issue is the observed player does not purchase BKB until the game ends, as is illustrated in Figure 3.2. Since buying decisions in *Dota 2* are made individually and BKB only benefits the hero who bought it, the reason why a player does not buy BKB should be attributed to either he does no have enough gold or he has but opts for other items.

$$L(\theta) = \prod_{T_i \in unc.} P(T = T_i|\theta) \prod_{T_j \in r.c.} P(T > T_j|\theta) \tag{2}$$

3.4 DATA

3.4.1 DATA SOURCES & COLLECTION

The data used in this dissertation are minute-by-minute *Dota 2* match statistics coming from two online sources. First, Dotabuff is a leading community website that documents in-depth statistics of *Dota 2* matches at multiple levels of competition, including premium, professional, and amateur, which are primarily classified based on the total purse of a tournament. Specifically, the data about BKB purchase time, individual net worth, hero type, team net worth, and experience points advantages, and kill differential were collected from this website. Second, player-specific data came from Liquipedia. Touted as esports wiki, Liquipedia has personal information of active and historical *Dota 2* players, including the starting years of their careers. In addition, Liquipedia summarizes the classification of hero types and levels, such as Nuker I & II and Initiator II & III, from which the nuker, disabler, durable, and escape scores are computed.

The relevant data were collected in the use of self-written Python scripts. Specifically, three programs were developed to obtain general match statistics including hero and item information, minute-by-minute match statistics including team- and individual-level gold, experience points, and net worth, and kill history that documents killing activities, respectively. Additionally, another program was used to glean player-specific information.

3.4.2 DATA STRUCTURE

Both time-varying and time-independent covariates, where time corresponds to one minute in the game, are used in this dissertation. Therefore, the data set is structured on a minute-by-minute basis. That is, for each minute, time-varying information is constantly updated while time-independent statistics are fixed throughout the game. Table 3.2 displays the details of the covariates, and Table 3.3 provides the summary statistics.

3.5 ALTERNATIVE SPECIFICATIONS

3.5.1 DECOMPOSING THE EFFECTS OF COMPETITION LEVELS

The main specification capitalizes on three levels of competition to proximate for players who possess varied experience and face payoffs of different magnitudes, which serves as a preliminary investigation of how the significance of loss aversion is affected by those two factors of interest. To further determine how experience and payoff size influence the degree of loss aversion, the classification based on competition levels is replaced with more direct and precise measures of these two factors. Specifically, an interaction term between the number of years spent on attending *Dota 2* tournaments and IG Lag corresponds to Hypothesis 1: experienced players who are trailing in the game tend to play less aggressively compared with rookie players in similar situations. On the other hand, considering that the subjects in this dissertation are individual esports players, who are arguably more attentive to the largest possible amount of prize money they can earn than the total purse of the tournaments, I use a fifth[6] of the top prize, which usually accounts for 40 percent of the total purse, to proxy for the payoffs. For testing Hypothesis 2, an interaction term between the prize and IG Lag is introduced to examine whether players facing an increased amount of prize and foreseeing unfavorable outcomes at the same time are inclined to play in a riskier manner.

[6] The prize money needs to be evenly distributed to the five players in the team.

Table 3.1 A Comparison between the Situational Returns of BKB and MKB

Item	*Price*	*Bonus*	*Ability*	*Probability*	*Damage*	*Expected Damage*
Black King Bar (BKB)	4050	+10 Strength +24 Attack damage	Grants spell immunity and 100% magic damage resistance.	100%	5,000	5,000
Monkey King Bar (MKB)	4175	+10 Attack speed +52 Attack damage	Grants a chance to pierce through evasion and deal bonus damage.	50%	10,000	5,000
				50%	0	

Table 3.2 Time-Varying and Time-Independent Variables

Variable	*Description*	*Type*	*Source*	*Expected Sign*
		Time-Varying		
Team net worth advantage	Team difference in combat ability measure by the value of items and gold	Numeric	Dotabuff	No
Team experience points advantage	Team difference in combat ability measure by experience points (levels)	Numeric	Dotabuff	No
Team kill differential	Team difference in achieved kills	Numeric	Dotabuff	No
		Time-Independent		
Position	The priority to glean in-game resources	Nominal	Dotabuff	No
Durable score	The ability to absorb damages without dying	Nominal	Liquipedia	Negative
Escape score	The ability to dodge damages without dying	Nominal	Liquipedia	Negative
Opponent nuker score	The opponent team's ability to deal instant damages	Nominal	Liquipedia	Positive
Opponent disabler score	The opponent team's ability to stun heroes	Nominal	Liquipedia	Positive

Table 3.3 Summary Statistics of the Variables Analyzed in the Dissertation

Variable	*Mean*	*Std*	*Min*	*Max*
IG Lag	0.5088	0.4999	0	1
Position	2.9877	1.4527	1	5
ONS	5.1905	1.7379	0	10
ODS	5.4899	1.5641	1	10
Durable	0.3662	0.4817	0	1
Escape	0.4063	0.4911	0	1

Note. Number of observations (tournament-match-player-minute) is 529,659. ONS represents opponent nuker score and ODS represents opponent disabler score.

