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The Impact of Consumer Perceptions of Tanking on National Basketball Association Attendance

Hua Gong

THE IMPACT OF CONSUMER PERCEPTIONS OF TANKING ON NATIONAL BASKETBALL ASSOCIATION ATTENDANCE

by

Hua Gong

Bachelor of Science
University of Nottingham Ningbo China, 2013

Master of Science
Texas A&M University, 2015

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Accepted by:

Matt Brown, Major Professor

Nick Watanabe, Major Professor

Mark Nagel, Committee Member

Brain Soebbing, Committee Member

Cheryl L. Addy, Vice Provost and Dean of the Graduate School

DEDICATION

To my parents, thank you for being open-minded. Thank you for your unwavering support along the way. Thank you for all the sacrifices.

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ABSTRACT

This dissertation studies the impact of consumer perceptions of tanking on National Basketball Attendance (NBA) attendance. The prevalence of tanking in the NBA raised concerns that some teams were purposely avoiding winning games in order to improve their draft position. The majority of previous studies on tanking have focused on developing empirical evidence of the existence of tanking in sport. Yet, no study systematically explored the impact of perceived tanking behavior on consumer demand for sport. As tanking teams rarely reveal their tanking strategy to the public, fans may not correctly identify tanking behavior in sport, and thus are likely to rely on their perceptions of tanking to make attendance decisions. The current dissertation employs tanking discussions on the social media platform Twitter along with data mining tools to quantify consumer perceptions of tanking. Econometric models are then utilized to analyze the effect of the perceived tanking behavior on demand for NBA games. The estimation results provide robust evidence that the increasing awareness of tanking for home teams hurts NBA attendance in both the short and long term. This dissertation also reveals that more negative attitudes toward visiting teams' tanking behavior can undermine consumer interest in attending NBA games. These findings offer important managerial implications on the urgency of restraining tanking behavior as well as the importance of maintaining integrity in sports competitions.

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LIST OF ABBREVIATIONS

API .... Application Programming Interface

BCSD .... Bias-Corrected Standard Deviation

EPL ....English Premier League

FCI ....Fan Cost Index

FIFA .... Fédération Internationale de Football Association

LOESS .... Locally Estimated Scatterplot Smoothing

LSVM ....Linear Support Vector Machine

MLB .... Major League Baseball

NASCAR ....National Association for Stock Car Auto Racing

NBA ....National Basketball Association

NCAA ....National Collegiate Athletic Association

NFL ....National Football League

NHL ....National Hockey League

NLP .... Natural Language Processing

OLS ....Ordinary Least Squares

RSD..................... Ratio of Actual Standard Deviation to the Idealized Standard Deviation

UFC ....Ultimate Fighting Championship

UOH ....Uncertainty of Outcome Hypothesis

CHAPTER 1

INTRODUCTION

Game attendance has long been a vital part of the professional sports business model (Hansen & Gauthier, 1989; Neale, 1964). Consumers attending sporting events contribute substantial ticket revenue to sports teams and leagues (Szymanski & Késenne, 2004). In addition, ancillary revenues such as merchandise sales and parking fees can also experience significant growth with high attendance (Mason, 1999). Key determinants of demand for sport are well documented in the literature (Borland & MacDonald, 2003; Villar & Guerrero, 2009). One such determinant is the quality of competition that generally encompasses the strength of the teams on the field and the uncertainty of game outcomes (Villar & Guerrero, 2009). For instance, prior studies of consumer demand for sport provide consistent evidence that team strength, normally measured by the team winning percentage, is positively linked to game attendance (Borland & MacDonald, 2003; Noll, 1974; Villar & Guerrero, 2009). That is, winning teams typically draw more fans to sporting events than losing teams. Furthermore, studies on the uncertainty of game outcomes find some evidence to support the hypothesis that demand for certain matches increases when game outcomes are unpredictable (Benz, Brandes, & Franck, 2006; Rascher, 1999; Rascher & Solmes, 2007).

At the same time, the prevalence of tanking in sport threatens the quality of competitions and may impact demand for games through both undermining team strength and the uncertainty of game outcomes (Price, Soebbing, Berri, & Humphreys, 2010). In

North American sports leagues, tanking could occur when teams do not exert their best winning effort. They often tank in order to improve their draft position in the upcoming amateur entry draft (Soebbing & Mason, 2009; Soebbing, Humphreys, & Mason, 2013). This form of tanking emerges as a result of the draft system where the ability to acquire high draft picks is determined by teams' regular-season win-loss record in reverse order (Soebbing et al., 2013). Tanking teams often field less competitive rosters, which therefore reduce team quality (McManus, 2019). With lower team quality, sports teams are more likely to lose games and also draw fewer fans to games. For example, after trading away high-quality players, the Miami Marlins drew mere 10,013 fans per game in 2018, the lowest attendance for any Major League Baseball (MLB) team since 2004 (Shafer, 2018). Teams like the Marlins also compromise the uncertainty of game outcomes by not fielding talented players, thereby not exerting maximum effort to win games and pursue a division, conference, or league championship (Soebbing & Mason, 2009; Taylor &Trogdon, 2002). Thus, if unpredictability attracts fans to games in sports leagues, the tanking strategy employed by the Marlins may seriously hurt attendance (Duvall, 2018; Kendall & Lenten, 2017; Soebbing & Mason, 2009). As the success of sport business relies on fan support, the presence of tanking can damage the quality of competitions, and thus impose significant threats to sports leagues and teams.

In addition to the compromised quality of competitions resulting from tanking, perceptions of tanking may further affect consumer demand for sport (Soebbing & Mason, 2009; Price et al., 2010). If fans perceive the existence of tanking by teams and within sports leagues, then they may decide not to attend games or stop following a sport in general, regardless of whether teams are actually tanking or not (Soebbing & Mason,

2009; Price et al., 2010). This is certainly a possibility as most teams do not acknowledge tanking to the public (Aldridge, 2018). With limited information on which teams are deliberately tanking, consumers may not differentiate actual tanking from below-average performance on the field or court. Therefore, it is likely that they rely on their perceptions tanking to make attendance decisions (Soebbing & Mason, 2009). While some fans are not interested in watching tanking teams, others may fully support tanking as it can ultimately help teams gain competitive advantages in the long term through acquiring higher draft picks (Lenten, Smith, & Boys, 2018). In light of various opinions on tanking, there is a need to further understand the relationship between perceptions of tanking and consumer interest in sport. The dissertation utilizes the National Basketball Association (NBA), where tanking has been a concern for decades, as the research context to explore this relationship.

Chapter 1 covers a variety of topics related to the background information on tanking, ranging from the definitions of tanking to draft reforms. The introduction serves as a basis for the later discussion on the relationship between consumer perceptions of tanking and demand for NBA games. To begin with, several definitions of tanking are compared and differentiated.

1.1 DEFINITION OF TANKING

Despite the prevalence of tanking in sport, its definition seems to be vague in literature. In fact, a range of studies have proposed different definitions of tanking (Balsdon, Fong, & Thayer, 2017; Lenten et al., 2018; Soebbing & Mason, 2009). To better explore tanking behavior in this dissertation, it is critical to first clarify the meaning of tanking. Soebbing and Mason (2009) defined tanking as the behavior of

teams deliberately losing games to improve draft position. This definition has been widely employed in numerous studies (e.g., Borland, Chicu, & Macdonald, 2009; Lenten et al., 2018; Motomura, Roberts, Leeds, & Leeds, 2016; Price et al., 2010; Soebbing et al., 2013; Soebbing & Humphreys, 2013). Balsdon et al. (2007) had a slightly different definition in their study examining tanking behavior in college basketball. They noted tanking took place when participants did not exert the best effort in winning a conference tournament championship. They suggested that this tanking behavior might arise from two reasons: (a) preserving energy for the National Collegiate Athletic Association (NCAA) tournament, and (b) maximizing conference revenue by conceding the title to another conference team which then will receive an automatic bid to the NCAA tournament. Kendall and Lenten (2017) offered a broader definition of tanking than the previous two, considering tanking as an act of intentionally dropping points or losing games in order to gain competitive advantages.

To better analyze the effect of consumer perceptions of tanking on demand for NBA games, Soebbing and Mason's (2009) definition of tanking is adopted in this dissertation. As such, this dissertation focuses on examining tanking behavior where NBA teams deliberately lose games in order to acquire higher draft picks. Other definitions of tanking are not considered in this inquiry.

1.2 LINK BETWEEN TANKING AND THE DRAFT SYSTEM

The previous section noted some links between tanking and the draft system. In fact, the emergence of the tanking behavior in the NBA since the early 1980s could be traced back to the draft system that the league adopted in 1947 (Soebbing & Mason, 2009). Initially, the draft policy was designed to promote competitive balance, or create

equal playing strength between league members (Forrest & Simmons, 2002; Sanderson & Siegfried, 2003). For instance, the reverse-order draft scheme helps the worst performing teams improve team quality through assigning the best draft prospect to them. After acquiring high quality young talent, the poor performing teams can shorten the team quality gap with other franchises. As such, the draft system serves to improve competitive balance in sports leagues, which is considered as a key determinant of demand for sport (Sanderson & Siegfried, 2003). However, the implementation of the draft system also creates an unintended consequence that teams may intentionally lose games to acquire the top draft pick (Soebbing & Mason, 2009). For instance, a range of studies have offered evidence that NBA teams are more likely to lose games after being eliminated from playoff contention, signaling that some NBA franchises are deliberately losing games for high draft picks (e.g., Price et al., 2010; Taylor & Trogdon, 2002).

1.3 AN OVERVIEW OF TANKING TACTICS AND STRATEGIES

The previous section established a clear link between the draft system and tanking. This section further introduces three tanking tactics and two tanking strategies that teams may use to strategically lose games.

1.3.1 TANKING TACTICS

McManus (2019) summarized three tanking tactics in sport. The first is to trade away key players in exchange for promising young players or valuable draft picks that have the potential to develop into superior players and contribute wins to teams (McManus, 2019). In this process, teams intentionally assemble less competitive rosters in the hopes of losing more games and improving their draft position. To ensure the effectiveness of this tanking tactic, teams can also choose not to sign high-profile and

high-performing players in the free agent market. This practice can help teams save valuable financial resources while also reinforcing their goal of losing more games. Among the major professional sports leagues in North America, MLB teams often use this tactic (Sheinin, 2018). Due to the absence of a salary floor in MLB, setting a minimum amount of salary each team has to pay in a given season, it is easier for MLB teams to avoid signing high priced players in the free agent market as compared to teams in other leagues where a strict salary floor is a part of many league's collective bargaining agreements (Sheinin, 2018).

The second tanking tactic is resting healthy, key players. By resting top players and assigning more playing time to young and less experienced players, tanking franchises deliberately play a less competitive roster thereby making them more likely to lose games (McManus, 2019). Resting healthy players does not only improve teams' odds of losing games and winning the draft lottery, but also gives young players opportunities to develop. These young players may have the potential to help teams gain competitiveness in the long term (Soebbing et al., 2013).

The third tanking tactic is giving up games. For instance, Preston and Szymanski (2003) provided an example of Barbados intentionally kicked the ball into their own goal at the end of regulation in order to tie their match with Grenada at the Shell Caribbean Cup. Barbados had to win the game by two goals to advance to the next round, but only led by one goal when there were three minutes left on the game clock. Therefore, Barbados had to force the match into overtime so that they would have more time to score more goals.

1.3.2 TANKING STRATEGIES

The previous section described three tanking tactics that teams could employ to purposely lose games. This section centers on discussing how teams may use these tactics to successfully deploy tanking strategies. McManus (2019) noted two tanking strategies that were widely employed by major professional sports teams. The first strategy is to intentionally lose games late in the regular season when teams are already eliminated from playing in the postseason (Price et al., 2010; Taylor & Trogdon, 2002). After being eliminated from playoff contention, the benefit of winning additional games can be minimal (Soebbing et al., 2013). However, if teams lose more games and lower their standing in the league, they will have better opportunities to obtain a high draft pick under the reverse-order draft system (Soebbing et al., 2013). Thus, it is not surprising that teams may choose to tank once they lose the hope to compete in the postseason.

This tanking strategy is often accomplished by resting key players (McManus, 2019). Teams resting key players utilize less talented rosters on the court, which reduces the odds of winning games. Clearly, teams can also deliberately lose games by asking players not to exert the best effort in competition. However, given the competitive nature of sporting contests, players generally exert full effort to win games (McManus, 2019). For this reason, resting key players theoretically becomes the more effective tactic to deliberately lose games. Without key players on the field or court, the disparity in team quality between tanking teams and their opponents makes it more difficult for tanking clubs to win, even though players expend their best effort in competitions.

Unlike the first tanking strategy that is often deployed toward the end of the season, the second tanking strategy is more extreme whereby teams attempt to

deliberately lose games for multiple seasons (McManus, 2019). Using the second tanking strategy often reflects management's belief that rebuilding their franchise through the draft system is the best path to win championships (McManus, 2019). Rather than perpetually staying in the middle or bottom of a league's standings, these teams purposely endure losing seasons in the hopes of maximizing their odds of acquiring the best young talent through the draft system (Motomura et al., 2016). After accumulating sufficient talent over time, teams are well positioned to contend for championships.

This second strategy is often executed with tanking tactics such as trading away key players or avoiding signing high-profile free agents (Vamplew, 2018). By removing key players and not signing quality free agents, teams intentionally construct less competitive rosters in order to access higher draft position. Not only does the reduction of talent level improve draft position, but it also aids in acquiring additional draft picks and young talent from other franchises through player trades (McManus, 2019). High draft picks and young talent are invaluable assets because they may turn into high quality players and contribute numerous wins to the franchise in the long term (McManus, 2019).

In practice, MLB and NBA teams had the history of using this tanking strategy to rebuild franchises (Lenten, 2016). In MLB, the Houston Astros tanked from the 2011 to 2013 seasons. During this period of time, the Astros lost an average of 108 of 162 games per season and, as a result, received three consecutive first overall draft picks, along with other draft picks and young talent they acquired from team trades (Miller, 2018). In the meantime, the Astros significantly cut player payroll by not signing any high-profile player in the free agent market. After years of piling high draft picks and developing young talent through tanking, the Astros won the World Series in 2017. In the NBA, the

Philadelphia Sixers, under the leadership of General Manager Sam Hinkie, employed this tanking strategy from the 2013 to 2016 seasons (Steinberg, 2018). After trading away quality players, the Sixers only won 47 of 246 games they played over these three seasons. The poor win-loss record, however, allowed the Sixers to obtain two second and one first draft pick in the 2014-2016 NBA drafts. The Sixers also purposely accumulated high draft picks from trades they made with other NBA franchises. With these draft picks, the Sixers selected promising young players such as Joel Embiid and Ben Simmons, who helped improve the quality of the Sixers and led the team to the Eastern Conference Semifinals in 2019.

1.4 TANKING IN THE NBA

While tanking is not rare in the sport industry, perhaps the NBA has dealt with tanking more often than any other North American professional sports leagues (Soebbing & Mason, 2009). For this reason, this dissertation uses the NBA as the research context to examine the relationship between consumer perceptions of tanking and demand for sport. Here, a brief explanation of why tanking occurs more frequently in the NBA than other leagues and some notable NBA tanking incidents are discussed.

With basketball games featuring only five players per team on the court, an individual basketball player can significantly influence game results (Sanderson & Siegfried, 2003; Soebbing & Mason, 2009). As such, NBA teams may have greater incentives to acquire high-quality talent via the draft than teams in other leagues as the presence of a superior basketball player may drastically improve team quality (Soebbing & Mason, 2009).

The NBA teams had a long history of employing tanking tactics and strategies discussed before to deliberately lose games. For instance, the Houston Rockets were alleged to have tanked late in the 1984 regular season in an attempt to acquire Hakeem Olajuwon in the 1984 NBA draft (Webb, 2012). Desiring to acquire Olajuwon through the draft, the Houston Rockets lost 14 of their last 17 regular-season games during the 1983-84 season and successfully improved their draft position. Based on their season record, the Rockets finished the first half of the season winning nearly 50% of games. In the second half of the season, the team gave more playing time to its bench players and began losing games more frequently (Vaccaro, 2019). The Rockets eventually finished the season with a 29-53 record and received the first draft pick to Hakeem Olajuwon after winning the coin flip with the Portland Trail Blazers. The coin flip was the procedure used to determine the first overall pick at the time. It was between the last place team in each conference (Soebbing & Mason, 2009).

A decade later, the San Antonio Spurs allegedly tanked during the 1996-1997 season in order to draft Tim Duncan. They actively rested key players and completed the season with a 20-62 record. While this was not the worst record in the 1996-1997 NBA season, the Spurs fortunately won the draft lottery and used the first draft pick to select Tim Duncan in the 1997 draft (Dorsey, 2012).

Generally, an NBA team's decision to tank is not disclosed to the public. However, in certain cases, team executives later reveal their tanking philosophy to the media. For example, former Toronto Raptors general manager, Bryan Colangelo, publicly admitted that the Toronto Raptors attempted to tank in part of the 2011-12 season (Amick, 2014). To improve their draft position, Colangelo noted that the Raptors sought to tank

by resting key players and assigning more playing time to young players. Mark Cuban, the owner of the Dallas Mavericks, also openly admitted that the Mavericks tanked during the 2016-2017 and 2017-2018 seasons (Bieler, 2018). To compete for better draft picks, the team purposely fielded a less competitive roster to increase their odds of losing games.

1.5 NBA DRAFT REFORMS

The NBA has well noted the tanking problem over the past decades. To address the issue, the league has conducted a number of draft reforms since its first use of the draft system in 1947 (NBA, 2017). However, none of these reforms seems to be effective as tanking still frequently takes place in the NBA. This section highlights the draft systems that the NBA has employed and explains why tanking continues to be a problem in the league after multiple reform attempts.

1.5.1 REVERSE ORDER DRAFT

The first NBA draft system was established in 1947 when draft picks were assigned to teams based on their win-loss records in reverse order. Teams also were allowed to forfeit their first-round draft pick and select a territorial player who came from the geographic area where the franchise was located. The use of territorial draft picks aimed to attract more local fans as the presence of ‘local heroes’ could significantly improve attendance (Brandes, Franck, & Nüesch, 2008; Yamamura, 2011). The territorial draft system was replaced by a full reverse-order draft format in 1966. Under the reverse-order draft system, the first draft pick was determined by a coin flip between two worst performing teams in each of the West and East Conferences. The winner of the coin flip would receive the first draft pick and the loser would receive the second. The rest of the

draft picks were assigned to teams based on their regular season win-loss records in reverse order.

1.5.2 EQUAL-CHANCE DRAFT LOTTERY

The reverse-order draft system was used until 1985 when the NBA replaced it with the equal-chance draft lottery system. The new draft scheme gave each non-playoff team an equal chance of receiving the first draft pick. This draft reform arose from the concerns that teams were purposely losing games in order to improve their draft position under the reverse-order draft system (Gerchak, Mausser, & Magazine, 1995). These concerns reached a new height during the 1983-1984 season when the Houston Rockets deliberately lost their 14 of the last 17 regular-season games in order to draft Hakeem Olajuwon, a future member of the Basketball Hall of Fame (Soebbing & Mason, 2009).

1.5.3 WEIGHTED DRAFT LOTTERY

The equal-change draft lottery format ultimately led to fears that it did not provide sufficient help for poor-performing teams to regain competitiveness, which was the original purpose of implementing draft systems in sports leagues (Bondy, 2007). Therefore, the NBA reformed the draft system again in 1990 (Soebbing et al., 2013). Specifically, the league launched a weighted lottery system that gave the worst performing team the best chance of acquiring the first draft pick, which is close to 16.67%. The remaining non-playoff teams had decreasing odds to obtain the first pick based on the inverse of their final regular season standings.

In 1993, the Orlando Magic won the draft lottery with only a 1.52% chance. Witnessing the unfolding of such an improbable outcome, the NBA decided to revise the draft lottery by increasing the probability for the worst-performing team to receive the

first draft pick from 16.67% to 25% in 1994 (Figure 1.1). The new weighted draft system remained intact until 2017 when the public worried that it incentivized numerous teams to tank for the entire season. Therefore, the NBA board of governors again voted to reform the weighed lottery draft by decreasing the odds for the top seed to receive the first draft pick in 2017 (Lowe, 2017). Under the new lottery draft system that was officially instituted in 2019, the bottom three teams shared the same 14% chance to win the draft lottery. The odds for the remaining non-playoff teams to win the lottery gradually decreased based on win-loss records (Figure 1.1).

1.6 PURPOSE OF STUDY

The purpose of this dissertation is to analyze the link between consumer perceptions of tanking and fan demand for NBA games. To explore this relationship, I analyze social media posts from Twitter to quantify consumer perceptions of tanking. Specifically, the two variables, namely, the volume and sentiment of tanking tweets, are constructed to represent perceptions of tanking. After the quantification of consumer perceptions of tanking, econometric models are employed to systematically explore how perceived tanking behavior can affect NBA attendance.