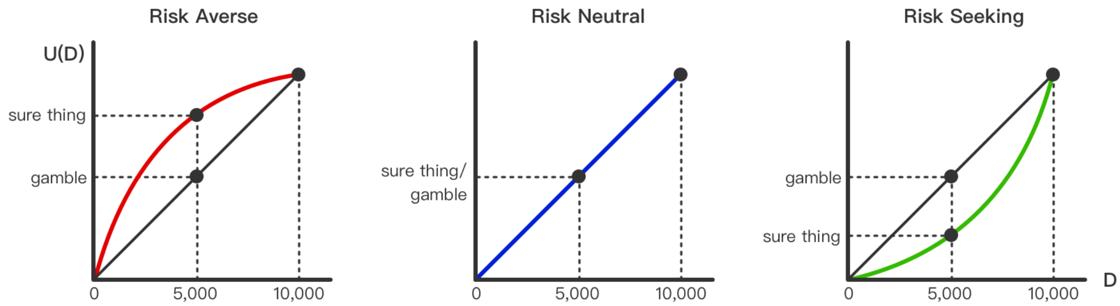

Figure 3.1 A Graphic Representation of Risk Preferences

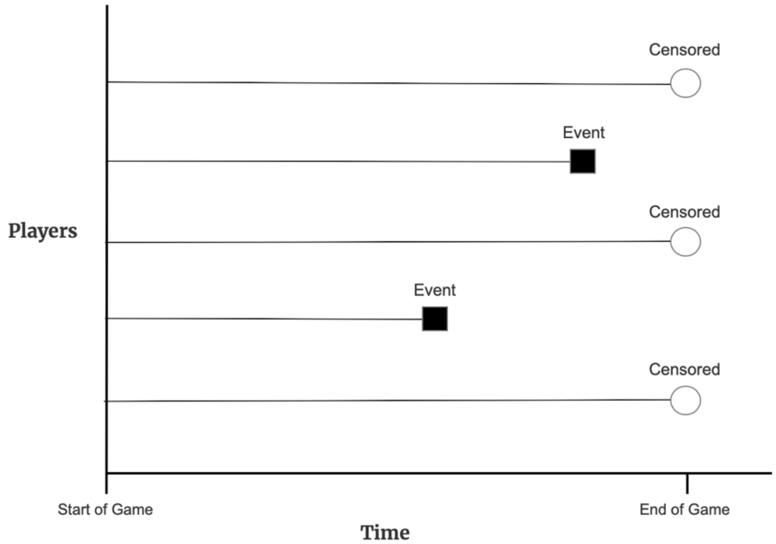

Figure 3.2 The Censoring Issue in *Dota 2* Matches

CHAPTER 4

RESULTS

4.1 THE LEVEL OF COMPETITION AND LOSS AVERSION

The main specification of this dissertation was to examine whether *Dota 2* players' propensity to avoid losses changed with the level of competition. The estimation results of conducting survival analysis on the in-game event of buying BKB are shown in Tables 4.1-4.4. According to the results reported in Table 4.1, which were derived from a pooled model containing players at all levels of competition, *Dota 2* players consistently exhibited a strong tendency to avoid potential losses. For example, the coefficient on *IG Lag* was -0.188 ($p<0.01$) when both the year and player fixed effects were included (Model 4), suggesting they were 17.1% less likely to buy BKB in the trailing situation than in the leading situation. Moreover, the coefficients on the categorical variables associated with players competing in professional (e.g., -0.066; $p>0.1$) and premium tournaments (e.g., -0.003; $p>0.1$) indicate they were not systematically different from those players attending amateur tournaments in terms of loss aversion.

Tables 4.2-4.4 show the results of separately estimating the coefficients related to players attending amateur, professional, and premium tournaments. To be precise, when the year and player fixed effects were not included (Model 1), the coefficient on *IG Lag* was -0.150 ($p<0.01$) for players attending the amateur tournaments (Table 4.2), meaning they became 14% less likely to buy BKB if they were trailing behind compared with the cases in which they gained the lead. Since buying BKB was identified as a risk-averse behavior in the setting of *Dota 2*, such a result validated the presence of loss aversion among the amateur players. Likewise, for players who participated in the professional and premium tournaments, the estimated coefficients on *IG Lag*, without the year and player fixed effects (Model 1), were -0.229 ($p<0.01$; Table 4.3) and -0.155 ($p<0.01$; Table 4.4). That is to say, players became 20.5% and 14.4% less probable to buy BKB if they were in the loss domain compared to the gain domain, which is also consistent with the predictions of loss aversion.

To check robustness, the year and player fixed effects were added sequentially to the main model in the alternative specifications. As shown in Tables 4.2-4.4, when only incorporating the year fixed effects (Model 2), the coefficients on *IG Lag* were -0.150 ($p<0.01$), -0.231 ($p<0.01$), and -0.156 ($p<0.01$) for players attending the amateur, professional, and premium *Dota 2* tournaments. In other words, the probabilities of players buying BKB became 14%, 20.7%, and 14.6%, respectively, lower if they were trailing behind than being in the lead. Similarly, when only the player fixed effects were included (Model 3), the coefficients on *IG Lag* were -0.148 ($p<0.01$; Table 4.2), -0.231 ($p<0.01$; Table 4.3), and -0.154 ($p<0.01$; Table 4.4), indicating that the amateur contestants became 13.9% less likely to buy BKB if unfavorable outcomes were foreseeable, whereas their counterparts competing in the professional and premium tournaments were 20.7% and 14.3% less probable to do so under comparable circumstances, respectively. Finally, when both the year and player fixed effects were added to the model specification (Model 4), the estimated coefficients on *IG Lag* were -0.152 ($p<0.01$; Table 4.2), -0.231 ($p<0.01$; Table 4.3), and -0.162 ($p<0.01$; Table 4.4) for players attending the amateur, professional, and premium tournaments. That is, they became 14.2%, 20.7%, and 15%, respectively, less probable to buy BKB in the loss domain than in the gain domain. Provided there were limited changes in the coefficient of interest, i.e., *IG Lag*, with the addition of the year and player fixed effects, the results obtained in the main specification should be considered robust.

According to the estimation results from examining *Dota 2* players' risk-avoiding behavior at three levels of competition, including amateur, professional, and premium tournaments, it can be seen they consistently exhibited a stronger inclination to opt for the risky solution of not buying BKB if they were trailing behind in the game than when they had the lead. Moreover, considering the coefficients on *IG Lag* for players attending different levels of esports competition were close in terms of magnitude, it is proper to state that loss aversion persisted among players of different performance levels rather than increased or decreased with the performance level. As such, the results of the main specification in this dissertation provided preliminary evidence for how *Dota 2* players' loss aversion tendency was affected by their experience and the tournaments' prize money, which are typically assumed to be positively correlated with the level of competition. Further investigations on these relationships in question were carried out in the following alternative specifications.

4.2 EXPERIENCE AND LOSS AVERSION

The first alternative specification in this dissertation aimed to procure more direct evidence on the relationship between *Dota 2* players' experience, measured by the number of years they had been playing professionally, and their propensity to avoid losses. Instead of classifying the subjects based on the level of competition they participated in, the current model specification focused on a much smaller sample of players (*N*=150) whose career information was accessible. Table 4.5 shows the estimation results of survival analysis conducted on this sample of players with two variables *Experience* and *IG Lag*Experience* being added to the model. In particular, while *Experience* was used to capture how players' risk-taking tendency, despite they were in the loss or gain domain, changed as their related experience increased, the interaction term between *IG Lag* and *Experience* (i.e., *IG Lag*Experience*) was introduced to examine the relationship between players' experience and the significance of loss aversion. To be more precise, for example, a negative sign of the coefficient on *IG Lag*Experience* denoted that experienced *Dota 2* players, compared to their rookie counterparts, had a weaker propensity to buy BKB and thus a stronger willingness to take risks if they were trailing behind in the game.

In Table 4.5, Models 1 and 2 did not include *IG Lag*Experience* whereas Models 3 and 4 contained the interaction term. The following results were focused on the latter two models. Specifically, the coefficients on *IG Lag* were -0.167 ($p<0.01$) without the inclusion of the year fixed effects (Model 3) and -0.180 ($p<0.01$) with the addition of the year fixed effects[7] (Model 4), indicating the observations in the current sample became 15.5% and 16.6% less probable to buy BKB if they anticipated unfavorable outcomes rather than favorable ones, respectively. Therefore, akin to the findings of the main specification, players displayed situational risk preference consistent with the predictions of loss aversion. Furthermore, the coefficients on *Experience* were -0.124 ($p<0.01$) in Model 3 and -0.147 ($p<0.01$) in Model 4. That is, with each additional year in professional experience, players would become 11.8% and 13.8% less probable to buy

[7] To avoid multicollinearity, the player fixed effects were not included because experience per se pertains to individual players.

BKB, respectively, suggesting an increased risk-taking tendency. In regard to how *Dota 2* players' experience influenced their risk preference in the loss and gain domains, the estimated coefficients on *IG Lag*Experience* were 0.001 (p=0.75) in Model 3 and 0.003 (p=0.48) in Model 4. It should be noted that the two variables *Experience* and *IG Lag*Experience* differ in that the former variable centers on the relationship between players' experience and their risk-seeking preference regardless of whether they are trailing behind or having the lead, whereas the latter variable emphasizes the linkage between players' experience and their propensity to avoid losses (i.e., individuals tend to react more strongly to losses than gains in a systematic manner). Provided the coefficients on *IG Lag*Experience* in Models 3 and 4 were extremely small in magnitude and not statistically significant, it can be concluded that *Dota 2* players' relevant experience had no significant impact on the salience of loss aversion.

4.3 THE MAGNITUDE OF PAYOFFS AND LOSS AVERSION

The second alternative specification was to examine the relationship between the magnitude of payoffs and the significance of loss aversion. Table 4.6 shows the estimation results of survival analysis carried out on the sample that contained all the players (*N*=2,128) with two variables *Prize* and *IG Lag*Prize* being added to the model. Models 1 and 2 did not include *IG Lag*Prize* whereas Models 3 and 4 contained the interaction term. The following results were again focused on the latter two models. Specifically, the coefficient on *Prize* indicates how the magnitude of payoffs influenced *Dota 2* players' risk-taking tendency regardless of whether they were in the loss or gain domain. Additionally, the interaction term between *IG Lag* and *Prize* (i.e., *IG Lag*Prize*) was employed to examine how the significance of loss aversion, that is, the players' risk preference contingent on being in the loss or gain domain, changed with the size of prize money.

In Table 4.6, the coefficients on *IG Lag* were -0.178 ($p<0.01$) without the year fixed effects (Model 3) and -0.180 ($p<0.01$) with the addition of the year fixed effects[8] (Model 4), meaning that *Dota 2* players became 16.4% and 16.6%, respectively, less probable to buy BKB if they were trailing behind in the game than when they gained the lead. Hence, the result regarding loss aversion was still in concert with those in the main and the first alternative specifications. Next, the coefficients on *Prize* were 0.116 ($p<0.01$) in Model 3 and 0.081 ($p<0.01$) in Model 4. That is, with an increase of one million US dollars that an individual contestant could earn by outperforming others in the esports tournament, players tended to be 12.3% and 8.5%, respectively, more probable to buy BKB, which suggests that they preferred conservative gameplay when the stakes were high. Concerning the relationship between the magnitude of payoffs and the significance of loss aversion, the coefficients on *IG Lag*Prize* were 0.045 ($p<0.01$) in both Models 1 and 2, indicating that players became 4.6% more likely to buy BKB if they were facing large stakes and potential losses at the same time. As such, the salience of loss aversion seemed to be attenuated by an increase in prize money. Furthermore, the finding that *Prize* had an attenuating effect on loss aversion could help explain, to some extent, why the coefficients on *IG Lag* for premium players (-0.229, -0.231, -0.231, and -0.231; Table 4.4) were smaller than those for professional players (-0.155, -0.156, -0.154, and -0.162; Table 4.3) in the main specification.

[8] When pooling the players attending amateur, professional, and premium tournaments in one sample, the number of players would become so large that the estimation coefficients were not computable. Therefore, the player fixed effects were not included in the second alternative specification.

4.4 SUMMARY

The results of both the main and alternative specifications indicate that, despite the level of competition, *Dota 2* players systematically displayed an increased tendency to take risks when they were trailing behind in the game compared to the situations in which they had the lead. This finding, in accordance with the predictions of loss aversion, is considered robust with or without the fixed effects. Additionally, more direct evidence obtained by further examining the relationship between players' experience and their propensity to avoid losses shows that *Dota 2* players' relevant experience did not significantly impact their loss aversion tendency, which does not support Hypothesis 1. The examination of the relationship between the size of prize money and the significance of loss aversion reports a mitigating effect of tournament prizes on loss aversion, which does not support Hypothesis 2 either.