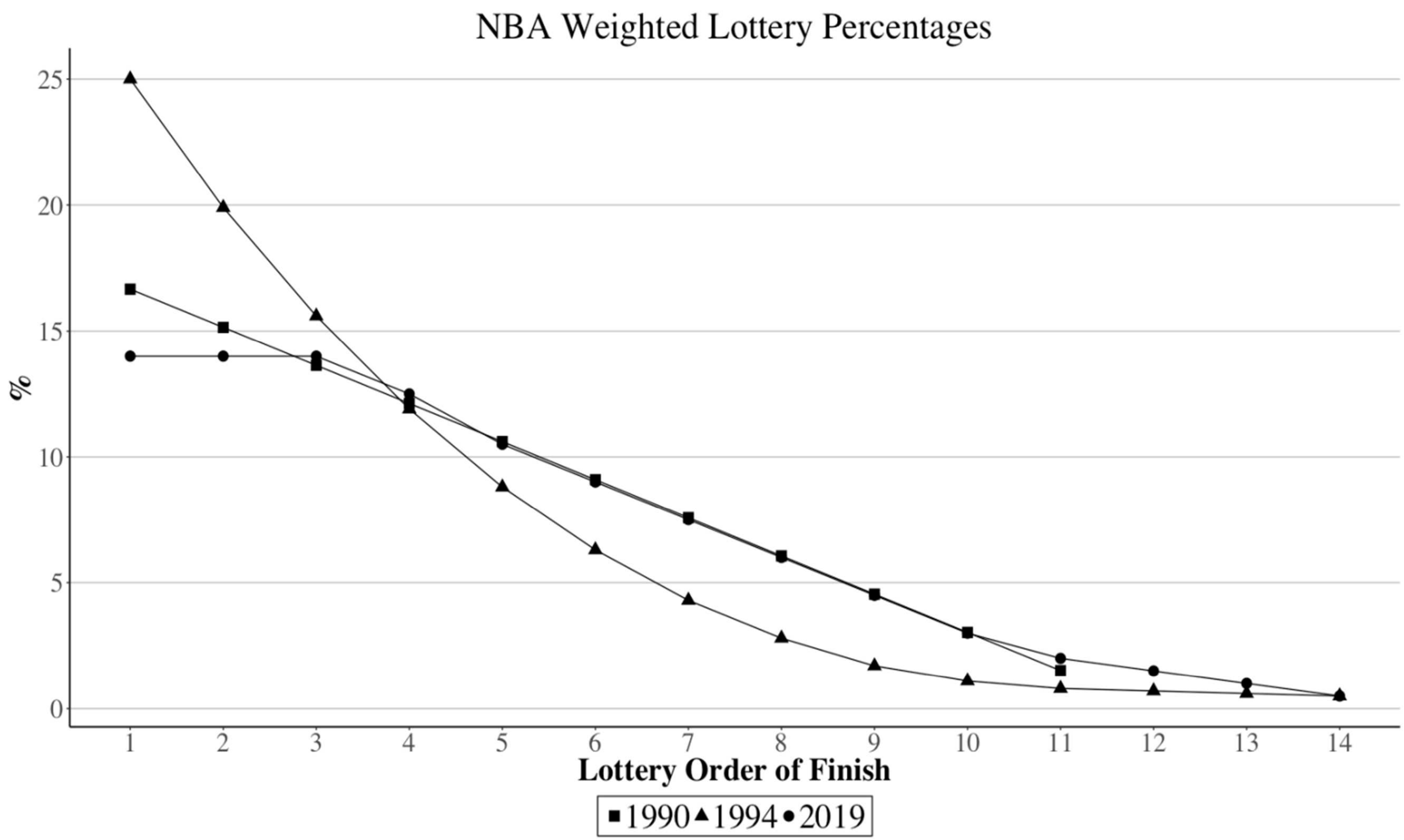

Figure 1.1 NBA Weighted Lottery Percentages

CHAPTER 2

LITERATURE REVIEW

The following chapter discusses a wide range of literature that relates to the main themes of this dissertation. The first section highlights the differences between tanking and other similar concepts, including match fixing, rebuilding, and shirking. The second section reviews the studies showing empirical evidence of tanking. The next section discusses tournament theory, which has been employed to explain the rise of tanking in sport. The fourth section notes the key determinants of demand for sport in order to set the theoretical foundation for this dissertation. The last section considers social media research in the sport industry.

2.1 TANKING AND OTHER SIMILAR CONCEPTS

In discussing tanking, concepts like match fixing, rebuilding, and shirking are sometimes used interchangeably (Lenten et al., 2018; McManus, 2018; Vamplew, 2018). While these concepts share some similarities with tanking, a clear distinction has to be drawn here in order to better understand the nature of tanking in sport.

2.1.1 TANKING AND MATCH FIXING

Match fixing takes place when contestants attempt to fix game outcomes by reducing their effort in competitions (Blair, 2018). Preston and Szymanski (2003) summarized three types of match fixing, claiming tanking should be treated as a form of match fixing. In their categorization of match fixing, the first type often involves bribery that one team is willing to provide benefits to opponents or referees in order to obtain a

particular game outcome (Blair, 2018). For instance, in sports leagues using the promotion and relegation system, teams on the verge of being relegated may pay opponents or referees to ask for a win. In this case, match fixing occurs as marginal teams bribe opponents or referees in order to save themselves from being relegated to lower divisions.

The second type of match fixing relates to gambling activities where players or officials gain financial benefits from a specific match result (Preston & Szymanski, 2003). For instance, the 1919 World Series between the Chicago White Sox and Cincinnati Reds was alleged to be controlled by gamblers. While the White Sox were considered as the overwhelming favorite, they lost the series. The belief was some White Sox players received money from gamblers to throw games. In this case, gamblers fixed game results in order to gain financial returns from betting markets (Anderson, 2001).

The third type of match fixing occurs when manipulating game outcomes helps contestants obtain competitive benefits in the long term (Preston & Szymanski, 2003). Unlike the other two match-fixing practices, the third type may not be strictly prohibited by sports leagues, although it is certainly against the spirit of sport (McManus, 2019). Tanking fits this type of match fixing as it aims to produce a particular result that can help teams gain a favorable position in the draft (Preston & Szymanski, 2003). For instance, MLB teams have attempted to deliberately lose games in order to win high draft picks (Sheinin, 2018). With high-quality draft prospects, tanking teams expect to regain competitiveness or win championships in the near future. The Chicago Cubs tanked to obtain talent and subsequently won the World Series in 2016 (Sheinin, 2018). Before

securing the title, the Cubs lost an average of 96 games per season from 2011 to 2013 as they employed low-priced marginal talent.

2.1.2 TANKING AND TEAM REBUILDING

The word 'tanking' is often associated with the phrase 'team rebuilding' in the press (McManus, 2019). In general, sports leagues, teams, and media believe that tanking is an effective way to rebuild sports franchises (Motomura et al., 2016; Mullin, 2018; Sheinin, 2018). Tanking teams intend to restore competitiveness through high draft picks that they may acquire under the reverse-order draft system by deliberately losing games. However, not all tanking practices are favored by leagues to rebuild sports franchises. For instance, NBA commissioner Adam Silver noted that there was a clear distinction between effort teams might put forth to rebuild franchises, such as trading players, and actions teams might take on the court to lose games, such as deliberately missing shots or giving up on defense (Aldridge, 2018). The former can be accepted while the latter is clearly against league rules. According to Silver's tanking comments, it appears the tanking tactic of trading away quality players is regarded as an acceptable action under league rules, whereas other tactics such as resting key players and throwing games seem to be inappropriate (Amick, 2018).

Interestingly, Los Angeles Dodgers President Stan Kasten made similar comments regarding the distinction between tanking and team rebuilding (Aldridge, 2018). He considered strategic tanking as a process of cutting payrolls and acquiring bright young players who, through years of training, could be developed into impactful athletes. In the rebuilding process, teams are willing to endure consecutive years of losses in order to regain competitiveness by acquiring talent and draft picks. However, he

viewed purposely losing games on the field as improper. Clearly, Kasten treated the tanking practice of trading superior players or not signing high-profile free agents as a reasonable way to rebuild sports franchises, but deliberately giving up games on the field as an unacceptable practice.

To further highlight the link between tanking and team rebuilding, the NBA fining Dallas Mavericks owner Mark Cuban during the 2017-18 season for his tanking comments provides a specific example to demonstrate the league's stance on these two notions (Bieler, 2018). Specifically, Mark Cuban publicly admitted the Dallas Mavericks tanked during the 2016-2017 and 2017-2018 seasons. He also suggested losing was the best and quickest option for the franchise to regain competitiveness in the NBA. Shortly after the comments, the NBA fined Mark Cuban $600,000, stating that Cuban's comments were detrimental to the NBA. Yet, in a memo sent to all NBA teams following Cuban's tanking comments, the NBA noted it had no basis to conclude that Dallas Mavericks exerted less than the best effort to compete on the court (Aldridge, 2018). Mark Cuban also assured the league that he did not ask players or coaches to throw games to tank. In fact, Mark Cuban was fined because his comments might jeopardize the perceived integrity of competitions that the league attempted to protect by all means. Given the fact that the integrity of sport is the cornerstone of any sport, actions that undermine the actual and perceived integrity of the game should be penalized (McLaren, 2011). Nevertheless, this incident illustrates that while not exerting maximum effort on the court is clearly against NBA rules, the league seems to consider strategic tanking as an acceptable practice, since the Dallas Mavericks trading away experienced players to tank did not receive penalties from the NBA. The rationale of fining Mark Cuban for his

tanking comments is consistent with what Adam Silver defined tanking that roster changes to rebuild franchises are inherently distinct from throwing games.

2.1.3 TANKING AND SHIRKING

Although tanking sometimes serves as an alternative word to shirking, these two notions are distinct from each other in the context of sport (Vamplew, 2018). In defining shirking, Vamplew (2018) suggested that shirking took place when contestants underperformed by not exerting their best effort in competition. Although tanking also involves contestants not expending maximum effort in games, shirking contestants do not necessarily aim to lose games (Vamplew, 2018). For instance, prior research sought to explain why players tended to shirk after signing long-term guaranteed contracts (Scroggins, 1993). This shirking behavior can be explained through the principle-agent theory in which the principles (teams) may not recognize the nuance between shirking and below-average performance, and thus allow the agents (players) to act opportunistically (Krautmann, 1990). In other words, long-term contracts disincentivize contestants to play with their best effort because stakeholders may not explicitly identify shirking behavior in practice (Berri & Krautmann, 2006). Thus, shirking players underperform because they do not have sufficient incentives to work hard, not that they intend to deliberately lose games in order to gain long-term competitive advantages like tanking teams do (Vamplew, 2018).

2.2 EVIDENCE OF TANKING IN SPORT

Tanking is a widespread phenomenon in sport (Kendall & Lenten, 2017). An abundance of studies developed evidence of tanking (e.g., Price et al., 2010; Taylor & Trogdon, 2002). In North American sports leagues, tanking is a particular concern in the

NBA (Soebbing & Mason, 2009). As NBA teams rarely reveal their tanking plan to the general public, scholars have sought to provide empirical evidence that teams deliberately lose games in the NBA. This section of the literature review will firstly review prior research seeking to prove the existence of tanking in the NBA. The rest of the section will cover empirical studies revealing the evidence of tanking in other sports leagues.

2.2.1 EVIDENCE OF TANKING IN THE NBA

The seminal study conducted by Taylor and Trogdon (2002) tested whether NBA teams were more likely to lose games after being eliminated from postseason contention. Looking at the 1983-1984, 1984-1985, and 1989-1990 NBA season data, Taylor and Trogdon (2002) found evidence that teams eliminated from playoff contention tended to lose more game late in the regular season under the reverse-order and weighted lottery draft systems. However, during the 1984-1985 season when the league adopted the equal-chance draft lottery, there was no strong evidence of tanking. That is, teams ceased to compete for draft picks by intentionally losing games when each non-playoff team shared the same odds of winning the draft lottery.

Price et al. (2010) explored the same research question as Taylor and Trogdon (2002) while employing a longer period of time. Using NBA data spanning from 1978 to 2008, they drew similar conclusions as the Taylor and Trogdon's (2002) study, except under the reverse-order draft format. In contrast to the Taylor and Trogdon's (2002) finding that NBA teams tanked under the reverse-order draft system, Price et al. (2010) did not find strong evidence of tanking under this draft mechanism. They explained that this inconsistent result might emerge from different econometric models employed in these two studies. Nevertheless, Price et al. (2010) consolidated the evidence of tanking

in the NBA under the weighted lottery draft system but questioned the previous finding of tanking under the reverse-order draft format.

Soebbing and Humphreys (2013) followed the previous two studies and developed evidence of tanking by using NBA betting odds data from the 2004-2005 to 2008-2009 seasons. The betting market is chosen as the research context because it generally takes all available data, including any tanking information, into consideration when making predictions. Thus, if gamblers believed that tanking takes place in the NBA, they will adjust the betting odds accordingly. Following this premise, Soebbing and Humphreys (2013) tested whether bookmarkers would set different point spreads for games involving eliminated teams. They found strong evidence that there was a systematic change in point spreads, suggesting that the betting markets believed that tanking existed in the NBA.

To further understand tanking in the NBA, Soebbing et al. (2013) explored whether tanking took place more often in NBA conference games, as compared to nonconference games. Considering that teams move down their standings faster when they lose to teams from the same conference than teams from the other conference, teams may have greater incentives to tank when facing conference opponents. After analyzing NBA data from the 1983-1984, 1984-1985, 1989-1990, and 1993-1994 seasons, Soebbing et al. (2013) concluded that NBA teams were more likely to tank in conference games than nonconference games under the weighted draft lottery adopted since 1994. For other draft systems, including the reverse-order draft, equal-chance draft, and the early weighed draft lottery imposed in 1990, there was no strong evidence that teams tanked more often in conference games than nonconference games.

Prior studies provide evidence of tanking in the NBA, particularly toward the end of the regular season (Soebbing et al. 2013). While the NBA attempted to eliminate tanking by tweaking draft formats, incentives to tank remained as a big concern for the league (Soebbing et al. 2013; Taylor & Trogdon, 2002). Recently, the NBA passed another draft reform that would be implemented in 2019 (Ward-Henninger, 2017). The new draft policy aimed to further diminish teams' incentives to tank as the league has observed certain extreme tanking cases (Greenstein, 2019). For example, unlike other NBA teams that have been accused of tanking late in the regular season, the Philadelphia Sixers were alleged to have tanked for several seasons from 2013 to 2016 (Steinberg, 2018). The prevalence of tanking today raises concerns that tanking may undermine fans' interest in the NBA. In light of such concerns and limited research on the topic, there is a need for further investigation on how tanking can affect consumer demand for NBA games.

2.2.2 EVIDENCE OF TANKING IN OTHER SPORTS LEAGUES

Outside the NBA, there also exists the evidence of tanking. Balsdon et al. (2007) noted that tanking might happen in college basketball where regular-season conference champions were less likely to win conference tournament championships. They suggested that such underperformance was plausibly motivated by two factors. First, teams were saving themselves for the NCAA tournament. For regular-season conference champions with guaranteed bids to the NCAA tournament, conference tournaments become meaningless. In fact, the earlier teams finished in conference tournaments, the more rest time they could receive. The second factor was financial gains from participating in March Madness. As the winner of conference tournaments often receives

an automatic bid to March Madness, regular-season conference champions losing conference tournaments to other conference members can allow more schools from the same conference as conference champions to participate in the NCAA tournament. With the NCAA distributing tournament revenue to conferences partially based on the number of schools selected into the tournament, and considering that some conferences equally distributed tournament revenue to their members, more participants in March Madness implies increased revenue for each member of a conference. After investigating these two possible motivations of tanking, Balsdon et al. (2007) concluded that the financial gain might be the primary motivation for regular-season champions to underperform in conference tournaments.

Kendall and Lenten (2017) pointed out that tanking occurred even in mega sporting events like the Olympic Games. Specifically, they showed that women's doubles badminton teams deliberately lost games at the 2012 Olympic Games in order to gain competitive benefits in the wider context of tournament play. Due to the timing of games, when two tanking teams faced each other, they had known whom they would compete against in the next rounds of the tournament. After knowing that the losing team would face weaker opponents, both teams actively sought ways to lose games. Noticing two teams not competing with their best winning efforts, the Badminton World Federation quickly disqualified both teams, claiming that their behavior was against the spirit of sports competition (Kendall & Lenten, 2017).

Research indicates that tanking is pervasive in sport. Not only does the NBA suffer from tanking but also other sports leagues and tournaments around the world. Although it is clear that tanking undermines the quality of competitions, the damage that

tanking brings to sports leagues may be worse than what the existing research suggests (Soebbing & Mason, 2009). That is, fans who perceive the existence of tanking may question sports leagues' credibility, and thus choose not to attend games. Given the pervasiveness of tanking in the sport industry, it is crucial to thoroughly investigate the effects of tanking on demand for sport. With the findings from this dissertation, sports leagues can better evaluate the consequences of tanking, and thus take actions to protect sports leagues' credibility as needed.

2.3 TOURNAMENT THEORY AND TANKING

Preston and Szymanski (2003) suggested that tanking was largely caused by ill-designed tournament rules. For most tanking cases in the NBA, these rules are the draft systems that the NBA has deployed since 1947. However, not all NBA draft systems give teams incentives to tank. For instance, prior research offered consistent evidence that the equal-chance draft system did not cause tanking in the NBA. In fact, the decision for teams to tank depends on the marginal benefit of the draft picks (Price et al., 2010; Taylor & Trogdon, 2002). When the value of the first draft pick is exceedingly higher than the rest of the draft picks, teams will likely exert stronger losing efforts to tank. To systematically explain why sports franchises have incentives to lose under certain NBA draft formats, tournament theory is used (Price et al., 2010; Taylor & Trogdon, 2002).

2.3.1 TOURNAMENT THEORY AND DRAFT SYSTEMS

Tournament theory was originally developed to describe the rank-based compensation structures in corporations (Lazear & Rosen, 1981). For instance, this theory helps explain why CEOs often receive disproportionally higher salaries relative to managers. In a rank-based reward system, wages are determined by the relative rank

instead of the absolute value of outputs employees produce. For instance, CEOs' salary is not calculated based on their absolute value of outputs. Rather, their rank in companies determines salary. Tournament theory predicts that, when employees' actual production is difficult to monitor, the rank-based payment system is superior to the piece rate payment scheme that compensates employees based on their outputs (Lazear & Rosen, 1981). For instance, it is difficult to quantify the absolute value of outputs that CEOs create for companies in practice. Thus, paying CEOs based their ranks rather than their absolute value of outputs is a rational compensation scheme. Not only does the rank-based compensation system save the cost to monitor employees' output, but it also ensures that employees will exert sufficient effort in the workplace (Lazear & Rosen, 1981). Specifically, tournament theory suggests that employees' effort level is determined by the prize gap in a rank-based reward system. Hence, setting the proper level of the prize gap between the winner and loser of a tournament can elicit ideal effort levels from participants. However, when organizers of a tournament set an overly high prize gap, such a reward structure may create a substantial financial burden for organizers. On the contrary, if the prize gap is too small, contestants may not put forth enough effort in competition.

Some draft systems in professional sports leagues resemble a rank-based compensation system, with draft picks as rewards. For instance, the reverse-order draft format allocates the rewards, draft picks, to teams based on their regular-season performance in reverse order. Tournament theory predicts that teams will exert significant losing effort to compete for draft picks when the marginal benefit of draft picks exhibits a nonlinear structure (Price et al., 2010). Thus, the key to determining

whether draft systems motivate teams to tank is centered on the value of draft picks. Soebbing and Humphreys (2013) noted the value of draft picks came from two main areas. The first area is additional team wins and related revenue generated by draft prospects. High draft picks, particularly the first draft pick, are expected to contribute many wins to teams, and thus help the team generate more revenue through improved team performance (Price et al., 2010). The second area lies in the advertising effect of top draft prospects. Price et al. (2010) estimated the presence of the first draft pick itself could bring $2.8 million in revenue to teams that selected the prospect. Given these estimations of the value of NBA draft picks, Price et al. (2010) concluded the reverse-order draft format did not create a nonlinear structure of the value of draft picks. Thus, NBA teams will not have incentives to tank under the reverse-order draft scheme based on tournament theory. Meanwhile, Price et al. (2010) illustrated the nonlinear structure of the probabilities under weighted draft lottery which created incentives for teams to tank..