Table 4.1 Estimation Result of Survival Analysis on *Dota 2* Players (Pooled Model)

	Model 1		Model 2		Model 3		Model 4	
Variable	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*
IG Lag	-0.184*** (0.006)	0.832	-0.185*** (0.006)	0.831	-0.188*** (0.006)	0.829	-0.188*** (0.006)	0.829
Position	0.080*** (0.002)	1.084	0.080*** (0.003)	1.083	0.080*** (0.002)	1.083	0.079*** (0.002)	1.082
ONS	0.057*** (0.002)	1.059	0.048*** (0.002)	1.050	0.059*** (0.002)	1.061	0.050*** (0.002)	1.051
ODS	-0.016*** (0.002)	0.984	-0.003 (0.002)	0.997	-0.016*** (0.002)	0.984	-0.003* (0.002)	0.997
Durable	0.121*** (0.006)	1.128	0.115*** (0.006)	1.122	0.106*** (0.006)	1.112	0.101*** (0.006)	1.106
Escape	0.165*** (0.006)	1.179	0.178*** (0.006)	1.194	0.141*** (0.006)	1.152	0.154*** (0.006)	1.167
Professional	-0.072* (0.034)	0.931	-0.067 (0.042)	0.935	-0.070* (0.033)	0.932	-0.066 (0.042)	0.936
Premium	-0.003 (0.005)	0.997	-0.003 (0.005)	0.997	-0.003 (0.005)	0.997	-0.003 (0.005)	0.997
Year FE	No		Yes		No		Yes	
Player FE	No		No		Yes		Yes	

Note. Number of periods is 529,659 and number of events is 103,445. Standard errors in parentheses. ONS represents opponent nuker score and ODS represents opponent disabler score. FE represents fixed effects. The reference category is players attending amateur tournaments.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4.2 Estimation Result of Survival Analysis on *Dota 2* Players Attending Amateur Tournaments

	Model 1		Model 2		Model 3		Model 4	
Variable	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*
IG Lag	-0.150*** (0.011)	0.860	-0.150*** (0.011)	0.860	-0.148*** (0.011)	0.861	-0.152*** (0.011)	0.858
Position	0.046*** (0.003)	1.047	0.044*** (0.003)	1.045	0.048*** (0.003)	1.049	0.047*** (0.003)	1.048
ONS	0.052*** (0.002)	1.054	0.049*** (0.002)	1.050	0.054*** (0.003)	1.055	0.052*** (0.003)	1.053
ODS	0.006* (0.003)	1.006	0.009*** (0.003)	1.009	0.012*** (0.003)	1.012	0.014*** (0.003)	1.014
Durable	0.279*** (0.011)	1.322	0.276*** (0.011)	1.317	0.249*** (0.011)	1.283	0.252*** (0.011)	1.287
Escape	0.233*** (0.011)	1.262	0.232*** (0.011)	1.261	0.199*** (0.011)	1.220	0.196*** (0.011)	1.217
Year FE	No		Yes		No		Yes	
Player FE	No		No		Yes		Yes	

Note. Number of periods is 178,754 and number of events is 33,248. Standard errors in parentheses. ONS represents opponent nuker score and ODS represents opponent disabler score. FE represents fixed effects.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4.3 Estimation Result of Survival Analysis on *Dota 2* Players Attending Professional Tournaments

	Model 1		Model 2		Model 3		Model 4	
Variable	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*
IG Lag	-0.229*** (0.010)	0.795	-0.231*** (0.010)	0.793	-0.231*** (0.010)	0.793	-0.231*** (0.010)	0.793
Position	0.047*** (0.003)	1.048	0.048*** (0.003)	1.049	0.043*** (0.003)	1.044	0.045*** (0.003)	1.046
ONS	0.065*** (0.002)	1.067	0.051*** (0.002)	1.052	0.070*** (0.002)	1.072	0.054*** (0.003)	1.056
ODS	-0.025*** (0.003)	0.975	-0.002 (0.003)	0.997	-0.028*** (0.003)	0.972	-0.006* (0.003)	0.993
Durable	-0.099*** (0.011)	0.905	-0.086*** (0.011)	0.917	-0.142*** (0.011)	0.867	-0.137*** (0.011)	0.871
Escape	0.216*** (0.010)	1.241	0.224*** (0.010)	1.251	0.151*** (0.011)	1.163	0.157*** (0.011)	1.170
Year FE	No		Yes		No		Yes	
Player FE	No		No		Yes		Yes	

Note. Number of periods is 198,614 and number of events is 35,935. Standard errors in parentheses. ONS represents opponent nuker score and ODS represents opponent disabler score. FE represents fixed effects.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4.4 Estimation Result of Survival Analysis on *Dota 2* Players Attending Premium Tournaments

	Model 1		Model 2		Model 3		Model 4	
Variable	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*
IG Lag	-0.155*** (0.010)	0.856	-0.156*** (0.010)	0.854	-0.154*** (0.011)	0.857	-0.162*** (0.011)	0.850
Position	0.159*** (0.003)	1.172	0.158*** (0.003)	1.171	0.096*** (0.004)	1.101	0.097*** (0.004)	1.102
ONS	0.073*** (0.003)	1.075	0.064*** (0.003)	1.066	0.092*** (0.003)	1.096	0.085*** (0.003)	1.088
ODS	-0.052*** (0.003)	0.948	-0.039*** (0.003)	0.961	-0.037*** (0.003)	0.963	-0.030*** (0.003)	0.969
Durable	0.158*** (0.011)	1.171	0.150*** (0.011)	1.162	-0.346*** (0.012)	0.707	-0.342*** (0.012)	0.710
Escape	-0.020* (0.011)	0.980	-0.004* (0.011)	0.995	-0.489*** (0.012)	0.612	-0.478*** (0.012)	0.619
Year FE	No		Yes		No		Yes	
Player FE	No		No		Yes		Yes	

Note. Number of periods is 152,291 and number of events is 34,262. Standard errors in parentheses. ONS represents opponent nuker score and ODS represents opponent disabler score. FE represents fixed effects.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4.5 Estimation Result of Survival Analysis on *Dota 2* Player Experience

	Model 1		Model 2		Model 3		Model 4	
Variable	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*
IG Lag	-0.167*** (0.023)	0.845	-0.180*** (0.024)	0.834	-0.167*** (0.023)	0.845	-0.180*** (0.024)	0.834
Experience	-0.125*** (0.003)	0.882	-0.147*** (0.003)	0.863	-0.124*** (0.003)	0.882	-0.147*** (0.003)	0.862
IG Lag*Experience	---	---	---	---	0.001 (0.005)	1.001	0.003 (0.005)	1.003
Position	0.132*** (0.003)	1.141	0.134*** (0.003)	1.143	0.138*** (0.003)	1.148	0.136*** (0.003)	1.145
ONS	0.057*** (0.003)	1.060	0.047*** (0.002)	1.048	0.058*** (0.002)	1.060	0.047*** (0.002)	1.048
ODS	-0.038*** (0.003)	0.963	-0.028*** (0.003)	0.972	-0.041*** (0.003)	0.959	-0.030*** (0.003)	0.970
Durable	0.022* (0.010)	1.022	0.014 (0.010)	1.014	0.025* (0.010)	1.025	0.017 (0.010)	1.017
Escape	-0.036*** (0.010)	0.964	-0.022* (0.010)	0.978	-0.037*** (0.010)	0.963	-0.023* (0.010)	0.976
Year FE	No		Yes		No		Yes	

Note. Number of periods is 166,038, number of events is 37,669, and number of players is 150. Standard errors in parentheses. ONS represents opponent nuker score and ODS represents opponent disabler score. FE represents fixed effects. Experience in years.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.6 Estimation Result of Survival Analysis on *Dota 2* Tournament Prize

	Model 1		Model 2		Model 3		Model 4	
Variable	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*	*Coef*	*Exp(Coef)*
IG Lag	-0.183*** (0.006)	0.832	-0.184*** (0.006)	0.832	-0.178*** (0.006)	0.836	-0.180*** (0.006)	0.834
Prize	0.137*** (0.005)	1.147	0.108*** (0.005)	1.114	0.116*** (0.007)	1.123	0.081*** (0.007)	1.085
IG Lag*Prize	---	---	---	---	0.045*** (0.010)	1.046	0.045*** (0.010)	1.046
Position	0.084*** (0.002)	1.087	0.083*** (0.002)	1.087	0.087*** (0.002)	1.090	0.086*** (0.002)	1.089
ONS	0.058*** (0.001)	1.060	0.048*** (0.002)	1.050	0.057*** (0.001)	1.059	0.047*** (0.001)	1.048
ODS	-0.011*** (0.001)	0.988	-0.004** (0.002)	0.996	-0.017*** (0.001)	0.982	-0.001 (0.002)	0.999
Durable	0.132*** (0.006)	1.141	0.128*** (0.007)	1.136	0.127*** (0.006)	1.135	0.125*** (0.006)	1.133
Escape	0.170*** (0.006)	1.186	0.182*** (0.006)	1.200	0.158*** (0.006)	1.172	0.170*** (0.006)	1.185
Year FE	No		Yes		No		Yes	

Note. Number of periods is 529,659 and number of events is 103,445, and number of players is 2,128. Standard errors in parentheses. ONS represents opponent nuker score and ODS represents opponent disabler score. FE represents fixed effects. Prize in million dollars. *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER 5

GENERAL DISCUSSION AND LIMITATIONS

The results obtained in this dissertation contribute to the literature on loss aversion by not only examining the significance of loss aversion at three levels of competition including amateur, professional, and premium *Dota 2* tournaments but also by providing more direct evidence concerning how players' experience and tournaments' prize money impact the salience of loss aversion.

5.1 GENERAL DISCUSSION OF RESULTS

The results of the main specification indicate *Dota 2* players across different levels of competition consistently exhibited a strong tendency to avoid losses, which is likely to be a novel finding in the behavioral economics literature. To interpret this finding, it is necessary to discuss what factors esports players typically take into account when they make risk-taking decisions pertinent to how the game outcomes will be realized. Meanwhile, it should also be pointed out whether amateur, professional, and premium players behave differently in these aspects.

First, like contestants who participate in any form of competition, esports players, whether they be amateur, professional, or premium, have an internal motivation to win the game they, also known as the "play to win" culture in the gaming community (Cullen, 2018). Accordingly, players are predisposed to dynamically adjust their gameplay strategies and tactics, contingent on the in-game situations, to materialize the intended outcome. Specifically, if players and their team are in the lead, it would be natural for them to adopt conservative play as a means of maintaining the status quo in their favor and ultimately achieve victory. On the other hand, when players and their team are trailing behind in the game, their receptiveness to risky solutions would increase considerably because they are eager to reverse the unfavored prospects by virtue of introducing extra uncertainties and thus creating comeback opportunities. Such situational risk preference in esports competition, shared by players of all performance levels, not only resonates with risk-taking behaviors in traditional sports such as basketball and soccer (Bartling et al., 2015) but also fits the theoretical description of loss aversion (Kahneman & Tversky, 1979).

Second, another important consideration in accordance with, though not totally identical to, the "play to win" motivation is the disproportionately large prize money that can be earned by outcompeting other contestants in esports tournaments. For example, the total prize pool of TI9 reached over 34 million US dollars with the rewards being increasingly concentrated in the top ranks. According to the relevant studies, economic incentives account for, to a substantial extent, why people take part in esports activities (Zavertiaeva & Parshakov, 2018) as well as why some players strive to become professionals (Ward & Harmon, 2019). Considering esports competitions often involve high monetary stakes, the related risk-taking behaviors therein can be conceptualized as a form of gambling. That is, following the principle that higher risk is associated with greater probabilities of higher return, esports players can opt for in-game tactics and strategies that contain varying levels of risk, like gamblers betting money on card games or sports, to exert their influence on the game and increase their chances of winning. In terms of monetary incentives, however, it should be noted that amateur tournaments typically do not offer prizes as large as those in professional and premium tournaments. Therefore, amateur players' risk decision-making in the game are not necessarily impacted by the motive for chasing prize money, though amateur tournaments might provide a stage for players to showcase their gaming skills and an opportunity to launch a professional career.