2.3.2 APPLICATION OF TOURNAMENT THEORY IN SPORT

Tournament theory is commonly used to study the effectiveness of policies in sports leasgues (Connelly, Tihanyi, Crook, & Gangloff, 2014). In particular, some scholars employ tournament theory to test whether the design of tournaments elicits the optimal level of effort from participants. Outside major professional sports leagues, McClure and Spector (1997) applied tournament theory to examine team behavior in the NCAA basketball tournament. As tournament theory suggests that actors' level of effort solely depends on the prize spread, they speculated that contestants in March Madness would expend different levels of effort in response to various prize structures that conferences adopted to distribute tournament revenue. In particular, certain conferences

largely allocate tournament revenue to schools which take part in the tournament, while other conferences tend to evenly distribute tournament revenue to all conference members. Although schools had various tournament reward structures, McClure and Spector (1997) did not find strong empirical evidence that schools subject to disparate revenue-sharing rules performed differently in the tournament. Such an indifferent response demonstrated that conference revenue sharing policies did not affect contestants' effort in the tournament. McClure and Spector (1997) further explained that while schools faced different reward structures, the real contestants, student athletes, would not receive any extra compensation, regardless of their tournament performance. Hence, conference revenue sharing policies did not create different incentives for players to compete in March Madness.

Von Allmen (2001) employed tournament theory to explain the rationale behind the National Association for Stock Car Auto Racing's (NASCAR) reward scheme. Compared to the PGA Tour, NASCAR adopted a relatively constant reward structure where the reward for the winner of a race was only slightly higher than the prizes received by other contestants. As tournament theory predicts that a contestant's level of effort depends on the prize gap, there were some concerns that NASCAR's constant reward structure might not elicit considerable effort from drivers. To address these concerns, Von Allmen (2001) pointed out that the implementation of a linear reward system in NASCAR was primarily aimed to restrain reckless driving behavior. When cars crash during contests, car sponsors will miss advertising opportunities. Sponsorship as the main revenue source for many NASCAR teams may be withdrawn if sponsored teams cannot provide sufficient exposure to sponsors' brands. To maintain the visibility of

advertisements, implementing a relatively linear prize structure can potentially reduce the number of car accidents on the track, and thus help teams and leagues retain sponsorship revenue. Thus, the relatively constant reward structure in NASCAR should be considered as an efficient policy as it ensures the sustainable development of the league.

While the theoretical explanations of tanking are extensively studied, little research sheds light on the connection between tanking and demand for attendance. To explore the impact of tanking on attendance in this dissertation, a thorough literature review on the economic theory of demand for sport is needed in order to establish a solid theoretical foundation for this research (Borland & MacDonald, 2003; Villar & Guerrero, 2009).

2.4 DEMAND FOR ATTENDANCE

The economic theory of demand for sport has been widely applied to study motives for fans attending sporting events (Borland & MacDonald, 2003; Villar & Guerrero, 2009). The theory is an extension of the consumer demand model that describes the choices of buying goods and services under constrained resources (Borland & MacDonald, 2003). Most demand studies have employed attendance at sporting events to measure consumer demand for sport (Borland & MacDonald, 2003). A growing line of research uses televised viewership as a proxy for consumer demand for sport (e.g., Tainsky, 2010; Feddersen & Rott, 2011). The rise of studies using viewership to explore demand for sport can be ascribed to the availability of broadcasting data (Feddersen & Rott, 2011; Tainsky & McEvoy 2012; Tainsky, 2010; Salaga & Tainsky, 2015). Compared with attendance data that only reflects ticket sales in the home market,

viewership data captures demand for sport in the home, away and neutral markets, providing researchers with a more disaggregated dataset to examine (Tainsky, 2010).

While research using television ratings to study demand for sport has gained momentum, this dissertation will employ attendance to examine the effect of consumer perceptions of tanking on consumer interest in the NBA, considering the availability of historical NBA attendance data. In reviewing consumer demand for attendance, Borland and MacDonald (2003) summarized five major determinants of demand for attendance, including consumer preferences, economic factors, quality of viewing, supply capacity, and the quality of sporting contests. Given the importance of understanding the demand model in this dissertation, the current section follows Borland and MacDonald's categorizations to review five major variable categories that will significantly affect fans' decisions to attend sporting contests.

2.4.1 CONSUMER PREFERENCES

Consumer preferences can take several forms (Borland & MacDonald, 2003). For instance, some fans develop a habit of attending games over the years. Such loyal fans are likely to support home teams by attending games, regardless of the performance of their teams. Lee (2006) pointed out that, in contrast to young sports leagues, consumers from established sports leagues were less concerned with the quality of competitions. In fact, historical sports franchises are often supported by loyal fans, some of whom regularly attend games, even though teams they support struggle to win games (Coates & Humphreys, 2005).

Empirical analyses of consumer demand for sport often employed the age of the franchise or one-year lagged attendance as a proxy of fan loyalty or habit (Ahn & Lee,

2007; Winfree, McCluskey, Mittelhammer, & Fort, 2004). While a number of studies provided consistent evidence that the age of the sports franchise and fan loyalty could positively affect game attendance, the calculation of the age of the team requires special attention (Ahn & Lee, 2007; Borland & Lye, 1992; Coates & Harrison, 2005). Specifically, team relocation can complicate the calculation of the age of the sports franchise. For instance, in the National Football League (NFL), the Oakland Raiders moved to Los Angeles in 1982, but returned to Oakland in 1994. Although the Raiders continually used the same nicknames over the years, scholars often considered them as three distinct teams. Hence, in determining the age of the team, the 1994-1995 season was often deemed as the inaugural season for the returning Oakland Raiders (Coates & Humphreys, 2002).

2.4.2 ECONOMIC FACTORS

A wide range of economic factors are proposed as determinants of demand for sport (Borland & MacDonald, 2003). First, the law of demand predicts that ticket prices are negatively correlated with attendance. Yet, empirical research provided mixed results in evaluating the impact of ticket prices on attendance. For instance, Rivers and DeSchriver (2002) showed there was a positive relationship between season average ticket prices and annual MLB attendance, while other research suggested fans bought fewer tickets when ticket prices increased (Fort, 2006). To address why studies reached contrary conclusions regarding the relationship between ticket prices and demand for attendance, Krautmann and Berri (2007) noted that ticket prices might not be the actual cost of attending a sporting event. Other related costs such as food and travel should be added to the total cost of attending a game. Hence, a few studies begun to utilize the Fan

Cost Index (FCI) that contained a more complete description of the costs of attending sporting events in analyzing the relationship between costs and demand (Coates & Humphreys, 2007; Gitter & Rhoads, 2010; Krautmann & Berri, 2007). Yet, studies employing the FCI as a measure of the cost of attending sporting events did not reach consensus (Krautmann & Berri, 2007). For instance, Coates and Humphreys (2007) concluded the FCI was negatively related to attendance in the NBA, but insignificant in the NFL and MLB.

Second, market size can affect demand for sport. Big market teams with more population face higher demand for sporting events than small market teams (Noll, 1974). Less clear is the link between income levels and demand for sport. The consumer demand model predicts that higher income consumers are willing to purchase more normal goods and less inferior goods. In the context of sport, if sporting events are regarded as normal goods, fans from affluent areas will have higher demand for sport than fans from poor regions. However, studies examining the link between income levels and demand for sport produced mixed results. For instance, Lee (2004) noticed that baseball was considered as a normal good in Japan, Korea, and the USA but Fort and Rosenman (1999) pointed out that baseball was only viewed as a normal good in the National League of MLB, not in the American League. Noll (1974) also posited that baseball was an inferior good as his empirical test showed a negative relationship between income levels and MLB game attendance.

The presence of entertainment alternatives is another factor that can impact demand for sport (Borland & MacDonald, 2003). With the availability of more entertainment activities, sports teams will face fiercer competition in drawing fans to

games. Such competition may arise from multiple sources (Borland & MacDonald, 2003). First, sports teams compete with clubs from other leagues that play the same sport. For example, scholars uncovered that minor league and junior league hockey teams served as primary cross-league substitutes for National Hockey League (NHL) fans during the NHL lockout season in 2004 (Winfree & Fort, 2008). Second, sports teams from cross-sports leagues also compete with NHL teams for consumers. Rascher, Brown, Nagel, and McEvoy (2009) estimated that the NHL lockout in 2004 increased NBA attendance by 2%. Third, there is strong evidence that sports franchises compete with teams from the same league and geographic area for fans. For instance, incumbent teams will experience a significant increase or decrease in attendance when other sports clubs from the same league enter or exit the territory, either through expansion or relocation (Winfree, 2009). Lastly, other entertainment activities, such as theater or cinema, are often deemed as substitutes for sporting events. While there is little academic research examining fan substitution to other forms of entertainment activities, anecdotal evidence showed that the MLB strike in 1994 considerably improved movie sales in that year (Winfree, 2009).

2.4.3 QUALITY OF VIEWING

The quality of viewing is a particular concern for many sports spectators. A range of factors affect the quality of viewing in a sporting event. First, the age of the facility can affect consumer experience at sporting events. A newly constructed stadium typically attracts a fair amount of spectators in the beginning years of operation. However, such a “novelty effect” can quickly vanish as attendance drops in the following years (Clapp & Hakes, 2005; Coates & Humphreys, 2005; McEvoy, Nagel, DeSchriver, & Brown, 2005; Leadley & Zygmont, 2005). It also appears that the attendance can spike in the last years

of operation of a stadium due to the “nostalgia effect” (Coates & Humphreys, 2007; McEvoy et al., 2005).

Game day weather conditions also play a significant role in determining demand for sport. Especially for outdoor sports such as baseball, soccer, and cricket, adverse weather may discourage fans from attending contests because of low viewing quality. Even for indoor sports, poor weather conditions can create an unpleasant customer experience due to increased travel costs. Empirical studies of the impact of weather on attendance found consistent evidence that rainy weather on game days would significantly reduce attendance (Hynds & Smith, 1994).

Game time is critical to demand for sport (Borland & MacDonald, 2003). In general, sporting contests scheduled on weekends or holidays will have larger crowds than games scheduled on other days (Hansen & Gauthier, 1989; Hill, Madura & Zuber, 1982; McDonald & Rascher, 2000). Prior studies suggested that consumers had more time to participate in leisure activities during weekends and holidays. Furthermore, research showed that afternoon games would have lower attendance than night games (Hansen & Gauthier, 1989). While afternoon games are uncommon in today’s sport industry, before World War II, the majority of baseball games took place in the daytime (Quinn, 2009). To meet the demand for baseball games from the working-class during wartime, baseball games were then moved to the late afternoon and night when the working class had enough time to attend games (Quinn, 2009).

2.4.4 SUPPLY CAPACITY

The fourth category is the supply capacity (Borland & MacDonald, 2003). In live sporting events, the number of tickets teams can sell is constrained at the facility’s

capacity. At sellouts, the actual demand for sporting events cannot be observed as the quantity of available tickets is limited. Among four major sports leagues in North America, game tickets are often sold out except for MLB (Quirk & Fort, 1997). Sell-out events are also fairly common in European top-level soccer leagues such as the English Premier League (EPL; Koning, 2000). Given the pervasiveness of sellouts in sport, it is crucial to consider censored attendance when analyzing determinants of demand for attendance. Otherwise, statistical models may produce biased estimations (Humphreys & Johnson, 2020). To correct censored attendance, some studies treated the capacity as an explanatory variable in statistical models (Jones, 1984). However, such an adjustment seems to be problematic as including the capacity as an independent variable in demand models still produces biased estimators (Cairns, Jennett, & Sloane, 1986). DeSchriver, Rascher, and Shapiro (2016) developed interval regression to account for the censor attendance data. Other studies chose to correct for unobserved attendance by employing the censored normal regression model (Amemiya, 1973; Welki & Zlatoper, 1994). It is suggested that estimators from the censored normal regression model will be less biased (Welki & Zlatoper, 1994). For instance, Humphreys and Johnson (2020) adopted the censored normal regression model to estimate the effect of star power on attendance, considering numerous sellouts in the NBA.

2.4.5 QUALITY OF SPORTING CONTESTS

One of the key components of the quality of sporting contests is team strength (Borland & MacDonald, 2003). It is suggested that sports fans prefer to watch or attend sporting events featuring high quality teams. Empirical analysis provided consistent evidence that attendance soars when the quality of home teams is high (Villar & Guerrero,

2009). However, the impact of the quality of visiting teams on attendance is less clear. Some studies showed a positive relationship between the quality of away teams and attendance, whereas others did not find a significant connection between the quality of visiting teams and demand for sport (Buraimo & Simmons, 2008; Villar & Guerrero, 2009). To quantify team strength, a variety of metrics were employed. The most common one is the team winning percentage or standing (Forrest & Simmons, 2002). More recently, a study conducted by Mills, Salaga, and Tainsky (2016) employed a team rating metric named Elo that took more information such as home court advantage and margin of victory into consideration. Therefore, the Elo rating system may better reflect true team strength than the team winning percentage or standing (Mills et al., 2016).

Tanking teams are often associated with poor team quality as they purposely assemble less talented rosters to compete (Taylor & Trogdon, 2002). This action of assembling less talented rosters is particularly true for teams seeking to tank for entire seasons. By trading away key players and avoid signing quality free agents, tanking teams deliberately compromise their team strength, and thus may hurt fan interest in games (McManus, 2019). In addition, some teams decide to tank toward the end of the regular season. This tanking strategy is to deliberately field less competitive rosters that may further deter fans from attending sporting events.

The quality of sporting contests is also determined by the presence of star players (Villar & Guerrero, 2009). Considering that NBA teams only field five players on the court and athletes do not wear gear such as helmets that may hide their faces from the spotlight, NBA star players can draw considerable attention from fans (Berri, Schmidt, & Brook, 2004; Hausman & Leonard, 1997). Empirical analyses of star power on NBA

attendance provided consistent evidence that the presence of star players was positively related to game attendance (Berri et al., 2004; Hausman & Leonard, 1997; Jane, 2016). Outside the NBA, Buraimo and Simmons (2015) found the significant impact of star players on attendance in the EPL. In individual sports such as tennis and the Ultimate Fighting Championship (UFC), star status was also an important predictor of demand for sport (Chmait et al., 2020; Reams & Shapiro, 2017).

Uncertainty of game outcomes makes up the other dimension of the quality of sporting contests. The Uncertainty of Outcome Hypothesis (UOH) predicts game uncertainty positively relates to demand for sport (Rottenberg, 1956; Neale, 1964). In other words, fans prefer more unpredictable events than certain outcomes. This hypothesis was recently challenged by the study conducted by Coates, Humphreys, and Zhou (2014) who suggeste home team fans might dislike uncertain home games due to loss aversion. Notably, loss aversion assumes that the utility lost from a team loss is higher than the utility gained from a team win. Based on this assumption, Coates et al. (2014) concluded unpredictable games might lead to lower attendance than predictable matches.

To measure the uncertainty of game outcomes, there exists two metrics that are particularly relevant to this dissertation. The first metric attempts to quantify league win distribution. For instance, the Ratio of Actual Standard Deviation to the Idealized Standard Deviation (RSD) has been widely employed to describe the dispersion of team wins in sports leagues for a given season (Noll, 1988). The high RSD implies an unbalanced league where matches lack unpredictability (Fort & Quirk, 1995). Recently, Lee, Kim, and Kim (2018) suggested that RSD could be a biased measure of competitive

balance when the number of games played within sports leagues was large. To correct the bias, they proposed a new competitive balance metric, the Bias-Corrected Standard Deviation (BCSD), which better captured league-wide competitive balance than RSD. Unlike RSD, BCSD is not subject to the number of matches teams play in a given season, and thus may be better employed to compare competitive balance across leagues and seasons that may host various number of games (Lee et al., 2018).

The second measure of game uncertainty measures the closeness of individual competitions. For example, the absolute difference between the home and away team's winning percentage prior to a game is considered as a valid proxy for game uncertainty (Meehan, Nelson, & Richardson, 2007). In addition, betting odds or point spreads from gambling markets are widely applied to measure game uncertainty (Buraimo & Simmons, 2008; Coates & Humphreys, 2010; Forrest & Simmons, 2002). While betting odds or point spreads may not always fully reflect true game uncertainty, they are considered as better estimators of the team quality gap than other metrics, as bookmakers of betting odds or point spreads have strong financial incentives to make as accurate predictions as possible (Forrest, Goddard, & Simmons, 2005).

In general, tanking undermines the uncertainty of game outcomes (Soebbing & Mason, 2009). If outcome uncertainty is a driving force of game attendance, the presence of tanking teams in sports leagues may hurt consumer demand for sport. An abundance of studies found evidence that tanking teams are more likely to lose games than they would have, implying that game uncertainty is compromised when participants do not exert their best effort in contests (Price et al., 2010; Taylor & Trogdon, 2002).

While the literature clearly indicated that tanking undermined the quality of sporting contests by threatening both team strength and the uncertainty of game outcomes, none of the prior research examines the link between consumer perceptions of tanking and their connections to demand for sport (Price et al., 2010). To address the gap, this dissertation analyzes consumer behavior in response to the existence of tanking in sports leagues. Such an inquiry provides useful insights in understanding the change of fan interest in sport when sports leagues' creditability is in jeopardy.

2.4.6 DEMAND FOR NBA ATTENDANCE

While five major determinants of demand of sport were well documented in sections 2.4.1 to 2.4.5, recent work of analyzing demand for NBA attendance seem scant. The most popular studies within the context of the NBA were to examine the effect of star power on attendance. With the relatively small number of players required in the game of basketball, the NBA served as a great context to understand the importance of star players in drawing fans (Berri & Schmidt, 2007; Hausman & Leonard, 1997; Humphreys & Johnson, 2020; Jane, 2016). In addition, a few studies investigating the impact of game uncertainty on demand selected the NBA as the research context (Mills et al., 2016). For instance, Rascher and Solmes (2007) examined NBA data and found evidence to support the UOH that fans preferred more uncertain games than predicable ones. The long-standing NBA was also considered as a great context to study the relationship between facility age and demand for sport. For example, both Coates and Humphreys (2005) and Leadley and Zygmont (2005) noted the novelty effects of new areas in attracting NBA fans.

Among the aforementioned studies of NBA attendance, a few factors were widely employed as control variables. For instance, most NBA attendance studies used team quality, population, income level, market competition, and game time to control for their effects on consumer interest in the NBA (Hansen & Gauthier, 1989). The results generally showed that these factors were significant predictors of NBA attendance. For instance, studies employed the team winning percentage as a proxy for team quality revealed that both home and visiting team quality were positively related to NBA teams demand (Mongeon & Winfree, 2012). Similarly, NBA teams located in markets with a bigger population, higher income, and fewer other professional sports teams largely experienced higher demand for NBA games (Coates & Humphreys, 2005; Coates & Humphreys, 2007; Mongeon & Winfree, 2012). Lastly, weekend and holiday NBA games could expect significantly higher demand than matches in other time slots (Humphreys & Johnson, 2020). Given the above observations, it is therefore crucial to control for these variables when examining the link between perceptions of tanking and demand for NBA attendance in this dissertation.

2.5 SOCIAL MEDIA AND SPORT

The emergence of social media has drastically changed the way sports fans consume sports media products (Billings, Broussard, Xu, & Xu, 2019). In the past, the traditional media such as newspapers and TV mainly served as a means to distribute sports content to broad audiences (Boyle & Haynes, 2002). That is, sports fans passively received information from these traditional media firms. The advent of social media platforms such as Facebook and Twitter allow fans to create their own sports content (Pegoraro, 2014). Thus, in the era of social media, sports fans do not only consume sports

products from traditional media companies, but also actively generate sports content and distribute it to other social media users. As such, social media data has been widely studied and used in understanding consumer opinions on products and services. This section sheds light on research using social media data to address research questions in the sport industry.

Filo, Lock, and Karg (2015) noted a few types of sports social media research that is fairly relevant to the present dissertation. First, a handful of studies examined consumer behavior on social media. For instance, Watanabe, Yan, and Soebbing (2015) examined key factors that affected the change of Twitter followers of MLB teams. Through analyzing Twitter follower data and performing a regression analysis, they concluded that factors such as the content of social media messages, certain calendar events, and postseason appearances were significant in drawing Twitter followers. Watanabe, Yan, and Soebbing (2016) further analyzed the statistical relationship between the total number of followers of MLB teams on Twitter and team characteristics. They offered evidence that the aggregate popularity (Twitter followers) of all starting players had a significantly positive impact on the change of Twitter followers of a team in the short term, implying that MLB players maintaining active Twitter accounts were crucial to attracting fans to team Twitter accounts. However, in models using the total number of Twitter followers of teams as the dependent variable, the authors did not find such a relationship. This suggested that sports franchises needed strategic plans to connect with fans in order to achieve lasting popularity on Twitter. The above two studies using Twitter data were valuable in understanding how to effectively build sport brands on digital platforms. Additionally, Watanabe, Yan, Soebbing, and Pegoraro (2017)

employed Twitter data to investigate discrimination issues in MLB. Through analyzing the total number of player followers on Twitter, they showed that Hispanic MLB players in general had much fewer followers than their counterparts on Twitter, indicating potential consumer bias toward Hispanic baseball athletes.