Third, while *Dota 2* players often make in-game purchase decisions on an individual basis, the game also underscores cooperation and teamwork, which require players' risk-related choices be compatible with those of their teammates as well as their coaching strategies, if any. In addition to winning games, good chemistry between teammates can help maximize synergistic efforts and maintain long-term cooperative relationships. Extant research on esports and online gaming has demonstrated social benefits, such as social support (Domahidi et al., 2018; Freeman & Wohn, 2017; Trepte et al., 2012), social capital (Hallmann & Giel, 2018; Kobayashi, 2010; Williams, 2007), and social interaction (Cole & Griffiths, 2007; Lee & Schoenstedt, 2011; Lo et al., 2005), can increase game users' engagement. Compared with amateur teams, which are loosely organized in most cases, professional esports teams have contractual obligations and thus attach greater weight to their stability and sustainability. As a result, *Dota 2* players attending professional and premium tournaments are supposed to make risk-related decisions in the game differently from their amateur counterparts as they need to accommodate their teammates and coach to a larger degree.

The examination of *Dota 2* players' propensity to avoid losses at different levels of competition facilitated the attribution of loss aversion to the "play to win" motivation. As mentioned above, players attending amateur tournaments differ from those attending professional and premium tournaments in the sense that they are not necessarily motivated by monetary rewards, as most *Dota 2* amateur tournaments do not provide prize money. Meanwhile, amateur teams are not formally organized as much as their professional and premium counterparts, making players comparatively less subject to their teammates' gameplay strategies and tactics. Despite the clear-cut differences in both monetary and nonmonetary aspects between amateur contestants and professional and premium players, the major finding of the current dissertation indicates that their loss aversion tendency was highly consistent and stable. As such, it is proper to attribute *Dota 2* players' propensity to avoid losses to the "play to win" culture, which epitomizes the spirit of competition shared by esports players of all performance levels.

In addition to examining loss aversion at three levels of competition, this dissertation conducted in-depth investigations centering on the relationships between players' experience, the magnitude of payoffs, and the significance of loss aversion. Evidence obtained in the first alternative specification showed players' responses to potential losses were not significantly impacted by their relevant experience. This result does not support Hypothesis 1, i.e., the significance of loss aversion is attenuated by increased experience but echoes Pope and Schweitzer's (2011) finding that experience did not necessarily attenuate the salience of loss aversion. However, the authors did not provide further explanations about why the effect of experience on loss aversion was insignificant.

Considering the lack of explanations for the impact of experience on loss aversion, the dissertation attempts to discuss some possible reasons for these findings. First, behavioral science research demonstrated that capuchin monkeys were observed to exhibit trading behaviors indicative of loss aversion (Chen et al., 2006; Lakshminaryanan et al., 2008; Silberberg et al., 2008). Therefore, it is reasonable to infer that loss aversion, as a systematic behavioral bias, might be engrained in our behavior. If so, loss aversion should be deemed as a human instinct that cannot be easily modified by increased experience. Second, the subjects recruited to participate in the related behavioral experiments probably did not possess an understanding of loss aversion equivalent to that of psychologists and behavioral economists. As a result, they were not fully cognizant of loss aversion and its implications on their choices when the experiments were conducted, making the process of accumulating relevant experience extremely slow. Third, it is worth noting that esports performance as well as sporting performance differ drastically from real market behaviors, such as item exchange (List, 2003, 2004), stock trading (Dhar & Zhu, 2006; Feng & Seasholes, 2005), and real estate pricing (Bokhari & Geltner, 2011), in the sense that the related training and competing activities occur on a much more frequent basis. That is, esports players' daily gaming practice can entail a considerably large number of consecutive matches. As a result, theoretically sensible gameplay tactics and strategies might not necessarily turn out to be effective as there exists randomness that makes it complicated to understand and evaluate them. Assuming that people are predisposed to reaffirm and reinforce choices leading to favorable outcomes but correct behaviors that result in unintended outcomes, esports players probably receive random feedback that has limited valuable information for helping them calibrate their in-game behaviors and choices to increase winning odds.

Based on the evidence obtained from the second alternative specification in this dissertation, *Dota 2* players became more risk-averse when the prizes were larger, which is consistent with the previous findings on this topic (Binswanger, 1980; Holt & Laury, 2002; Kachelmeier & Shehata, 1992). One of the widely accepted explanations for such an increased risk-avoiding tendency is that when the stakes were low, the subjects' attention tended to be mainly captured by emotional factors such as the excitement of participating in a lottery experiment (Harrison, 1986). Once the stakes had been raised, however, monetary incentives would play a dominant role in the participants' risk decision-making. To be more specific, considering that the marginal utility of money would decrease as its amount increases (i.e., the law of diminishing marginal utility), individuals' tolerance with risk should be assumed to become weaker when they are guaranteed to gain a relatively large amount of money (i.e., the risk-free option in the choice experiments), though not as large as the amount they could reap if accepting the risky options (Fehr-Duda et al., 2010). As a result, their risk-seeking tendency decreases with the size of stakes. In the same vein, within the context of high-stakes esports tournaments, players would tend to lean toward conservative gameplay if they are facing a nontrivial amount of prize money, which can help explain why *Dota 2* players' risk-taking behaviors occurred less frequently when the tournament prizes became larger.

Additionally, the results of the second alternative specification showed that increased prize money had a mitigating effect on loss aversion, which does not support Hypothesis 2, i.e., the significance of loss aversion increases with the magnitude of payoffs. This mitigating effect of prize on loss aversion is strikingly different from the previous finding that loss aversion was either eliminated or reversed in the cases of small payoffs but became prominent when involving large payoffs (Erev et al., 2008; Ert & Erev, 2007; Harinck et al., 2007). In the relevant literature, behavioral economists attempted to explain the relationship between the magnitude of payoffs and the significance of loss aversion. For example, Harinck et al. (2007) assumed it is easier for a small loss to be cognitively discounted than a large loss and accordingly individuals' loss aversion tendency would not be pronounced when the payoffs are small. However, contrary to previous research, this dissertation found loss aversion could be attenuated by increased payoffs. To interpret such an uncommon result, this dissertation capitalized on the finding about how players' risk-seeking behaviors were impacted by the size of payoffs. Specifically, the above discussion indicates that *Dota 2* players were inclined to be risk averse when facing high stakes no matter whether they were trailing behind or leading in the game. Therefore, increased payoffs could prohibit risk-seeking behaviors in both loss and gain domains. If such a mitigating effect on risk-seeking tendency was stronger in the loss domain than in the gain domain, the behavioral differences in risk preference between trailing and leading players would be reduced and so would the significance of loss aversion.