The second line of social media research in sport centers on analyzing sentiments expressed in social media posts. In particular, researchers took various methods to extract sentiments from social media data in an attempt to understand consumer feelings on products and services. First, a number of studies chose to manually analyze social media content. For instance, Delia and Armstrong (2015) used Twitter data to analyze sponsorship effectiveness in the 2013 French Open. After collecting 1,138 tweets containing sponsor names, they manually labeled each with positive and negative sentiments. They concluded that almost all tweets mentioning sponsors contain positive sentiments. Burton (2019) sought to understand consumer sentiment toward ambush marketing and used Twitter data from the 2018 Fédération Internationale de Football Association (FIFA) World Cup Finals as the context to address the research questions. He gathered 2,136 Twitter posts and asked two coders to manually label each tweet with one of the sentiments, negative, neutral, and positive. After calculating the average sentiment of tweets, he concluded that consumer attitudes toward non-sponsor campaigns during the World Cup were exceedingly more positive than sponsor campaigns, highlighting that ambush marketing might not be as immoral as previously thought.

Another popular method to estimate sentiments in social media posts is the lexicon-based approach that uses a pre-defined dictionary of positive and negative words (Hong & Skiena, 2010). The sentiment is derived by counting the number of positive

words minus the number of negative words in a message. A handful of studies in sport have adopted this approach to estimate sentiments in social media posts (Chang, 2019; Yu & Wang, 2015). For instance, Chang (2019) explored the relationship between sports spectators' emotional reaction and team performance in Super Bowl 50 through Twitter data. He used a lexicon-based method to estimate sentiments in Twitter posts. In sum, he noted fans showed strong positive emotions when their supporting teams scored and negative emotions when opponents scored. While such emotions diminished in intensity as teams continued to score, a surge of emotions was observed when supporting teams scored after a touchdown from opposing teams.

Similarly, Yu and Wang (2015) studied American fans' emotional responses toward the 2014 FIFA World Cup matches by using real-time Twitter data. After analyzing sentiments extracted from live tweets posted during the World Cup by using a lexicon-based method, they found evidence American fans primarily exhibited negative sentiments such as fear and anger throughout the games that Team USA played. Such negative emotions faded away when Team USA scored but were enhanced when opponents scored.

Schumaker, Jarmoszko, and Labedz (2016) employed Twitter data to predict match outcomes and goal spreads in the English Premier League. Specifically, they used a software named CentralSport, a lexicon-based program to collect Twitter data and analyze sentiments in tweets. Evidence showed that sentiments hidden in tweets could effectively predict game outcomes and goal spreads, implying how fans perceive games was useful information in understanding the nature of sport competition.

The final approach to understand sentiments in social media content is the machine learning method where statistical models are used to learn patterns in textual data from a training set and then applied to predict sentiments in remaining datasets. While scant sports social media studies adopted the machine learning approach, a wide range of research from other fields have greatly relied on machine learning models to analyze social media content. For instance, Kang, Yoo, and Han (2012) used the machine learning model Naïve Bayes to estimate sentiments in restaurant reviews. The authors collected 70,000 restaurant reviews from various websites and were able to correctly identify sentiments in 81% of the reviews by using machine learning models. McGurk, Nowak, and Hall (2019) analyzed inventor sentiment expressed in tweets and its relationship with stock returns. After estimating sentiments in 3.9 million tweets by using Naïve Bayes models, they found evidence that investor emotion embedded in social media posts could successfully predict stock directions.

Despite diverse techniques researchers may use to identify sentiments in social media content, the above sports social media studies demonstrate that social media data contains valuable information regarding consumer attitudes toward products and services (Filo et al., 2015). Following this observation, it is fair to argue that social media platforms may also contain thoughts and opinions reflecting consumer perceptions of tanking. As such, this dissertation will draw data from social media posts to gauge consumer perceptions of tanking and study its relationship with demand for sport.

In sum, a thorough literature review shows that the prior studies of tanking have focused on developing evidence of tanking. However, there has been limited research examining the link between perceptions of tanking and demand for attendance. To

address this research gap, attention is placed on the NBA where concerns over tanking have existed for decades (Soebbing & Mason, 2009). Following the economic theory of demand for sport, this dissertation seeks to evaluate how perceptions of tanking will impact NBA attendance. The social media research in sport management has offered evidence that discussions on social media platforms may reflect how sports fans perceive tanking. As a result, the current research collects data from the social media platform Twitter to quantify consumer perceptions of tanking. Considering the possible long-term effect of perceived tanking behavior on demand for sport, this dissertation also uses Twitter data to construct variables measuring the past consumer perceptions of tanking and examines their relationships with NBA attendance in the current season. Taken together, this dissertation proposes the following four research questions:

RQ1: How do consumer perceptions of tanking for home teams affect NBA attendance in the short term?

RQ2: How do consumer perceptions of tanking for home teams affect NBA attendance in the long term?

RQ3: How do consumer perceptions of tanking for visiting teams affect NBA attendance in the short term?

RQ4: How do consumer perceptions of tanking for visiting teams affect NBA attendance in the long term?

CHAPTER 3

METHODOLOGY

3.1 OVERVIEW

Following the prior empirical examinations of demand for sport, this dissertation employs a panel dataset to investigate the relationship between consumer perceptions of tanking and NBA attendance. The panel data consists of 29 of the 30 NBA teams and all regular season games played between the 2013-2014 and 2017-2018 NBA seasons. The Toronto Raptors are not included in the dataset due to their location in Canada and the differences between how federal governments calculate economic variables such as population. In addition to gathering team and game data, social media platform Twitter is employed to gauge consumer perceptions of tanking.

Twitter data is selected to quantify consumer perceptions of tanking for several reasons. First, while other popular social media platforms such as Facebook and Instagram are available, the underlying function of Twitter is different from others (Waterloo, Baumgartner, Peter, & Valkenburg, 2018). In particular, Twitter emphasizes the function of sharing ideas and topics, whereas Facebook highlights the ability to connect people and Instagram underlies the capability of sharing photos with friends (Davenport, Bergman, Bergman, & Fearrington, 2014; Van Dijck & Poell, 2013; Watanabe et al., 2016). Given this observation, it is believed that Twitter is the platform where users will express strong feelings and emotions toward tanking. Thus, Twitter may be considered as a better channel to measure perceptions of tanking than other social

media websites. Second, Twitter has gained significant popularity since 2011. It was reported that Twitter had 140 million daily users by 2012 (Kywe, Lim, & Zhu, 2012). Hence, there exists a large quantity of data on Twitter that can be analyzed to understand consumer options and feelings toward tanking (Vicente, Batista, & Carvalho, 2019).

The first section of this chapter describes key variables used in the data analysis, including the two variables of interest measuring consumer perceptions of tanking and a set of control variables. The next section presents detailed steps of acquiring Twitter data and constructing the variables of interest. The last section discusses model specifications and estimation methods used in data analysis.

3.2 DATA DESCRIPTIONS

3.2.1 UNIT OF ANALYSIS AND POPULATION

The current dissertation analyzes game-level NBA attendance data from the 2013-2014 to 2017-2018 seasons. Using game-level data can explain more variances of game attendance than aggregated season-level data (Bradbury & Drinen, 2006). In general, NBA teams play 41 home and 41 away regular-season games in a given season. Thus, there are 5,945 unique regular season NBA games from 29 NBA teams across five seasons available to examine. However, subsets of games are used in different models depending on the focus of research questions. For instance, for models exploring the short-term effect of perceptions of tanking for home teams on attendance, 2,870 games featuring non-playoff teams at home in a given are used. For analysis studying the impact of perceptions of tanking for home teams on attendance in the long term, 2,829 matches featuring home teams that did not qualify for the playoffs in the prior season are identified. In addition, 2,769 and 2,774 NBA games are respectively investigated in

models analyzing the impact of perceptions of tanking for visiting teams on NBA attendance in the short and long run. The reason to consider only non-playoff teams in various models is due to the fact that playoff teams often undertake tanking for reasons other than competing for higher draft picks. For example, teams after clinching the playoff berth may begin to purposely lose games in order to gain better playoff seeds or saving energy for the playoffs (Balsdon et al, 2007). However, neither of these behaviors relates to the focus of the current dissertation, which is to examine the behavior of teams purposely losing games to acquire high draft picks. Therefore, to accurately capture how consumers perceive teams tanking for draft picks, only games involving non-playoff teams are considered.

The population in the current dissertation consists of 29 NBA teams. The Toronto Raptors are excluded due to their geographic location in Canada. Additionally, the rebranding of the Charlotte Bobcats after the 2013-2014 season needs special attention. The Charlotte Bobcats joined the NBA in 2004 as an expansion team and used the nickname Bobcats until 2014 when team owners decided to rebrand the franchise from the Charlotte Bobcats to Charlotte Hornets which was the original name for a franchise in the city from 1988 to 2002 prior to the franchise moving to New Orleans. While the team adopted a new team name and logo upon the conclusion of the 2013-2014 season, the ownership and physical location of the franchise remained the same. For this reason, the Charlotte Bobcats and Charlotte Hornets are treated as the identical team in this dissertation.

3.2.2 VARIABLES

To examine the effect of perceptions of tanking on NBA attendance, a set of variables is employed in econometric models (Table 3.1). The summary statistics can be found in Table 3.2. The dependent variable, game attendance (*Attendance*), for NBA matches played from the 2013-2014 through 2017-2018 regular seasons is collected from basketball-reference.com. While attendance is an effective measure of consumer demand for sporting events, it is important to note that the reported game attendance reflects the number of tickets sold, not the actual number of fans attended NBA games. In some cases, fans may buy tickets but decide not to attend matches for some reason (Forrest & Simmons, 2002). As such, the actual attendance may be slightly lower than the reported one. The average attendance for games included in this dissertation is 17,734 per game and 45.8% of games are sold out.

Moving to the independent variables, the two variables of interest, the volume and sentiment of tanking tweets, are created to approximate perceptions of tanking. The volume of tanking tweets reflects consumer awareness of tanking and is measured by the quantity of tanking tweets posted over a certain period of time. The increasing discussion of tanking on Twitter may signify that people become more aware of the concept of tanking (Hutter, HautzDennhardt, & Füller, 2013). The sentiment of tanking tweets represents consumer sentiments (i.e., positive, negative, and neutral) toward tanking. If fans consider tanking as a viable strategy, then positive sentiments are likely to be detected on Twitter. However, Twitter users may express disappointment or dissatisfaction if they dislike the idea of tanking. Furthermore, if people feel indifferent to tanking, neutral sentiments shall be observed on Twitter.

To address four research questions proposed in Section 2.5, the two variables of interest are constructed based on two timeframes, the short term and long term. First, the short-term variables calculate the volume and sentiment of tanking tweets posted within 31 days before the tipoff of an NBA game.[1] It is likely that consumer perceptions of tanking formed prior to an NBA match will affect fans' decisions to buy tickets. Therefore, the short-term variables are used to quantify how fans perceive tanking behavior approaching an NBA game. Second, the long-term variables estimate the volume and sentiment of tanking tweets posted from the previous season[2] (July 1 as the season cutoff[3]). These lagged variables are created in an attempt to examine whether the past consumer perceptions of tanking affect attendance decisions in the current season.

When constructing the two variables of interest, the volume and sentiment of tanking tweets for home teams and visiting teams are also differentiated. It is likely that local fans who intend to attend NBA games do not only consider tanking behavior for home teams but also for visiting teams. In other words, consumer perceptions of tanking related to both home and away teams can potentially affect attendance decisions. Therefore, the two variables of interest for opponents are also added in this dissertation. In sum, a total of eight variables measuring consumer perceptions of tanking are

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[1] 31 days is chosen as the timespan for short-term variables. Other timespans such as 15 days, 62 days, and 93 days will be used in the robustness checks.

[2] The previous season is chosen as the timespan for long-term variables. Other timespans such as the entire regular season will be used in the robustness check.

[3] July 1st is chosen as the cutoff between the current NBA season and the previous NBA season because the NBA considers July 1st as the beginning of a new fiscal year.

examined in this dissertation (*Short_Volume_Home, Short_Sentiment_Home, Long_Volume_Home, Long_Sentimnet_Home, Short_Volume_Away, Short_Sentiment_Away, Long_Volume_Away, Long_Sentiment_Away*).

The demand for sport literature also documents a range of control variables that may affect attendance decisions. These control variables include economic factors, the quality of viewing, and the quality of sporting contests as summarized by Borland and MacDonald (2003). For economic factors, the first variable concerns the Metropolitan Statistical Area (MSA) population (*Population*), which is a proxy for the market size of the city where an NBA team locates. A range of empirical studies shown that more populated regions would experience higher demand for sporting contests (Noll, 1974). The MSA population data is drawn from the U.S. Bureau of Economic Analysis website. The second economic factor, namely, Coincident Indexes (*Coincident_Index*) is a continuous variable, measuring monthly economic conditions in the state where an NBA team resides (Oga, 1998). Previous research revealed that people living in wealthier areas tended to have higher demand for games if sporting events were considered as normal goods (Carson, Cenesizoglu, & Parker, 2011; Hansen & Gauthier, 1989). Coincident Index data is retrieved from the Philadelphiafed.org website. Demand for attendance also depends on pressure from competitors (Rascher et al., 2009). Fierce competition for the same market may lead to low demand for certain individual sports teams and leagues (Winfree & Fort, 2008). To account for this competition, a continuous variable counting the number of teams from other professional sports leagues (*Competition*) sharing the same market is considered. This data is acquired from sports-reference.com.

One aspect of the quality of viewing concerns the condition of the sports facilities. For instance, facility age (*Facility_Age*) can affect consumer experience at sporting events, and thus determines demand for sport. Previous research showed a convex relationship between facility age and game attendance (Coates & Humphreys, 2005). That is, attendance seems higher in the early years of the operation of sport facilities and begins to decrease over time. However, attendance may surge again in later years of the facility's lifespan. As such, a quadratic term for facility age is added into models ($Facility\_Age^2$). Facility age data is retrieved from NBA media guides.

Another aspect of the quality of viewing is the timing of sporting events, which plays a crucial role in determining consumer demand for sport (Schofield, 1983). Time-related dummy variables, such as holidays (*Holiday*), the day of a week (*Day*), the month of a year (*October, November, December, January, February, March, and April*), and NBA seasons are employed in statistical models (Hansen & Gauthier, 1989). Following previous studies on demand for sport, the following holidays are used: *Christmas Day, Memorial Day, Labor Day, Independence Day, New Years' Day, Thanksgiving Day,* and *Martin Luther King Day* (Hansen & Gauthier, 1989). It is commonly assumed that teams face higher demand for sporting events on holidays and weekends where fans have more time to attend or watch games.

Turning to variables measuring the quality of sporting contests, it is well documented that team quality and game uncertainty are vital determinants of demand for attendance. In this dissertation, Elo ratings created by *FiveThirtyEight.com* are employed to measure team strength. Compared with other measures of team quality such as the winning percentage, Elo ratings account for more performance information, and thus may

be regarded as a better measure of team quality. For instance, the calculation of the Elo ratings does not only consider current win-loss records, but also the expectation of game outcomes (Mills et al., 2016). Such consideration provides a more objective assessment of team quality than other scales (Silver & Fischer-Baum, 2015). The average Elo rating for NBA teams is 1,500. The score increases when teams win games and declines when they lose games over the course of the season. The Elo rating system is a particularly useful metric at the beginning of the season (Mills et al., 2016). In contrast to the winning percentage that may not truly reflect team quality when teams only play a few games, Elo ratings incorporate team performance from the previous season in calculating the Elo rating for the current season, and thus may better reflect team success than other metrics in the early of the season (Silver & Fischer-Baum, 2015). In this dissertation, both home and visiting team Elo rating variables (*Elo_Home, Elo_Away*) are included. A handful of studies offered evidence that home and visiting teams' quality were positively linked to fan interest in attending sporting events (Cairns et al., 1986; Humphreys & Johnson, 2020; Leadley & Zygmont, 2005).

Point spreads collected from betting markets are used to quantify game uncertainty (Soebbing & Humphreys, 2013). The closing point spread (*Point_Spread*) is a continuous variable, estimating the score difference between two competing teams in a given match. For instance, bookmakers set the following point spreads in the game between the Washington Wizards and Atlanta Hawks on October 27, 2016, (Goldsheet.com):

Washington Wizards	
Atlanta Hawks	-4

In this example, the negative sign of point spread indicates that the Atlanta Hawks were a four-point favorite to win the game. If the Hawks eventually win by more than four points, then gamblers who bet that win the wager. The point spread is considered as a better estimator of the team quality gap than other measures such as the absolute difference between the home and away team winning percentage, as bookmakers who rely on setting point spreads to make profits have strong motivations to make accurate predictions (Forrest et al., 2005). Considering a probable curvilinear relationship between game uncertainty and attendance, a quadratic term of the point spread variable is also added in models ($Point\_Spread^2$; Coates et al., 2014). Point spread data is retrieved from Goldsheet.com, a website offering betting odds for varying types of sports competitions.

3.3 DATA COLLECTION

The previous section noted that Twitter data was used to construct the two variables of interest, the volume and sentiment of tanking tweets. This section offers more details regarding the procedure of creating these two variables. The first part of this section delineates specific steps taken to acquire and clean Twitter data. The second part concerns the process of using Twitter data to build the two variables of interest.

3.3.2 TWITTER DATA COLLECTION

Both tanking tweets and NBA team tweets are needed in order to calculate the volume and sentiment of tanking tweets. First, to search for tanking tweets for individual NBA teams, the keywords 'tanking' and the NBA team nickname(s) such as 'Lakers' are

used in the Twitter Application Programming Interface (API), an access point where users retrieve Twitter posts. It is critical to note that the reason that NBA team nicknames are chosen here as search terms is that these words can produce a more complete list of tanking tweets, than full NBA team names such as the ‘Los Angeles Lakers’. All NBA team nicknames used are listed in Table 3.3. Among these names, the Philadelphia Sixers’ nickname can be refereed as either ‘Sixers’ or ‘76ers’. Thus, both ‘Sixers’ and ‘76ers’ are searched in gathering tanking tweets. Also, the keyword ‘tanking’ has to be used with caution. While ‘tanking’ may not be the sole word to describe the behavior of teams purposely losing games, other search terms such as ‘rebuilding’ generated a considerable amount of irrelevant results. For this reason, this dissertation only employs ‘tanking’ as the search term in collecting tanking tweets.

In addition to drawing tanking tweets from the Twitter API, NBA team tweets measuring the popularity of NBA franchises are acquired. The purpose of retrieving team tweets lies in the possibility that the number of tanking tweets may not fully reflect the intensity of tanking discussions on Twitter. For instance, big market teams such as the Los Angeles Lakers and New York Knicks may have bigger fan base than small market teams. Consequently, more tanking discussions related to big market teams tend to appear on Twitter. However, the absolute quantity of tanking tweets pertaining to big market teams does not effectively quantify the intensity of tanking discussions, which intends to measure how well fans are aware of the idea of tanking. The number of team tweets posted on Twitter signals the general popularity of NBA teams, and thus can be used to normalize tanking tweets in order to better measure the intensity of tanking discussions.

Similar to the process of retrieving tanking tweets, I collect NBA team tweets through the Twitter API. However, a different set of search keywords are used. Specifically, I use the keywords '#NBA' and the hashtag with an NBA team nickname such as '#Lakers' to collect team tweets. Considering computer processing time and the possible millions of tweets for each team, this combination of keywords can return sufficient number of tweets to represent team popularity.

In sum, a total of 166,875 tanking tweets and 6,389,698 NBA team tweets posted between July 1, 2012, to June 30, 2018, are collected. The downloaded Twitter data contains a few pieces of information. As shown in Table 3.4, each tweet contains a unique Twitter ID, publication date, tweet text, the number of retweets, and related NBA team names. However, after a careful examination of Twitter data, it seems that several search results are not correctly identified. For instance, with the search terms 'warriors' and 'tanking', a list of tanking tweets related to the video game World of Warcraft emerged in search results (See Table 3.4). To ensure the quality of tanking tweets, I took a few steps to tease out irrelevant tanking tweets from the downloaded dataset.

The procedure of removing unrelated tanking tweets is drawn in Figure 3.3. Overall, Natural Language Processing (NLP) combined with machine learning models is implemented to eliminate irrelevant tweets based on the analysis of tweet content. The raw tweets containing noisy information cannot be directly used in machine learning models. Thus, a series of steps is performed here to process raw tweets (Figure 3.1). The first step concerns data cleaning. Specifically, special symbols and characters including hashtags, punctuations, digits, URLs, '@', NBA team city names, NBA team nicknames, are removed from tweets. Also, all capital letters in tweets are transformed into lowercase

letters. The second step involves tokenization, which functions to split sentences into individual words. The third step aims to remove all stop words such as ‘the’ and ‘a’ that are commonly used in sentences but not useful in understanding tweet content. The fourth step is stemming and lemmatization, which intends to convert words into their base form. For instance, lemmatization transforms words such as ‘saw’ to the base form ‘see’ and stemming removes the derivational affixes in a word.

Next, feature extraction converting terms in a document into features that can be used in machine learning models is employed. In this step, I adopted the n-gram model with a unigram. In essence, the n-gram model is used to count the frequency of n consecutive words in a given text. The word frequency is then treated as features in machine learning models. For instance, a unigram employed in this model only considers individual words in a text, while a bigram examines the sequence of two consecutive words (See examples in Figure 3.2).

After raw tweets are cleaned and feature extraction is completed, a random sample of 5,000 tweets are selected from the dataset and manually labeled by a coder with one of the classes 1 and 0, with 1 meaning the tweet relates to the NBA and 0 indicating it does not. Next, the labeled tweets are fitted into several machine learning models. After comparing the prediction performance across all models, the best performing model is chosen to estimate the class in all remaining tweets. In this case, I select the XGBoost algorithm that yields 98.8% accuracy in predicting the class of tanking tweets.

In sum, of the original 166,875 tanking tweets collected through the Twitter API, I removed 5,173 irrelevant tweets based on the predication of the XGBoost models. As

such, a total of 161,702 tanking tweets are used in this dissertation. With cleaned Twitter data, I proceed to construct the two variables of interest, the volume and sentiment of tanking tweets that are used to approximate consumer perceptions of tanking.

3.3.3 VARIABLE OPERATIONALIZATION

While the Twitter posts gathered in the previous steps contained tweet publication date and text, neither could be directly used in econometric models. Thus, an additional step is needed to transform the Twitter data into a useful variable that can be applied in statistical models. In this section, I describe the detailed steps taken to construct the two variables of interest, the volume and sentiment of tanking tweets.

To begin with, the volume of tanking tweets concerns the number of tanking tweets posted within a certain period of time, adjusted for team tweets. Specifically, the short-term volume variables count the number of tanking tweets posted within 31 days before an NBA contest, divided by the quantity of team tweets published in the same period. Here, the calculation of the volume variables takes team tweets into consideration for normalization. As noted before, big market teams tend to draw more attention on social media than small market teams. Hence, the absolute quantity of tanking tweets may not truly reflect the intensity of tanking discussions on Twitter. Similarly, the long-term volume variable calculates the quantity of all tanking tweets published from the previous NBA season, adjusted for team tweets. It is critical to note that the number of retweets is also considered in computing volume variables. For instance, if a tanking tweet is retweeted 10 times, then 11, including 10 retweets and the tweet itself, will be added into the calculation of the volume variables.

The second variable of interest, the sentiment of tanking tweets, concerns the average sentiment expressed in tanking tweets. To extract sentiments from tweets, sentiment analysis is conducted. Sentiment analysis is the process of understanding people's opinions and feelings by analyzing textual data (Kumar & Jaiswal, 2020). Recently, a significant portion of sentiment analysis focuses on detecting valance on the positive-negative scale (Farhadloo & Rolland, 2013). That is, one of the three sentiment classes, positive, neutral, and negative is often assigned to entities based on the analysis of textual data.

The field of sentiment analysis has developed a range of methods to identify opinions and feelings in text messages (Feldma, 2013). As noted in the literature review section, perhaps the most popular sentiment analysis approach adopted in sport management research is the lexicon-based method, which estimates the sentiment of a document by using a pre-defined dictionary of positive and negative words and counting the quantify of net positive words.

The present dissertation utilizes machine learning models to perform sentiment analysis. A range of advantages of using machine learning methods to perform sentiment analysis have to be noted. First, machine learning models can automatically extract sentiments from textual data with good accuracy (Neethu & Rajasree, 2013). This merit is particularly useful in processing a large dataset such as social media posts where thousands or even millions of data points may exist. With the increasing popularity of social media, the sheer number of messages posted on social media platforms everyday is growing faster than ever (Witkemper, Lim, & Waldburger, 2012). In the meantime, social media posts contain valuable information regarding consumer sentiment, which is useful

data in understanding behavior (Watanabe et al., 2016). Compared with other measures of consumer sentiment such as surveys, using machine learning methods can quickly detect sentiments in a large set of social media data, and thus may better help capture emotions from customers (Aydoğan & Akcayol, 2016).

Second, machine learning methods take the context into consideration when attempting to estimate sentiments (Pang & Lee, 2004). Unlike the lexicon-based approach, the machine learning method does not rely on a pre-defined dictionary. Instead, a training set that consists of a randomly selected sample from the entire dataset with manually labeled sentiments is used. This merit is especially important for sports research as certain words may have special meanings in the context of sport. For instance, previous sentiment analysis of Twitter posts using the lexicon-based method labeled the following sentience with the sentiment disgust, 'NFL is sick but I have no idea what's happening' (Chang, 2019). The literal interpretation of the word 'sick' might regard the sentence as the expression of disgust. However, considering the context of sport, the author of this post seemed to show affection for the NFL, rather than disgust. As such, machine learning methods relying on statistical models rather than pre-defined dictionaries may better measure sentiments in social media posts under various contexts.

The detailed steps of conducting sentiment analysis using machine learning models are listed in Figure 3.3. The first step, data pre-processing, and the second step, feature extraction, are the same as the previous work of removing irrelevant tanking tweets, except that I employ the n-gram model with both unigram and bigram, not just unigram as in the previous work.

After raw tweets are cleaned and feature extraction is completed, the random sample of 5,000 tweets selected in the prior work of filtering out unrelated tanking tweets are manually labeled by coders with one of the sentiment classes, positive (1), negative (-1), and neutral (0) (See Table 3.4).

Next, the labeled tweets are fitted into machine learning models. Methodologically, sentiment analysis resembles a multiclass classification problem where models were trained to predict sentiments in new tweets. After comparing the prediction performance across all models, the best performance model is selected to estimate sentiment in all remaining tweets. For this sentiment analysis, I choose the Linear Support-Vector Machine algorithm (LSVM) that yields 70.1% accuracy in predicting sentiments in tanking tweets. In general, 70% prediction accuracy is considered as a benchmark for successful sentiment analysis (Kirilenko, Stepchenkova, Kim, & Li, 2018).

After identifying sentiments in all tweets, the next step is to construct the sentiment variables. This variable is derived by calculating the average sentiment from tweets posted within a certain period of time. The formula for calculating the sentiment of tanking tweets is shown below:

$$Sentiment = \sum_{i=1}^{3} P(S_i) * S_i \tag{1}$$

where *S* denotes the sentiment value, 1, -1, and 0; *i* indicates three sentiment categories, positive, negative, and neutral; *P(S)* measures the percentage of each type of sentiments in the sample tweets. It is important to note that *P(S)* accounts for the number of retweets.

For instance, if there are two tweets with one being labeled as negative and the other one being labeled as positive and have three retweets, then the average sentiment will be 0.6, not 0.

In sum, the value of the sentiment of tanking tweets spans from -1 to 1, with -1 indicating all discussions on Twitter are negative toward tanking and 1 implying that all discussions on Twitter exhibit positive sentiments toward tanking. Furthermore, similar to the volume of tanking tweets, both short-term and long-term sentiment of tanking tweets are derived. The short-term sentiment variable estimates the average sentiment of Twitter posts published within 31 days before an NBA match, while the long-term sentiment variable calculates the average sentiment of all tanking tweets posted from the prior season.

3.4 MODEL SPECIFICATIONS

Based on the literature review and collected Twitter data, the following econometric models are employed to evaluate the relationship between perceptions of tanking and NBA attendance. The equation (2) below shows that the dependent variable, the natural log of game-level NBA attendance (*Attendance*), is a function of a vector of explanatory variables (Table 3.1)

$$
\begin{aligned}
log(Attendance_{git}) \\
&= \beta_1 Short\_Volume\_Home_{git} + \beta_2 Short\_Sentiment\_Home_{git} \\
&+ \beta_3 Long\_Volume\_Home_{git} + \beta_4 Long\_Sentiment\_Home_{git} \\
&+ \beta_5 Short\_Volume\_Away_{git} + \beta_6 Short\_Sentiment\_Away_{git} \\
&+ \beta_7 Long\_Volume\_Away_{git} + \beta_8 Long\_Sentiment\_Away_{git} \\
&+ \beta_9 Facility\_Age_{git} + \beta_{10} Facility\_Age^2{}_{git} + \beta_{11} Point\_Spread_{git} \\
&+ \beta_{11} Point\_Spread^2{}_{git} + \beta_{12} Elo\_Home_{git} + \beta_{13} Elo\_Away_{git} \\
&+ \beta_{14} Population_{git} + \beta_{15} Coincident\_Index_{git} + \beta_{16} Competition_{git} \\
&+ \beta_{17} Holiday_t + \beta_{18} Day_t + \beta_{18} Month_t + \theta_t + \gamma_i + \varepsilon_{git}
\end{aligned}
\tag{2}
$$

where *i* represents teams in season *t* at game *g*. βs represent estimators for variables. θ_t is unobserved time effects and γ_i is team-specific effects. ε_{git} is the error term.

To estimate parameters in econometric models, this dissertation adopts a censored normal regression model (Humphreys & Johnson, 2020). Due to the overwhelming number of sell-out games in the NBA, most NBA attendance data is censored at the capacity level (Coates & Humphreys, 2005). The data analysis shows that 45.8% of NBA games in the sample were sold out. If the model would be estimated using the Ordinary Least Squares (OLS) regression, the estimators may be biased and inconsistent (Wooldridge, 2010). To overcome such an issue, the censored normal regression model that takes censored attendance data into consideration was employed. The model takes the form:

$$Attendance = \begin{cases} Attendance* & Att* < c \\ c & Att* \geq c \end{cases} \tag{3}$$

where c is the facility capacity. In some cases, the reported game attendance exceeds the arena capacity. Over-selling can emerge when NBA teams sell additional standing room tickets or temporarily expand the capacity of luxury boxes (Coates & Humphreys, 2005). Nevertheless, attendance is treated as censored data if the reported attendance is larger than capacity (Buraimo & Simmons, 2008). If attendance is smaller than capacity, the actual attendance was observed at the level of Attendance*.

The model also adds team and season fixed effects to account for unobserved factors that can affect demand for sport. Despite concerns that non-linear regression models with fixed effects may produce inconsistent estimators due to the incidental parameters problem (Lancaster, 2000; Neyman & Scott, 1948), Greene (2004) conducted the Monte Carlo simulation and noted that estimators from the censored normal regression model with fixed effects were consistent.

Additionally, the unobserved error term in econometric models may be serially correlated with one another within clusters (teams). To address this serial correlation concern and derive efficient estimators, cluster-robust standard errors are calculated (Woodridge, 2010).

In summary, a total of seven models are estimated and compared. The first model attempts to reveal the general relationship between consumer perceptions of tanking and game attendance by employing the entire dataset of 5,945 NBA matches. As noted before, to ensure Twitter data measuring consumer perceptions of tanking is related to the behavior of teams deliberately losing games for draft picks, not for other purposes, NBA

games featuring non-playoff teams which have incentives to tank for draft picks are considered in other main models.

The second main model addresses the first research question that explores the connection between perceptions of tanking for home teams and demand for sport in the short term. Specifically, 2,870 games featuring home teams that are not eligible for the playoffs in the observed season are examined in the second model. The third model focuses on studying the long-term effect of consumer perceptions of tanking for home teams on attendance. To do this, 2,829 matches involving home teams that did not compete in the playoffs in the prior season are considered. The fourth model is tested in an attempt to answer the third reason question whether consumer perceptions of tanking for visiting teams will affect attendance in the short term. As such, 2,769 games featuring away teams that do not enter the playoffs in the observed season are analyzed. The fifth model investigates the long-term impact of consumer perceptions of tanking for away teams on attendance. Here, 2,774 matches featuring visiting teams that do not compete in the playoffs in the previous season are selected to test the relationship. The last two models perform falsification tests by adding the variables gauging the future volume and sentiment of tanking tweets for home teams and away teams respectively. Falsification tests aim to examine whether an unlikely event is statistically significant in models. In this case, if models are correctly specified, the future volume and sentiment of tanking tweets should not impact NBA attendance.

Table 3.1 Variable Descriptions

Variable	Description
Attendance	Number of tickets sold in a game
Short_Volume_Home	Short-term (31 days before games) volume of tanking tweets for home teams
Short_Sentiment_Home	Short-term (31 days before games) sentiment of tanking tweets for home teams
Long_Volume_Home	Long-term (Prior season) volume of tanking tweets for home teams
Long_Sentiment_Home	Long-term (Prior season) sentiment of tanking tweets for home teams
Short_Volume_Away	Short-term (31 days before games) volume of tanking tweets for away teams
Short_Sentiment_Away	Short-term (31 days before games) sentiment of tanking tweets for away teams
Long_Volume_Away	Long-term (Prior season) volume of tanking tweets for away teams
Long_Sentiment_Away	Long-term (Prior season) sentiment of tanking tweets for away teams
Future_Volume_Home	Future (31 days after games) volume of tanking tweets for home teams
Future_Sentiment_Home	Future (31 days after games) sentiment of tanking tweets for home teams
Future_Volume_Away	Future (31 days after games) volume of tanking tweets for away teams
Future_Sentiment_Away	Future (31 days after games) sentiment of tanking tweets for away teams
Facility_Age	Age of sports facilities (in years)
Facility_Age^2	Age of sports facilities Squared (in years)
Point_Spread	Expected score differences between two competing teams
Point_Spread^2	Expected score differences between two competing teams Squared
Elo_Home	Elo ratings for home teams
Elo_Away	Elo ratings for away teams
Population	Population of city (in ten thousands)
Coincident_Index	Monthly coincident index for each of the 50 states

Competition	Number of MLB, NFL, and NHL teams in the same market as a NBA team
Holiday	Games held on National holidays (1=yes)
Monday	Games held on Monday (1=yes)
Tuesday	Games held on Tuesday (1=yes)
Wednesday	Games held on Wednesday (1=yes)
Thursday	Games held on Thursday (1=yes)
Friday	Games held on Friday (1=yes)
Saturday	Games held on Saturday (1=yes)
Sunday	Games held on Sunday (1=yes)
October	Games held in October (1=yes)
November	Games held in November (1=yes)
December	Games held in December (1=yes)
January	Games held in January (1=yes)
February	Games held in February (1=yes)
March	Games held in March (1=yes)
April	Games held in April (1=yes)
2014	Games held in the 2013-2014 NBA season (1=yes)
2015	Games held in the 2014-2015 NBA season (1=yes)
2016	Games held in the 2015-2016 NBA season (1=yes)
2017	Games held in the 2016-2017 NBA season (1=yes)
2018	Games held in the 2017-2018 NBA season (1=yes)

Table 3.2 Summary Statistics (n= 5945)

Variable	Mean	St. Dev.	Min	Max
Attendance	17,733.5	2,294.8	7,244	23,152
Short_Volume_Home	0.074	0.183	0.000	2.755
Short_Sentiment_Home	-0.628	0.264	-1.000	1.000
Long_Volume_Home	0.042	0.079	0.0002	0.597
Long_Sentiment_Home	-0.674	0.115	-0.909	-0.197
Short_Volume_Away	0.072	0.176	0.000	2.685
Short_Sentiment_Away	-0.629	0.265	-1.000	1.000
Long_Volume_Away	0.041	0.078	0.0002	0.597
Long_Sentiment_Away	-0.673	0.116	-0.909	-0.197
Future_Volume_Home	0.081	0.180	0.000	2.582
Future_Sentiment_Home	-0.632	0.247	-1.000	1.000
Future_Volume_Away	0.082	0.184	0.000	2.429
Future_Sentiment_Away	-0.627	0.256	-1.000	1.000
Facility_Age	19.8	10.1	1	52
Point_Spread	1.7	7.0	-18.5	21.0
Elo_Home	1,502.8	112.4	1,174.7	1,835.7
Elo_Away	1,504.5	111.6	1,175.5	1,838.6
Population	55.6	50.8	5.3	203.2
Coincident_Index	120.5	9.6	98.3	144.8
Competition	2.2	1.9	0	7
Holiday	0.016	0.125	0	1
Monday	0.14	0.347	0	1
Tuesday	0.117	0.321	0	1
Wednesday	0.205	0.404	0	1
Thursday	0.075	0.264	0	1
Friday	0.191	0.393	0	1
Saturday	0.15	0.357	0	1
Sunday	0.121	0.326	0	1

October	0.038	0.191	0	1
November	0.181	0.385	0	1
December	0.185	0.388	0	1
January	0.184	0.387	0	1
February	0.136	0.342	0	1
March	0.191	0.393	0	1
April	0.085	0.28	0	1
2014	0.2	0.4	0	1
2015	0.2	0.4	0	1
2016	0.2	0.4	0	1
2017	0.2	0.4	0	1
2018	0.2	0.4	0	1

Table 3.3 NBA Team Search Keywords

Number	NBA Franchises	Search Keywords (Nicknames)
1	Atlanta Hawks	Hawks
2	Boston Celtics	Celtics
3	Brooklyn Nets	Nets
4	Charlotte Hornets (2014-2015 – Present)	Hornets
	Charlotte Bobcats (Before 2013-2014)	Bobcats
5	Chicago Bulls	Bulls
6	Cleveland Cavaliers	Cavaliers
7	Dallas Mavericks	Mavericks
8	Denver Nuggets	Nuggets
9	Detroit Pistons	Pistons
10	Golden State Warriors	Warriors
11	Houston Rockets	Rockets
12	Indiana Pacers	Pacers
13	Los Angeles Clippers	Clippers
14	Los Angeles Lakers	Lakers
15	Memphis Grizzlies	Grizzlies
16	Miami Heat	Heat
17	Milwaukee Bucks	Bucks
18	Minnesota Timberwolves	Timberwolves
19	New Orleans Pelicans	Pelicans
20	New York Knicks	Knicks
21	Oklahoma City Thunder	Thunder
22	Orlando Magic	Magic
23	Philadelphia 76ers	76ers and Sixers
24	Phoenix Suns	Suns
25	Portland Trail Blazers	Blazers
26	Sacramento Kings	Kings
27	San Antonio Spurs	Spurs
28	Utah Jazz	Jazz
29	Washington Wizards	Wizards

Table 3.4 Tanking Tweet Samples

Twitter ID	Date	Text	Retweet	Team	Class	Sentiment
xxxx 7872	2013-03-06	Whether by design or through incompetence (more likely) I love that @Sixers are tanking! #SixersTalk #SixersNation #Sixers @SixersCEOAdam"	0	Sixers	1	Positive (1)
xxxx 5472	2016-01-26	I hate to admit it as a diehard laker fan but @Lakers I know your tanking. I hate it cause its not within our blood. I'll never support it	2	Lakers	1	Negative (-1)
xxxx 3424	2013-07-08	@JakeJ29 @zero_chill I'm fine with tanking. But we wont be top 5 worst teams either. We wont land Wiggins or Glen Robinson III. #Bucks	0	Bucks	1	Neutral (0)
xxxx 0672	2014-06-17	@Celestalon if protection warriors get a talent to make then DPS can there be a talent to make Frost DKs tank again I loved tanking frost	0	Warriors	0	-