Overall, the results of the current dissertation indicate that *Dota 2* players attending amateur, professional, and premium tournaments consistently displayed a strong propensity to avoid losses, which can be explained by the "play to win" culture among esports gamers. Further evidence shows players' experience did not significantly impact their loss aversion tendency, supporting Pope and Schweitzer's (2011) argument that experience did not necessarily attenuate loss aversion. Moreover, the magnitude of payoffs had a mitigating effect on loss aversion. However, few studies in the behavioral economics literature have reported similar results and discussed the possible reasons. As such, this dissertation provides not only counterevidence to the previous finding that the significance of loss aversion increases with the size of payoffs (Erev et al., 2008; Ert & Erev, 2007; Harinck et al., 2007) but also explanations for understanding such an unconventional result.

5.2 CONTRIBUTIONS OF DISSERTATION

While previous research examining loss aversion within the context of sport (Bartling et al., 2015; Card & Dahl, 2011; Pope & Schweitzer, 2011) predominantly revolved around top-performing players, the present dissertation investigated esports players' loss aversion tendency at three levels of competition in one study. In so doing, it helps to extend the scope of research on loss aversion by incorporating relatively less experienced and competitive players through contrasting them with high-performing players in terms of their propensity to avoid losses. Interestingly, the results of the main specification in this dissertation indicate that loss aversion persisted among amateur, professional, and premium *Dota 2* players. That is, they consistently displayed a strong inclination to be risk-seeking when they were trailing behind in the game but to opt for less risky solutions if they gained the lead. Since the current dissertation is likely the first one that examined loss aversion at multiple levels of esports competition, it is still unknown whether other types of sports or competitions alike are comparable to esports in the sense that players' loss aversion tendency does not change significantly with their performance levels, which would be an area for future behavioral economics research.

Furthermore, this dissertation provides additional empirical evidence on how the significance of loss aversion is affected by players' relevant experience and the magnitude of payoffs. Notably, different from previous experimental studies that mainly utilized experience that was gained in the laboratory environment (Engelmann & Hollard, 2010; Erev et al., 2008; List & Haigh, 2010), the first alternative specification in this dissertation leveraged esports gaming experience accumulated over a timespan measured by years. The results show players' experience had no significant impact on their loss aversion choices, which not only supports the strand of research arguing that experience does not necessarily attenuate loss aversion (Allen et al., 2016; Bartling et al., 2015; Pope & Schweitzer, 2011) but also reaffirms that loss aversion is a systematic human decision-making bias (Barberis, 2013).

This dissertation also examined whether the significance of loss aversion increased or decreased with the magnitude of payoffs. Unlike previous research that primarily capitalized on either hypothetical or real but small payoffs (Erev et al., 2008; Thaler et al., 1997), this dissertation used real tournament prizes, which can be as large as millions of US dollars, to proxy for the monetary incentives esports players were facing. The results obtained in the second alternative specification show that, though loss aversion consistently persisted, the size of payoffs had a significant mitigating effect on the salience of loss aversion. It is worth noting this finding is radically different from the existing consensus in the relevant literature that loss aversion becomes more prominent when the subjects are provided with higher stakes (Erev et al., 2008; Ert & Erev, 2007; Harinck et al., 2007). In order to explain such an unusual finding, this dissertation combined the results regarding the effects of increased payoffs on *Dota 2* players' risk preference in the general sense (i.e., without differentiating loss and gain domains) and loss aversion. That is, given that players tended to adopt conservative gameplay strategies when the stakes were high despite which domain they were in, the gap in risk-taking behaviors between trailing and leading situations (i.e., loss aversion) would be narrowed if the attenuating effect of increased payoffs on risky choices was comparatively stronger in the loss domain than in the gain domain.

Lastly, this dissertation capitalized on a modified Cox model to deal with both time-independent and time-varying covariates. While time-independent covariates are fairly common in extant research, only a limited number of studies have incorporated time-varying covariates into the analysis. For example, Bartling et al. (2015) investigated the risk-taking behaviors of soccer players and coaches with the on-field information being updated on a minute-by-minute basis. However, the count data method used in their study was not able to accommodate player-specific factors such as age or experience because the statistical model only counted the occurrence of the event in question but did not distinguish who triggered the event. By contrast, the modified Cox model facilitated the examination of player-specific factors in ways such as adding player fixed effects. Therefore, the modified Cox model should be a useful tool for researchers interested in conducting survival analysis with granular data.

5.3 LIMITATIONS AND FUTURE RESEARCH

There are several limitations to the present dissertation. First, only a single type of risky choice within the game of *Dota 2* was used to examine whether the significance of loss aversion changed with the level of competition as well as how it was affected by players' experience and the magnitude of prize money. There exist other candidates that can be utilized to quantify players' risk-seeking tendencies. For example, the talent tree system in *Dota 2* is characterized by a series of selectable talents a hero can choose at levels 10, 15, 20, and 25, with each talent selection reflecting the controlling players' situational risk preference. More specifically, while the talent Gold Per Minute represents a risk-free option as it can generate in-game gold at a fixed rate as long as the game is not closed, Bonus Damage is often considered as a risky choice because the return of selecting this talent can only be reaped when the hero manages to survive ambush attack and deal damages on enemies in team fights. Furthermore, the talent selections occur as the game proceeds, during which trailing situations alternate with leading situations. As such, through observing *Dota 2* players' in-game talent selections, more insights into their risk decision-making under uncertainty can be gleaned.