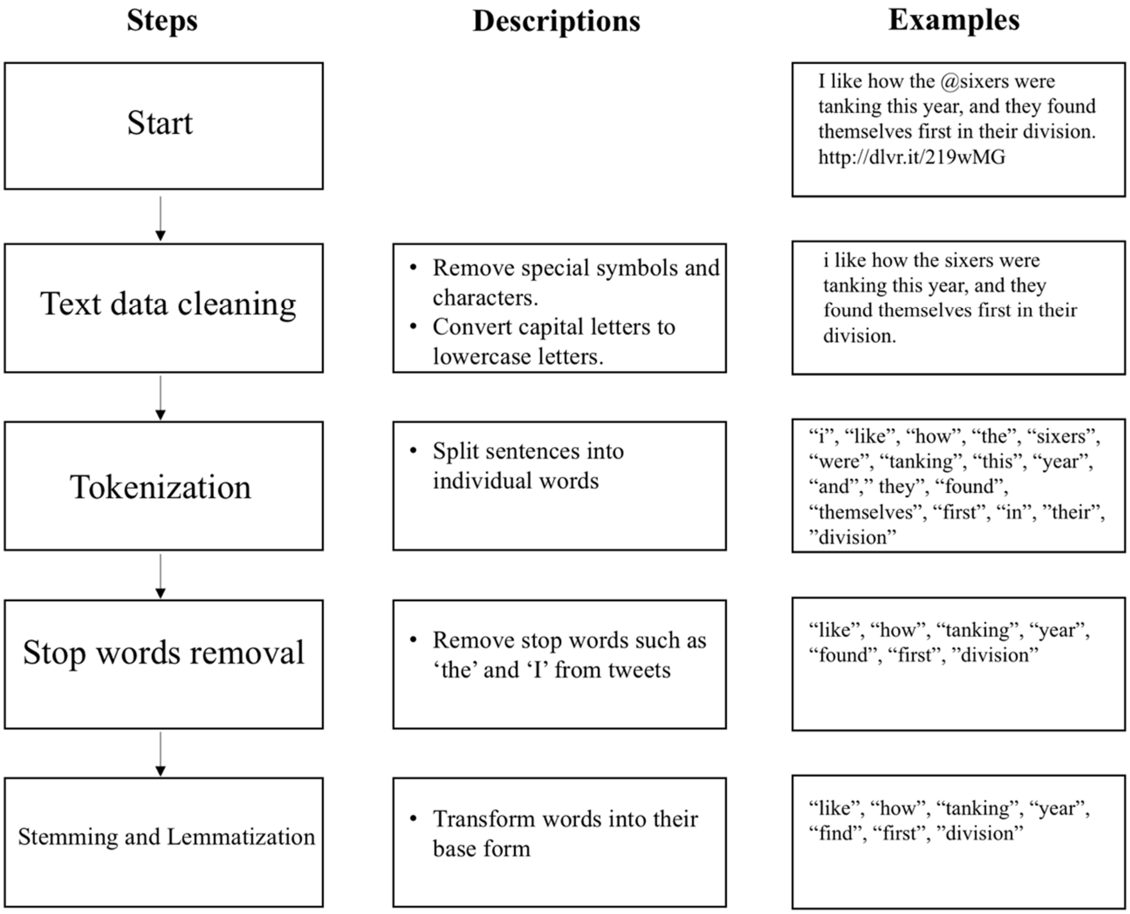

Figure 3.1 Textual Data Pre-Processing Steps

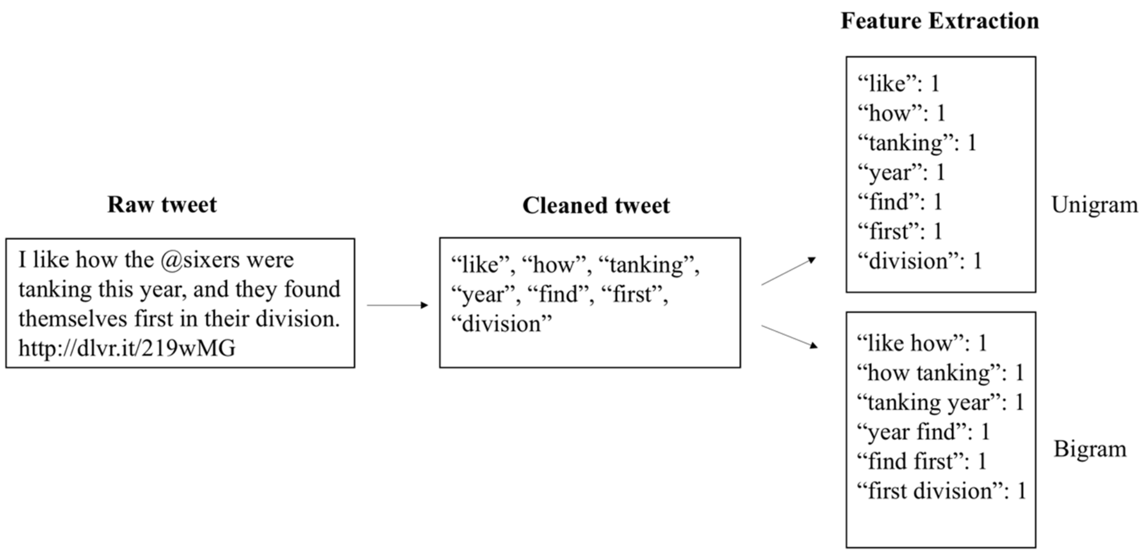

Figure 3.2 Feature Extraction Process

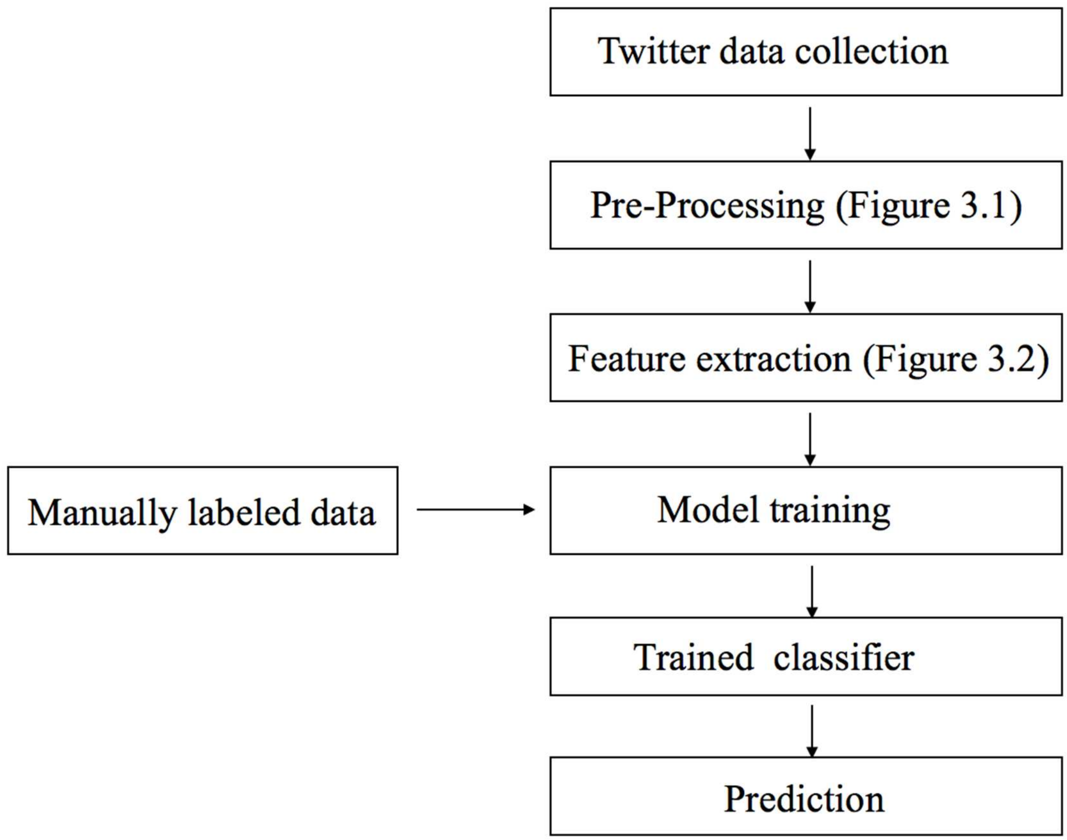

Figure 3.3 Data Analysis Process with Machine Learning Models and Twitter Data

CHAPTER 4

RESULTS

Chapter 4 describes the data analysis results. The first section of this chapter provides a detailed summary of the two variables of interest, the volume and sentiment of tanking tweets, which are derived from Twitter data. It is critical to note that the summary only includes non-playoff teams as they have incentives to tank for draft picks, while other teams do not. With the current dissertation focusing on examining the behavior of teams deliberately losing games for draft picks, attention is therefore placed on non-playoff teams. The second section of this chapter reports regression analysis results, along with robustness checks that test the strength of estimation results.

4.1 SUMMARY OF TWITTER DATA

4.1.1 VOLUME OF TANKING TWEETS

The volume of tanking tweets reflects the fans' awareness of tanking and is calculated by using the number of tanking tweets divided by the quantity of team tweets. Here, I summarize the volume of tanking tweets at the game, team, month, and season levels. First, in the Twitter dataset spanning from the 2013-2014 to 2017-18 NBA seasons, the highest short-term volume of tanking tweets for an individual game was the Chicago Bulls on March 23, 2018 when they played against the Milwaukee Bucks at home. Such extensive discussion of tanking could be attributed to the player rest strategy that the Bulls had adopted since the beginning of February that year. In particular, the Bulls rested Robin Lopez and Justin Holiday, both of whom were starters for the team

and had a significant amount of playing time before being requested to sit out (NBA, 2018). The NBA subsequently issued a warning to the Bulls on March 6, stating that their behavior violates the league player rest policy (NBA, 2018). The warning caused strong speculation among fans that the Bulls rested healthy players in order to tank for draft picks. As such, it was not surprising that the high volume of tanking tweets appeared prior to the Bulls' game on March 23.

At the team level, the 2014-2015 Philadelphia Sixers had the highest volume of tanking tweets among all team-season observations. With the hiring of Sam Hinkie, an advocate of using tanking to rebuild NBA franchises, on May 10, 2013 as the General Manager (ESPN, 2013), the Sixers implemented a tanking strategy (Hinkie, 2016). After only 18 wins out of 82 games played in the 2014-2015 NBA season, it was not surprising to see fans raise strong concerns that the Sixers were tanking. The second highest volume of tanking tweets at the team-season level was the previous Sixers' season (2013-2014). This season was the Sixers' first season under the leadership of Sam Hinkie. It appeared that a large quantity of tanking discussions related to the Sixers posted on Twitter throughout the entire 2013-2014 season. The ten highest season volume of tanking tweets and corresponding teams and seasons are listed in Table 4.1. Figure 4.1 plots the short-term volume of tanking tweets for the Sixers with Locally Estimated Scatterplot Smoothing (LOESS) that shows a general trend of volume over the sample period. Plots for other teams are available upon request.

At the season level, the 2013-2014 NBA season experienced a significant increase of tanking discussions on Twitter. The volume of tanking posts on Twitter seemed to progressively decline in the following seasons. However, tanking discussions spiked

again in the 2017-2018 NBA season. As Figure 4.2 showes, the volume of tanking tweets in the 2013-2014 and 2017-2018 NBA seasons were considerably higher than other seasons. Notably, the 2013-2014 NBA season marked the first season when Sam Hinkie became the general manager of the Sixers and planned to undertake the extreme tanking strategy by deliberately losing numerous games in consecutive seasons (Paxton, 2018). The 2017-2018 season was surrounded by several tanking-related incidents that caused the extensive discussion of tanking on Twitter. For example, in addition to the warning issued to the Bulls regarding resting healthy players, the NBA league office fined the Dallas Mavericks owner Mark Cuban $600,000 for publicly admitting tanking during the 2017-2018 NBA season (NBA, 2018).

Additionally, the volume of tanking tweets varies from month to month during the NBA regular season. Figure 4.3 summarizes and plots the volume of tanking tweets by month. It seems the volume of tanking tweets is exceedingly higher in February and March than other months during the NBA regular season. These findings are not surprising, given the fact that NBA teams are more likely to deliberately lose games toward the end of the NBA season, especially when they are eliminated from playoff contention (Price et al, 2010; Taylor & Trogdon, 2002).

4.1.2 SENTIMENT OF TANKING TWEETS

The second variable of interest, the sentiment of tanking tweets, measures consumer attitudes toward tanking and is estimated by the average sentiment expressed in tanking tweets. Recall that sentiment analysis is performed to extract sentiments from tanking tweets. Specifically, each tweet is assigned with one of the classes, negative (-1), neutral (0), and positive (1). When Twitter posts contain information supporting the

concept of tanking, these tweets are labeled as positive. Neutral tweets may include any posts that are in the middle of supporting and disliking tanking. Negative tweets often represent the fans' disappointment toward tanking.

After conducting sentiment analysis on tanking tweets, the overall sentiment toward tanking is clear. Specifically, of 161,702 tanking tweets collected, 75% of Twitter posts exhibit negative views toward the idea of tanking. Of the rest, 17.7% of posts are labeled as neutral and 7.3% of tweets show some positive attitudes toward the concept of tanking. Here, I report the summaries of the sentiment of tanking tweets at the team, month, and season levels. First, sentiment analysis revealed that 2015-2016 Chicago Bulls season had the strongest negative sentiment (-0.881) on tanking among all team-season observations in the dataset. Table 4.2 lists the ten worst sentiments on tanking and the related seasons and teams. Additionally, Figure 4.4 plots the short-term sentiment of tanking tweets for the Bulls, as an example, with LOESS that displays a general trend of sentiments over the seasons.

At the season level, it is interesting to note that while tanking tweets predominately exhibit negative views, the sentiment toward tanking becomes more positive over the five-season period. For instance, the sentiment of tanking tweets is scored at -0.703 in the 2013-2014 season but raises to -0.600 in the 2017-2018 season (Figure 4.5). A simple linear regression of the sentiment on NBA seasons also shows a positive relationship between the NBA seasons and sentiment toward tanking, indicating that fans seem to become more acceptable to the idea of tanking over the years. Another interesting result is that the 2013-2014 NBA seasons have the lowest sentiment on tanking among five seasons examined in this dissertation. The extremely low sentiment

might come from the fact that the Sixers were alleged to have tanked for the entire season. Specifically, as noted before, Sam Hinkie who was renowned for employing the tanking strategy to rebuild NBA franchises embarked on his career as the general manager of the Sixers in the 2013-2014 season. While the Sixers did not publicly admit to tanking, the appointment of Sam Hinkie and his subsequent public statements might make fans speculate that the team would be committed to tanking (Rappaport, 2017).

The sentiment of tanking tweets is also examined at the month level (Figure 4.6). Figure 4.6 suggests sentiment regarding tanking seems to improve first and then deteriorates over the course of the season. Early in the season (October and November), the sentiment on tanking is scored at -0.670 and -0.638 respectively. Then, the sentiment becomes more positive as the season progresses and reaches the peak in December. However, the sentiment appears to aggravate toward the end of the season (March and April). This observation is expected as abundant studies have shown that teams are more likely to tank toward the end of the NBA regular season (Price et al, 2010; Taylor & Trogdon, 2002). With an increasing number of tanking teams approaching the conclusion of an NBA season, more fans may express disappointment and displeasure in March and April (Price et al, 2010; Taylor & Trogdon 2002).

4.2 REGRESSION ANALYSIS RESULTS

The previous section summarized the two variables of interest and revealed some interesting observations. This section focuses on reporting regression analysis results for four research questions proposed in Chapter 2.

Table 4.3 reports the main findings. Column (1) presents the results for models using the entire dataset of 5,945 games. While all 5,945 games played between the 2013-

2014 to 2017-2018 NBA seasons are available to examine, some of which are not useful in addressing the proposed research questions. The reason rests on the fact that not all tanking teams aim to deliberately lose games to improve draft position. For instance, certain playoff teams may tank for other purposes such as reserving energy for the playoffs or competing for better playoff seeds (McManus, 2019). The current dissertation focuses on analyzing the behavior of tanking for draft picks and how fans perceive such behavior. Thus, subsets of games featuring non-playoff teams that have incentives to tank for draft picks are used in models.

Table 4.3, Column (2) contains the findings for the first research question whether consumer perceptions of tanking for home teams will affect attendance in the short run. To ensure the Twitter data can effectively reflect consumer perceptions of tanking for draft picks, the analysis employs 2,870 games featuring home teams that do not enter the playoffs in the observed season. The estimated coefficient on the short-term volume of tanking tweets for home teams is negative and significant at the 0.05 level, meaning that the higher volume of tanking discussions for home teams prior to an NBA game will result in lower demand for sport. The parameter estimate on the short-term sentiment of tanking tweets for home teams is insignificant, indicating that fan attitudes toward tanking related to home teams do not affect demand for NBA games in the short term.

The second research question investigates the possibility that consumer perceptions of tanking may have a prolonged impact on consumer interest in NBA games. To address this question, the same model specifications as Column (2) is used but a different set of 2,829 NBA games featuring home teams that did not qualify for playoffs in the previous season are examined. Recall that the long-term variables measure the

volume and sentiment of tanking from the previous season, while the short-term variables are calculated by using tweets posted within 31 days prior to the start of an NBA game. The estimation results in Column (3) show that the extensive discussion of tanking for home teams from the prior season can negatively affect NBA attendance as the estimated parameter on the long-term volume of tanking tweets for home teams is negative and significant at the 0.05 level. Yet, the estimated coefficient on the long-term sentiment of tanking tweets for home teams is not significant, implying that fan views of tanking for home teams formed in the past do not influence their attendance decisions.

The third and fourth questions aim to explore whether consumer perceptions of tanking for visiting teams will affect attendance decisions in both the short-term and long-term. To answer these questions, 2,769 games featuring away teams that are not eligible for playoffs in the observed season and 2,774 games featuring away teams that did not compete in playoffs in the prior season are employed in models in Column (4) and Column (5) respectively. The findings in Column (4) reveal that the parameter estimate on the short-term sentiment of tanking tweets for away teams is positive and significant at the 0.05 level, indicating that how fans view visiting teams' tanking behavior prior to an NBA match positively affect their attendance decisions. However, the estimate on the short-term volume of tanking tweets for visiting teams is not significant, meaning the decision to attend an NBA game does not hinge on how well local fans are aware of tanking related to away teams. Additionally, the results in Column (5) suggest estimated coefficients on the long-term volume and sentiment of tanking tweets for away teams are not significant at the 0.05 level, signaling that consumer

perceptions of tanking for visiting teams do not influence local fans' attendance decisions in the long run.

Lastly, two falsification tests are performed to test whether model specification are correctly identified (Goldhaber & Chaplin, 2015). To perform falsification tests, I add a set of variables that represents future consumer perceptions of tanking. Specifically, the future volume and sentiment of tanking tweets for both home and visiting teams are calculated by using tweets posted within 31 days after an NBA game. If the model specifications are correct, future perceptions of tanking should not have any effects on attendance decisions. The estimation results are displayed in Table 4.3, Column (6) and Column (7). The parameter estimates on future perceptions of tanking for home and visiting teams are all insignificant at the 0.05 level. Thus, my models pass falsification tests.

Moving to control variables, the estimated parameter on home team quality is significant and positive in all models in Table 4.3, suggesting that high quality home teams tend to attract more fans to games. The different estimation results are observed on away team quality variables. Specifically, the findings in Column (1), (2), and (3) show a positive and significant relationship between away team quality and NBA attendance, while the estimations in Column (4), (5) do not.

Economic factors such as population and income level may be important predictors of attendance in the NBA (Borland & MacDonald, 2003). The results in Column (1), (3), and (4) show that MSA population is positively associated with demand for NBA games. However, the finding in Column (2) concludes that there is a statistically negative link between population and NBA attendance. Additionally, the estimation in

Column (5) suggests that population may not be a determining factor of consumer interest in sport. Unlike the population variables revealing different relationships under various models, the parameter estimates on coincident indexes measuring monthly economic conditions in states produce consistent outcomes across all models. Specifically, the findings suggest coincident indexes have a statistically positive connection with demand for sport at the 0.05 level, indicating a stronger economy leads to higher attendance at NBA games. The number of professional sports teams in the same market as NBA teams does not seem to affect attendance. Only the results in Column (1) display a negative relationship between *Competition* and consumer interest in NBA games, meaning that stronger market competition will lead to lower demand for attendance. All other models suggest that market competition is not a key determinant of consumer interest in the NBA.

NBA game attendance may also be determined by game uncertainty (Mills & Fort, 2014). The current dissertation uses point spreads from betting markets to approximate game uncertainty. The model specifications also include a quadratic term on point spreads in order to catch the nonlinear relationship between game uncertainty and demand for sport. The estimation results suggest that the parameter estimate on the squared point spreads is positive and significant in Column (1), (2), (3), and (5), while the estimated coefficient on point spreads is not significant, except in Column (1). These findings suggest that the lowest attendance will appear when point spreads are 0, where game outcomes are most unpredictable. Thus, this dissertation does not offer evidence that more uncertain NBA games will increase ticket sales.

The literature on demand for sport also suggested that the facility age might play an important role in changing NBA attendance (Coates & Humphreys, 2005). The present dissertation produces inconsistent conclusions regarding the connection between facility age and consumer interest in NBA games. The findings in Column (3) and (5) suggest that facility age does not affect NBA attendance, while the result in Column (2) reveals a concave relationship between these two variables. Additionally, the parameter estimate on facility age is negative in Column (1), implying that demand will decline after the opening of a new sports facility. Furthermore, the result in Column (4) indicates a convex relationship between facility age and NBA attendance, meaning that attendance drops after a sports facility opens but increases toward the end of the lifespan of the facility.

The timing of NBA games seems to be a significant predictor of NBA attendance (Watanabe, Yan, Soebbing, & Fu, 2019). In this dissertation, the estimated coefficients on holiday games are positive and significant at the 0.05 level across all models. For instance, the estimation in Column (2) indicates that holiday games will attract 8.3% more fans than non-holiday games. The estimated coefficients on other timing variables such as the day of a week and the month of a year produce same conclusions as the prior studies of demand for sport. Due to limited space, their estimation results are not reported here.