Second, this dissertation used the number of years a player has been engaging in professional esports competition to proxy for his or her relevant experience. Such an approach might fail to accurately measure the player's gaming experience because it is highly likely that he or she has accumulated experience of the gameplay of *Dota 2* or other similar MOBA games prior to starting a professional career. On the other hand, although some researchers used a player's age to capture his or her experience in playing traditional sports such as basketball (Lucifora & Simmons, 2003; Simmons & Berri, 2011), it is not necessarily suitable in the case of esports considering that esports players can launch their professional careers at ages ranging from 14 to 30 years and their peak performances typically occur at early ages such as 24 years (Thompson et al., 2014). Hence, there remains a paucity of objective and accurate measures for quantifying esports players' relevant experience.

Third, provided that there is an increasing trend of leveraging sports performance to investigate individual behavior in the workplace or market environment (e.g., Bartling et al., 2015; Pope & Schweitzer, 2011), on-field performance in traditional sports and esports are essentially different real market behaviors. Specifically, in addition to monetary rewards, there are many nonmonetary incentives for employees to increase efforts in business (Coates & Parshakov, 2016), such as job promotions and social capital (Adler & Kwon, 2002; Robison et al., 2002). In a real market, consumers can psychologically benefit from transaction utility, i.e., the pleasure consumers derive from the deals per se (Dodonova & Khoroshilov, 2004; Lichtenstein et al., 1990; Thaler, 1983), which is difficult to be captured merely through observing on-field performance. Therefore, behavioral findings derived from sports competitions cannot be fully generalized to real business and market scenarios.

Lastly, it is reasonable to assume the timing of adopting risky solutions plays an important role in examining loss aversion. For example, a trailing basketball team is supposed to be more likely to make risky choices (e.g., attempts for three pointers instead of two) when approaching the end of the game than in the first quarter. However, *Dota 2* differs from traditional sports in that an early advantage can grow exponentially, known as 'snowballing' (Winn, 2015). As a result, the effects of risk-taking in *Dota 2* (e.g., not buying BKB) are accumulative throughout the match, making it technically difficult to identify which stage is relatively more important. In addition, the duration of a *Dota 2* match is not preset and thus highly variable, which does not end until one side destroys the main structure of the other side. Therefore, no clear-cut time points can be utilized to classify the match into different stages, though there are discussions about the phases of MOBA games in the literature (Ferrari, 2013).

For future research, one direction would be to integrate tournament theory into the examination of loss aversion. Specifically, Coates and Parshakov (2016) examined the incentive effects of esports tournament structures and found that the prize structure was convex in rank order, indicating that esports players were risk-averse. In addition, the observed propensity to avoid risks was more significant in team games than in individual games. However, how the significance of loss aversion changes with the rounds in esports tournaments has yet to be investigated. According to tournament theory (Lazear & Rosen, 1981; Rosen, 1986), if the prize structure is convex, contestants should exert nondecreasing efforts as the competition marches toward later stages and becomes increasingly intense. Therefore, esports players' risk preference should depend not only on whether they are trailing or leading in the game but also on their current positions relative to the top prize. As such, incorporating tournament theory can help further the inquiry of loss aversion.

Another direction would be to continue identifying risk-related behaviors closely aligned with the gameplay of esports, such as the in-game buying choices between wards and weapons. Specifically, wards are consumables that can provide visions for the whole team and thereby reducing risks resulted from being ambushed and killed by the enemies. On the other hand, weapons help increase the attack statistics, enabling a hero to deal additional damages in team fights. *Dota 2* players can choose to spend gold on wards so that they are more likely to gain information regarding the locations of their enemies and be prepared to escape their ambush attack. Alternatively, they can also use gold to buy weapons to enhance their attack abilities but they might fail to realize the benefits if they are disabled and eliminated quickly by their enemies. As such, these two types of in-game items are associated with different degrees of risk and therefore can be used to capture the controlling player's risk-taking tendency. Following the approach this dissertation conceptualizes risk preference within the context of *Dota 2*, as is illustrated in Table 3.1, future research can capitalize on the buying decision-making in the game to further the inquiry of loss aversion in esports.

5.4 CONCLUSION

This dissertation conducted an examination of loss aversion at three levels of esports competition by capitalizing on behavioral data from players attending amateur, professional, and premium *Dota 2* tournaments. Likely to be the first of its kind, this dissertation found that loss aversion persisted among esports players regardless of their performance levels. In addition, this dissertation further examined how the salience of loss aversion changed with players' experience and the magnitude of tournament prizes. In particular, the results suggested that players' experience had no significant effect on loss aversion, which is consistent with the strand of research supporting that experience does not necessarily attenuate loss aversion (Allen et al., 2016; Bartling et al., 2015; Pope & Schweitzer, 2011). On the other hand, the size of tournament prizes had a mitigating effect on loss aversion, which provides empirical evidence rarely observed in the existing literature (Erev et al., 2008; Ert & Erev, 2007; Harinck et al., 2007). Moreover, the dissertation attempted to provide explanations for the above findings from economic and psychological perspectives.

The behavioral economics literature has demonstrated people strive to avoid losses by means of taking risks or increasing efforts. Coincidentally, effort exertion is a central focus of labor economics. For example, tournament theory (Lazear & Rosen, 1981; Rosen, 1986) posits contestants put forth greater effort as they proceed to the later stages of a tournament in which prizes increasingly concentrate in the top ranks. While a plethora of empirical research examined the incentive effects of monetary prize on effort (e.g., Ehrenberg & Bognanno, 1990; Gilsdorf & Sukhatme, 2008), little attention has been given to how individuals' risk preferences vary depending on the round of a tournament.

Esports players' risk-taking behaviors that occur during high-stakes competition are good indicators of their natural responses to risks under uncertainty. Therefore, examining esports players' loss aversion tendency across tournament stages can help clarify the theoretical link between prospect theory and tournament theory. In addition, a better understanding of players' on-field risky choices has important managerial implications to designing compensation arrangements for motivational purposes. Since the empirical evidence indicate that esports players were systematically loss averse, esports clubs can utilize clawback provisions (i.e., to pay compensations in advance but demand for return if the preset goals are not met) to elicit players' efforts. Future research can continue to explore the linkage between esports' risk-taking behaviors and their effort exertion.

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