4.3 ROBUSTNESS CHECKS

To test the strength of the findings, I perform a number of robustness checks. First, the short-term volume and sentiment variables for both home teams and away teams are recalculated by using tweets posted within 15, 62, and 93 days before the tipoff of an NBA game rather than 31 days used in the main models. Originally, the construction of

the two variables of interest assumes that fans on average book tickets to NBA games within a month prior to the start of an NBA game (Mills, Salaga, & Tainsky, 2016), However, some fans may choose to buy tickets earlier or later than the one-month window. Thus, it is important to check the robustness of the findings under different timeframes. As such, I re-estimated models by using variables calculated from 15-day, 62-day and 93-day data.

The estimation results are shown in Table 4.4. In general, all models produce similar results as the main models in terms of the sign and significance. For models investigating the effect of perceptions of tanking for home teams on attendance in Table 4.4, Column (1), (2), and (3), the estimated parameters on the short-term volume of 15-day, 62-day and 93-day tanking tweets for home teams are negative and significant at the 0.05 level, meaning the increasing discussion of tanking related to home teams prior to an NBA game undermines consumer interest. Comparing the magnitude of the parameter estimates across three models, it appears that tanking discussions occurred within 93 days before the start of an NBA match has the highest impact on attendance and such effects diminish as the time window shortens. In other words, the awareness of tanking formed within at least 93 days before an NBA game can negatively affect attendance decisions. Moving to the short-term sentiment of tanking tweets for home teams, the findings are consistent across three robustness check models in Table 4.4, Column (1), (2), and (3) that the estimated coefficients are not significant at the 0.5 level. Despite different ways of calculating sentiments, all models draw the same conclusion that fan attitudes toward tanking for home teams measured prior to an NBA match do not affect consumer behavior in attending NBA games.

For models studying the impact of perceptions of tanking for visiting teams on attendance in Table 4.4, Column (4), (5), and (6), the estimated coefficients on the short-term sentiment of 15-day, 62-day and 93-day tanking tweets for visiting team are all positive and significant at the 0.5 level. These estimation results are consistent as the main models in terms of the sign and significance. The magnitude of these coefficients is slightly different. Table 4.4, Column (4) shows that the sentiment of 15-day tanking tweets for visiting teams has the smallest positive impact on attendance, while the sentiment of 93-day tanking tweets for away teams has the largest positive impact on attendance among three models. Additionally, the estimated coefficients on the short-term volume of 15-day, 62-day, and 93-day tanking tweets for visiting teams are not significant at the 5% for all models. These findings are similar to the main models that the broad discussion of tanking for away teams prior to an NBA game will not affect local fans' attendance decisions.

The second robustness check concerns the long-term impact of consumer perceptions of tanking on demand for NBA games. Recall that the long-term volume and sentiment of tanking tweets are calculated from tanking tweets posted in the previous NBA season and are employed to quantify the past consumer perceptions of tanking. To calculate the long-term variables, an entire NBA season spanning from July 1 to June 30 is considered. However, Twitter posts over the entire NBA may not adequately quantify the past consumer perceptions of tanking. For instance, it is likely that fans may develop their perceptions of tanking over the course of the season when they watch games (Aday & Phelan, 2016). Therefore, the second robustness check uses tanking tweets published during the prior regular season, rather than the entire season, to construct the long-term

variables. The models in Table 4.3, Column (3) and (5) are re-estimated with the revised long-term variables and the results are reported in Table 4.4, Column (7) and (8).

Overall, the findings with the new long-term variables are largely the same as the main models, indicating the robustness of findings pertaining to the long-term effect of perceptions of tanking on demand for sport. Specifically, the results in Table 4.4, Column (7) show that the long-term volume of tanking tweets for home teams is negatively related to attendance. This conclusion is similar to the previous analysis. However, the findings related to the long-term sentiment of tanking tweets for home teams are different from the main models. As shown in Column (7), the robustness check model suggests that the long-term sentiment of tanking tweets for home teams negatively relates to attendance as the estimated coefficient is negative and significant at the 0.05 level, while the main models revealed an insignificant relationship. One possible explanation for this difference is that fans who developed negative attitudes toward tanking for home teams during the prior regular season are curious about what teams have changed in the current season. As such, local fans may express higher demand for home games this year, although they may hold negative attitudes on tanking for home teams in the previous season. Focusing on the estimations pertaining to the long-term variables for visiting teams, the results in Column (8) are the same as prior examinations that neither the awareness nor attitudes toward tanking for visiting teams can influence local fans' attendance decisions in the long run.

The third robustness check re-estimated the effect of the volume of tanking tweets on attendance without adjusting for team tweets. Recall that NBA team tweets are collected to normalize the quantity of tanking tweets since big market teams such as Los

Angeles Lakers and New York Knicks may intrinsically have more social media posts, and thus have a higher quantity of tanking tweets than other NBA teams (Robinson & DeSchriver, 2003; Késenne, 2000). Here, the first five models listed in Table 4.3 are re-estimated without counting team tweets in the volume variables. The results are presented in Table 4.5. Overall, the significance and sign of the parameters of interest are consistent as the main models. The only exception is that the estimate parameters on the short-term volume of tanking tweets for visiting teams become positive and significant at the 0.05 level across five modes in Table 4.5 but are insignificant in the main models. This difference may arise from the fact that the volume of tanking tweets is not normalized, and thus is not a proper proxy for the fan awareness of tanking. Nevertheless, this robustness check generally reconfirms the finding that the increasing awareness of tanking for home teams can significantly harm consumer interest in both the short term and long term. In sum, the above three robustness checks largely show consistent results as the main models. Thus, I am confident of the robustness of the findings in these models.

The fourth robustness check relates to the concern that Elo ratings may be highly correlated with the volume and sentiment of tanking tweets variables, as the calculation of Elo ratings may take teams' tanking behavior into consideration (Silver & Fischer-Baum, 2015; Soebbing & Humphreys, 2013). To perform the fourth robustness check, seven main models are re-estimated by using team winning percentage prior to the start of NBA game for home and away teams (Win_home, Win_away) instead of Elo ratings. The estimation results can be found in Table 4.6. In sum, the parameter estimates on the

variables of interest in Table 4.6 have similar significance and sign as estimated coefficients in main models, confirming the robustness of main findings.

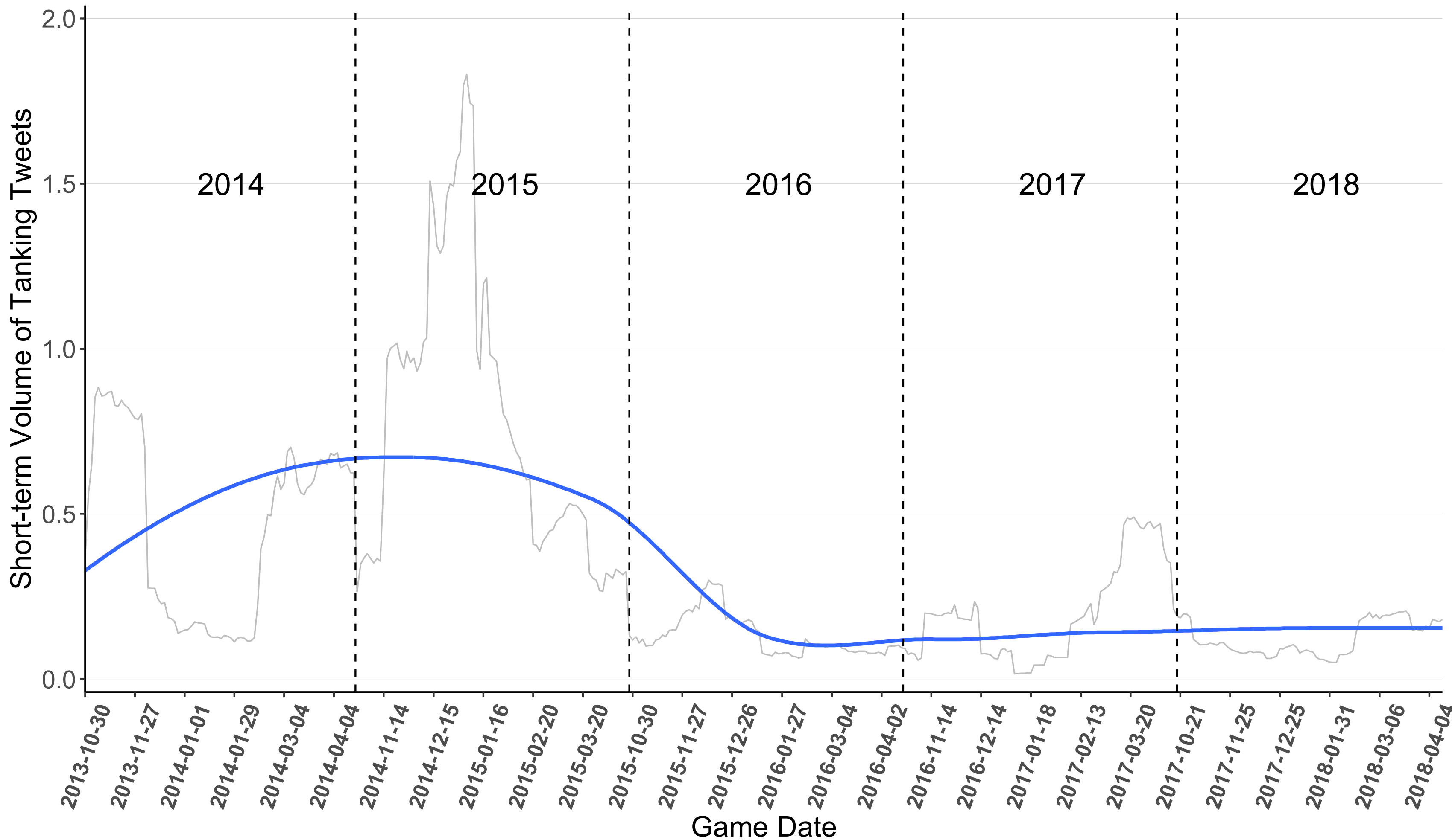

Figure 4.1 Short-term Volume of Tanking Tweets for the Philadelphia Sixers from the 2013-2014 to 2017-2018 Season

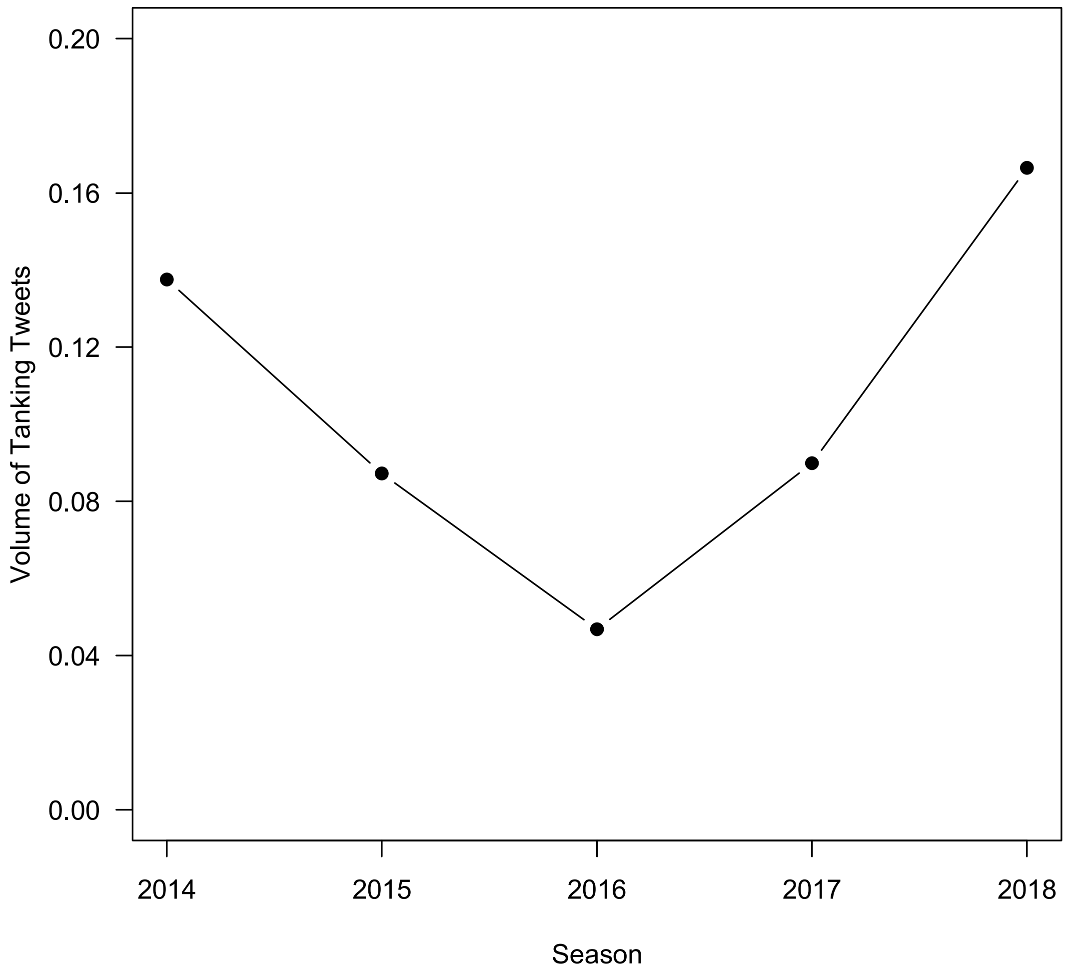

Figure 4.2 Volume of Tanking Tweets by Season

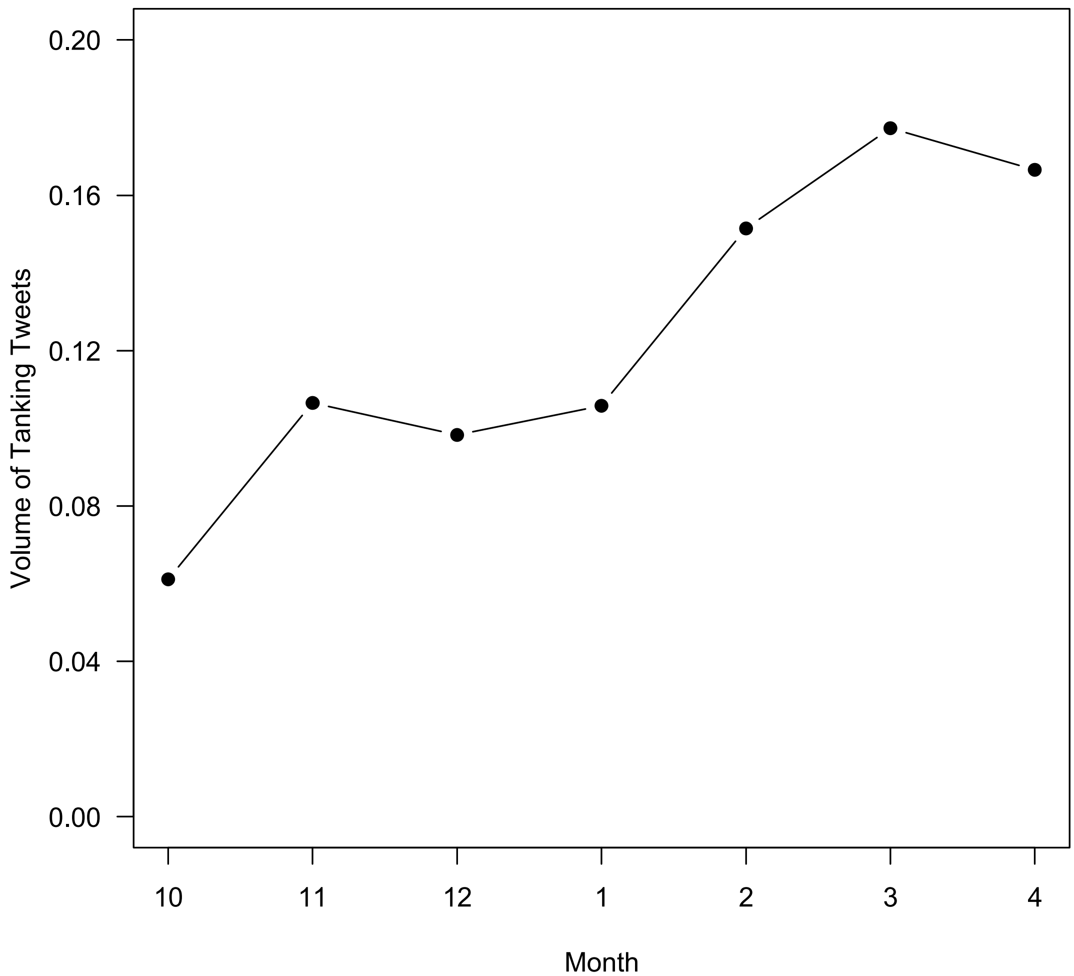

Figure 4.3 Volume of Tanking Tweets by Month

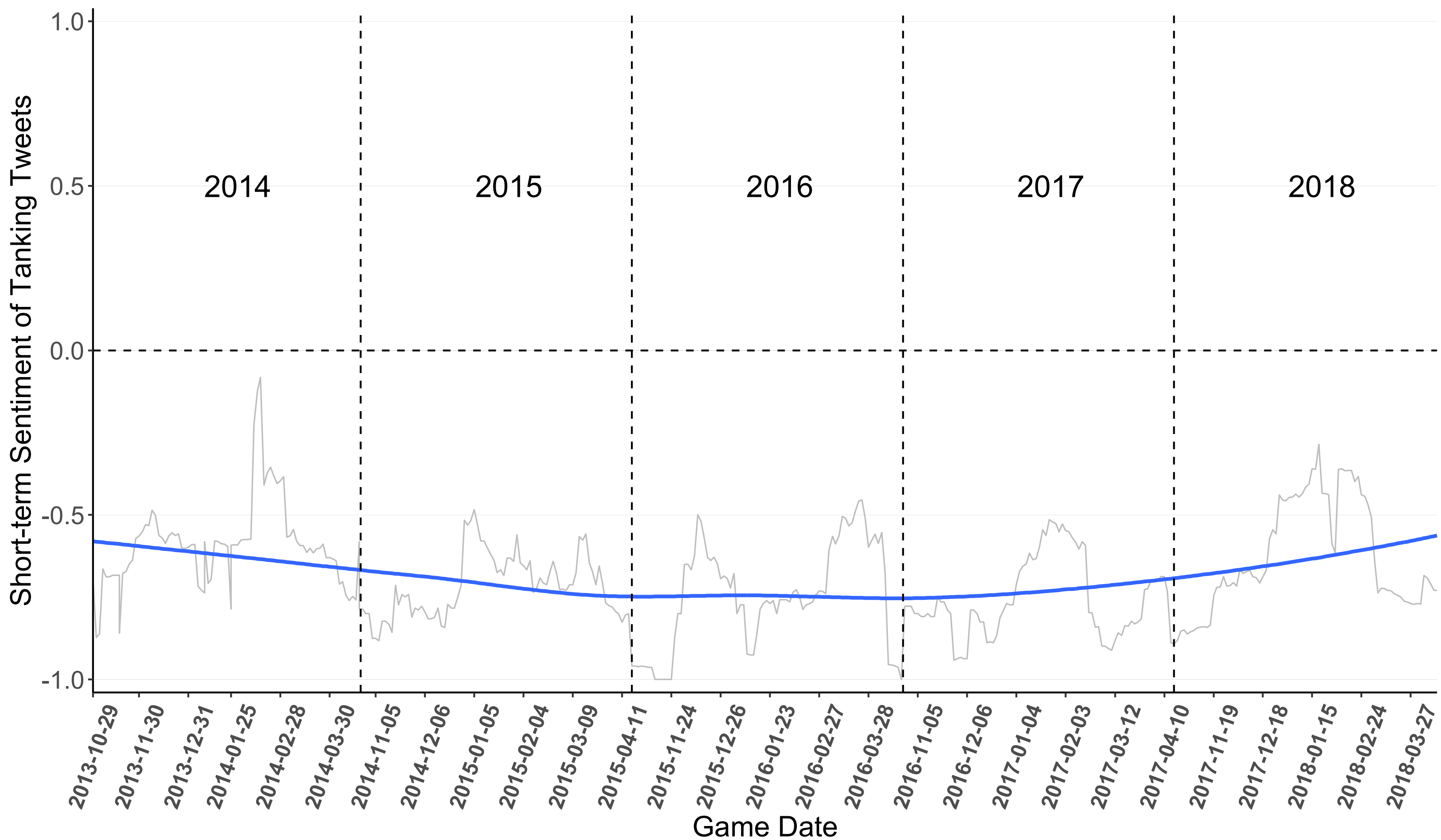

Figure 4.4 Short-term Sentiment of Tanking Tweets for the Chicago Bulls from the 2013-2014 to 2017-2018 Seasons

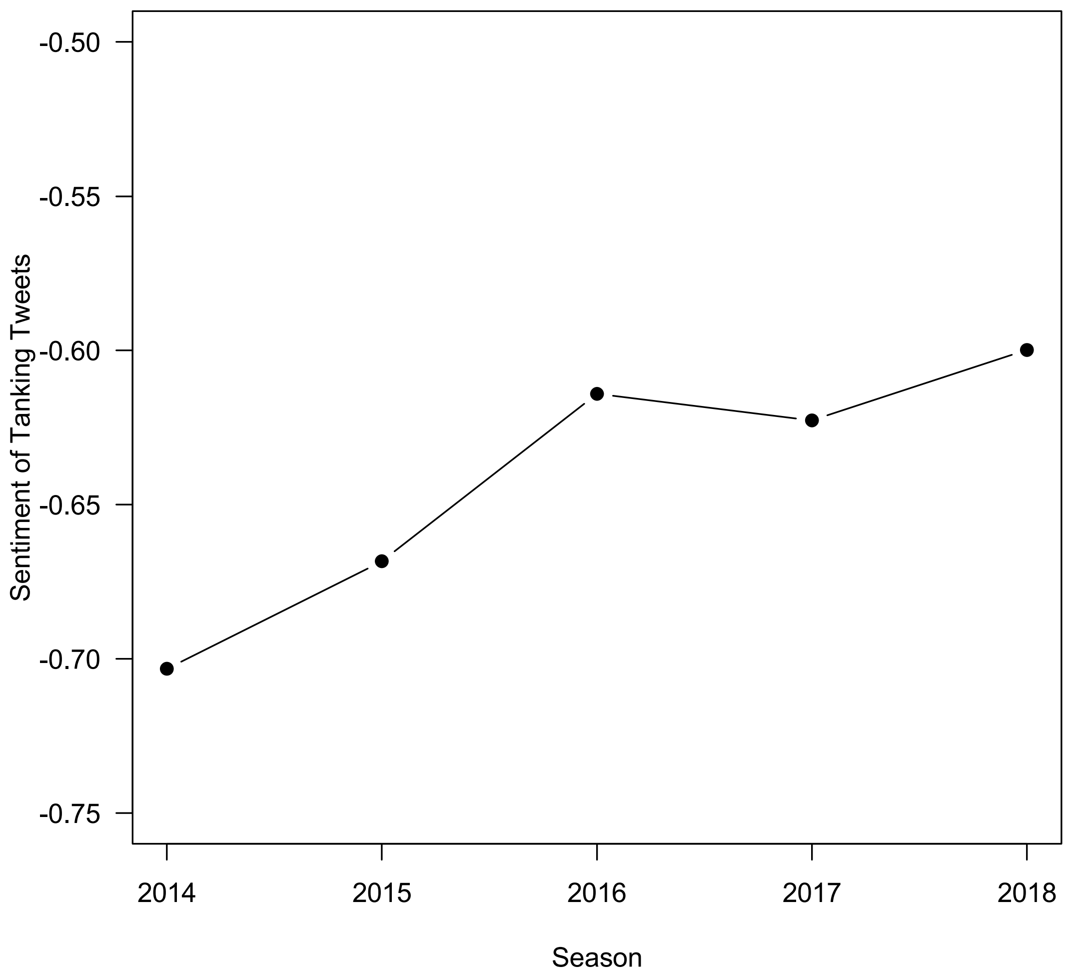

Figure 4.5 Sentiment of Tanking Tweets by Season

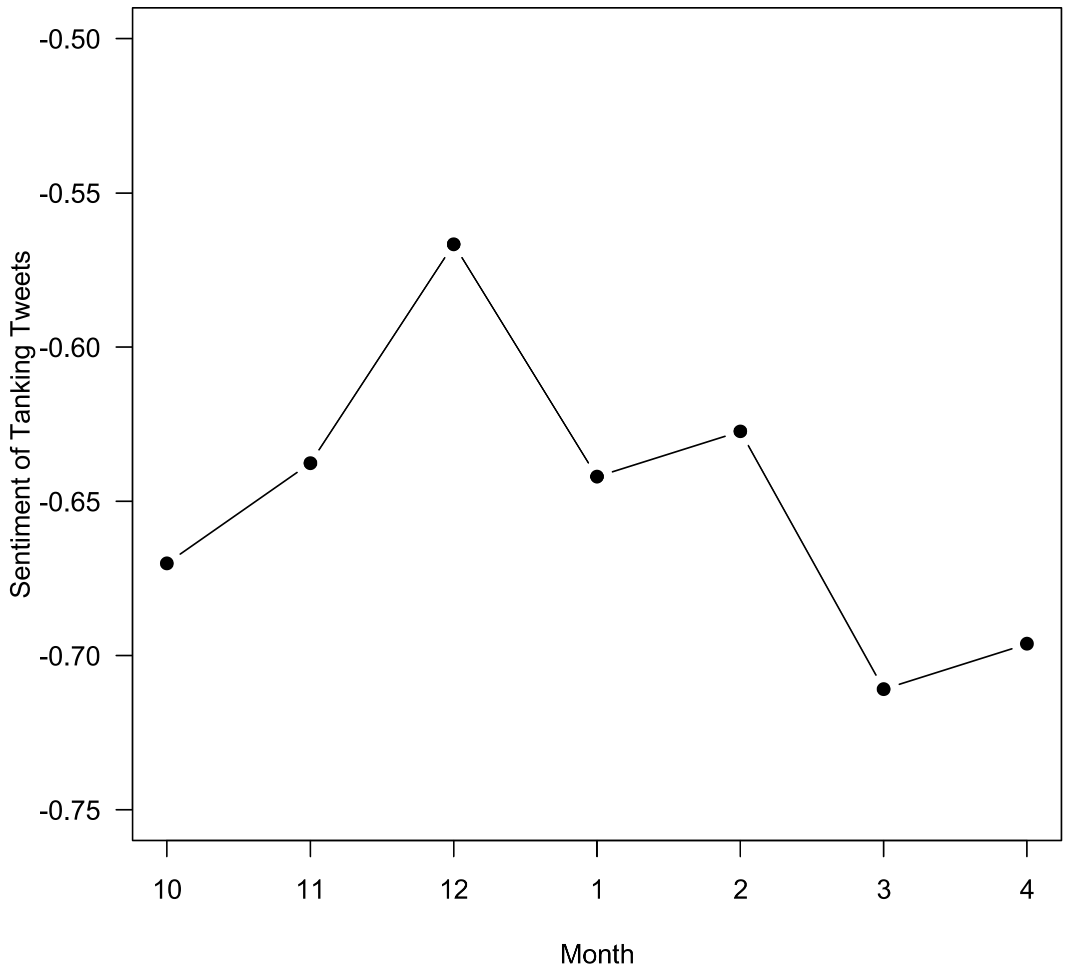

Figure 4.6 Sentiment of Tanking Tweets by Month

Table 4.1 Ten Highest Volume of Tanking Tweets by Team and Season

Rank	Team	Season	Volume
1	Philadelphia 76ers	2014-2015	0.597
2	Chicago Bulls	2017-2018	0.588
3	Philadelphia 76ers	2013-2014	0.485
4	Dallas Mavericks	2017-2018	0.431
5	Utah Jazz	2013-2014	0.378
6	Atlanta Hawks	2017-2018	0.369
7	Memphis Grizzlies	2017-2018	0.367
8	Milwaukee Bucks	2013-2014	0.285
9	Orlando Magic	2017-2018	0.250
10	Phoenix Suns	2017-2018	0.206
	League Average		0.101

Table 4.2 Ten Lowest Sentiment of Tanking Tweets by Team and Season

Rank	Team	Season	Sentiment
1	Chicago Bulls	2015-2016	-0.881
2	New York Knicks	2013-2014	-0.847
3	New York Knicks	2015-2016	-0.805
4	Orlando Magic	2015-2016	-0.802
5	Minnesota Timberwolves	2016-2017	-0.795
6	Utah Jazz	2015-2016	-0.787
7	Sacramento Kings	2014-2015	-0.783
8	Brooklyn Nets	2016-2017	-0.762
9	Philadelphia 76ers	2013-2014	-0.759
10	Charlotte Hornets	2014-2015	-0.757
	League Average		-0.653

Table 4.3 Regression Analysis Results for Main Models

	Full	Non-playoff (home)	Non-playoff (home last year)	Non-playoff (away)	Non-playoff (away last year)	Non-playoff (home)	Non-playoff (away)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Short_Volume_Home	-0.075***	-0.074***	-0.102***	-0.057**	-0.054*	-0.078***	-0.058**
	(0.015)	(0.016)	(0.021)	(0.021)	(0.022)	(0.018)	(0.021)
Short_Sentiment_Home	-0.010	-0.010	0.005	-0.001	-0.015	-0.009	-0.001
	(0.009)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
Long_Volume_Home	-0.213***	-0.088	-0.299***	-0.195***	-0.163**	-0.086	-0.196***
	(0.039)	(0.046)	(0.044)	(0.056)	(0.057)	(0.046)	(0.056)
Long_Sentiment_Home	-0.017	-0.055	0.011	0.028	0.024	-0.060	0.027
	(0.025)	(0.043)	(0.044)	(0.035)	(0.036)	(0.044)	(0.035)
Short_Volume_Away	0.009	0.004	-0.012	-0.0002	-0.029	0.002	-0.012
	(0.015)	(0.018)	(0.019)	(0.015)	(0.022)	(0.018)	(0.018)
Short_Sentiment_Away	0.011	0.005	0.009	0.042**	0.036**	0.005	0.042**
	(0.009)	(0.012)	(0.012)	(0.014)	(0.013)	(0.012)	(0.014)
Long_Volume_Away	0.006	0.014	0.032	-0.046	-0.052	0.014	-0.047
	(0.034)	(0.044)	(0.045)	(0.037)	(0.038)	(0.044)	(0.037)
Long_Sentiment_Away	-0.036	-0.030	-0.041	-0.017	0.021	-0.031	-0.015
	(0.020)	(0.026)	(0.027)	(0.030)	(0.029)	(0.026)	(0.031)
Future_Volume_Home						0.011	
						(0.019)	
Future_Sentiment_Home						-0.017	
						(0.015)	
Future_Volume_Away							0.024

							(0.016)
Future_Sentiment_Away							0.002
							(0.015)
Facility_Age	-0.011***	0.015***	0.004	-0.016***	-0.006	0.015***	-0.016***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Facility_Age^2	0.0002	-0.001***	-0.0003	0.0003*	0.00001	-0.001***	0.0003*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Point_Spread	0.001*	0.001	0.001	-0.0001	0.0003	0.001	-0.00005
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Point_Spread^2	0.0003***	0.0003***	0.0004***	0.0001	0.0002*	0.0003***	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Elo_Home	0.001***	0.0003***	0.001***	0.001***	0.001***	0.0003***	0.001***
	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Elo_Away	0.0003***	0.0003***	0.0003***	0.0001	0.0001	0.0003***	0.0001
	(0.00003)	(0.00004)	(0.00004)	(0.0001)	(0.00005)	(0.00004)	(0.0001)
Population	0.0003*	-0.001***	0.002***	0.0004*	0.0004	-0.001***	0.0004*
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Coincident_Index	0.004**	0.008***	0.004**	0.006***	0.004*	0.008***	0.006***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Competition	-0.052*	0.015	0.063	-0.050	-0.035	0.017	-0.050
	(0.023)	(0.031)	(0.037)	(0.030)	(0.030)	(0.031)	(0.030)
Holiday	0.111***	0.083**	0.096**	0.118***	0.102***	0.083**	0.119***
	(0.021)	(0.030)	(0.030)	(0.029)	(0.027)	(0.030)	(0.029)
Observations	5945	2870	2829	2769	2774	2870	2769

Note: The dependent variable is log(attendance). *p<0.05; **p<0.01; ***p<0.001.

Table 4.4 Regression Analysis Results for Robustness Check 1 and 2

	Non-playoff (home)			Non-playoff (away)			Non-playoff (home last year)	Non-playoff (away last year)
	15 days	62 days	93 days	15 days	62 days	93 days	Regular season	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short_Volume_Home	-0.040**	-0.139***	-0.185***	-0.022	-0.115***	-0.177***	-0.177***	-0.127***
	(0.013)	(0.021)	(0.025)	(0.016)	(0.027)	(0.031)	(0.025)	(0.028)
Short_Sentiment_Home	-0.013	-0.003	0.0002	-0.007	-0.009	-0.001	0.018	-0.025
	(0.010)	(0.015)	(0.017)	(0.010)	(0.014)	(0.015)	(0.014)	(0.014)
Long_Volume_Home	-0.081	-0.091*	-0.093*	-0.189***	-0.193***	-0.195***	-0.212***	-0.090*
	(0.046)	(0.046)	(0.046)	(0.056)	(0.056)	(0.056)	(0.033)	(0.044)
Long_Sentiment_Home	-0.049	-0.058	-0.062	0.033	0.026	0.026	-0.205***	0.014
	(0.043)	(0.044)	(0.044)	(0.035)	(0.035)	(0.035)	(0.042)	(0.036)
Short_Volume_Away	0.010	0.003	-0.013	0.009	0.00003	-0.010	-0.015	-0.034
	(0.013)	(0.023)	(0.027)	(0.012)	(0.020)	(0.023)	(0.023)	(0.025)
Short_Sentiment_Away	0.002	-0.008	-0.003	0.027*	0.037*	0.050**	0.003	0.046**
	(0.009)	(0.013)	(0.014)	(0.011)	(0.015)	(0.016)	(0.013)	(0.015)
Long_Volume_Away	0.013	0.013	0.020	-0.050	-0.046	-0.038	0.044	-0.023
	(0.044)	(0.044)	(0.044)	(0.037)	(0.038)	(0.038)	(0.037)	(0.031)
Long_Sentiment_Away	-0.029	-0.032	-0.034	-0.018	-0.015	-0.019	-0.043	0.015
	(0.026)	(0.026)	(0.026)	(0.030)	(0.030)	(0.030)	(0.026)	(0.029)
Facility_Age	0.015***	0.015***	0.015***	-0.017***	-0.016***	-0.015***	0.008*	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Facility_Age^2	-0.001***	-0.001***	-0.001***	0.0003*	0.0003*	0.0003*	-0.0004**	-0.00001

	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Point_Spread	0.001	0.001	0.001	-0.0002	-0.0001	-0.0001	0.001	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Point_Spread^2	0.0003***	0.0003***	0.0003***	0.0001	0.0001	0.0001	0.0004***	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Elo_Home	0.0003***	0.0003***	0.0003***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Elo_Away	0.0003***	0.0003***	0.0003***	0.0001	0.0001	0.0001	0.0003***	0.0001
	(0.00003)	(0.00004)	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.00004)	(0.00005)
Population	-0.001***	-0.001***	-0.001***	0.0004*	0.0004*	0.0004*	0.002***	0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Coincident_Index	0.008***	0.008***	0.008***	0.006***	0.006***	0.006***	0.004**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Competition	0.014	0.017	0.017	-0.052	-0.050	-0.052	0.077*	-0.034
	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)	(0.037)	(0.030)
Holiday	0.083**	0.081**	0.078**	0.117***	0.119***	0.120***	0.093**	0.104***
	(0.030)	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)	(0.030)	(0.027)
Observations	2870	2870	2870	2769	2769	2769	2829	2774

Note: The dependent variable is log(attendance). *p<0.05; **p<0.01; ***p<0.001.

Table 4.5 Regression Analysis Results for Robustness Check 3

	Full	Non-playoff (home)	Non-playoff (home last year)	Non-playoff (away year)	Non-playoff (away last year)
	(1)	(2)	(3)	(4)	(5)
Short_Volume_Home	-0.035***	-0.026***	-0.034***	-0.027***	-0.028***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
Short_Sentiment_Home	-0.012	-0.011	-0.002	-0.005	-0.017
	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
Long_Volume_Home	-0.006***	-0.002	-0.006***	-0.005**	-0.004*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Long_Sentiment_Home	-0.025	-0.052	-0.008	0.024	0.018
	(0.025)	(0.043)	(0.044)	(0.035)	(0.036)
Short_Volume_Away	0.009*	0.010	0.010	0.006	-0.002
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Short_Sentiment_Away	0.010	0.003	0.006	0.041**	0.036**
	(0.009)	(0.011)	(0.012)	(0.014)	(0.013)
Long_Volume_Away	0.005***	0.007***	0.006***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Long_Sentiment_Away	-0.032	-0.025	-0.036	-0.008	0.022
	(0.020)	(0.026)	(0.027)	(0.030)	(0.029)
Facility_Age	-0.011***	0.015***	0.007	-0.016***	-0.006
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)

Facility_Age^2	0.0002	-0.001***	-0.0004*	0.0003*	0.00000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Point_Spread	0.0005	0.0005	-0.00004	-0.001	-0.001
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)
Point_Spread^2	0.0002***	0.0003***	0.0003***	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Elo_Home	0.001***	0.0003***	0.001***	0.001***	0.001***
	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Elo_Away	0.0004***	0.0003***	0.0004***	0.0002**	0.0001**
	(0.00003)	(0.00003)	(0.00003)	(0.0001)	(0.00005)
Population	0.0004*	-0.001***	0.001***	0.0004**	0.0004*
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Coincident_Index	0.004***	0.009***	0.006***	0.006***	0.005**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Competition	-0.063**	0.001	0.008	-0.059*	-0.046
	(0.023)	(0.031)	(0.037)	(0.030)	(0.030)
Holiday	0.108***	0.082**	0.094**	0.113***	0.097***
	(0.021)	(0.030)	(0.030)	(0.029)	(0.027)
Observations	5945	2870	2829	2769	2774

Note: The dependent variable is log(attendance). $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Table 4.6 Regression Analysis Results for Robustness Check 4

	Full	Non-playoff (home)	Non-playoff (home last year)	Non-playoff (away)	Non-playoff (away last year)
	(1)	(2)	(3)	(4)	(5)
Short_Volume_Home	-0.131***	-0.093***	-0.142***	-0.116***	-0.129***
	(0.015)	(0.016)	(0.021)	(0.021)	(0.022)
Short_Sentiment_Home	-0.011	-0.012	0.005	-0.004	-0.018
	(0.009)	(0.013)	(0.012)	(0.013)	(0.013)
Long_Volume_Home	-0.307***	-0.120**	-0.361***	-0.291***	-0.267***
	(0.040)	(0.046)	(0.045)	(0.057)	(0.058)
Long_Sentiment_Home	-0.002	-0.075	0.011	0.034	0.015
	(0.026)	(0.044)	(0.045)	(0.036)	(0.037)
Short_Volume_Away	-0.013	-0.010	-0.032	-0.013	-0.038
	(0.015)	(0.017)	(0.018)	(0.015)	(0.022)
Short_Sentiment_Away	0.012	0.004	0.011	0.041**	0.032*
	(0.009)	(0.012)	(0.012)	(0.014)	(0.013)
Long_Volume_Away	-0.074*	-0.047	-0.017	-0.079*	-0.070
	(0.034)	(0.043)	(0.044)	(0.037)	(0.039)
Long_Sentiment_Away	-0.023	-0.017	-0.028	-0.001	0.037
	(0.021)	(0.026)	(0.028)	(0.031)	(0.030)
Facility_Age	-0.016***	0.012**	0.006	-0.020***	-0.011*
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)

Facility_Age^2	0.0004***	-0.001***	-0.0003	0.0005**	0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Point_Spread	0.002***	0.001	0.001	0.001	0.002**
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)
Point_Spread^2	0.0003***	0.0004***	0.0004***	0.0003***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Win_Home	0.180***	0.049*	0.161***	0.179***	0.181***
	(0.018)	(0.025)	(0.025)	(0.026)	(0.026)
Win_Away	0.155***	0.125***	0.135***	0.043	0.075**
	(0.015)	(0.019)	(0.020)	(0.026)	(0.025)
Population	0.0003	0.0004	0.002**	0.0003	0.0003
	(0.0001)	(0.001)	(0.001)	(0.0002)	(0.0002)
Coincident_Index	0.002	0.004*	0.003	0.004*	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Competition	-0.057*	0.053	0.079*	-0.054	-0.037
	(0.024)	(0.033)	(0.039)	(0.032)	(0.031)
Holiday	0.114***	0.086**	0.098**	0.130***	0.103***
	(0.022)	(0.030)	(0.031)	(0.030)	(0.028)
observations	5866	2832	2791	2733	2740

Note: The dependent variable is log(attendance). $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

CHAPTER 5

DISCUSSION

The previous chapter presented some interesting results from the regression analysis regarding the impact of consumer perceptions of tanking on demand for NBA games. Chapter 5 focuses on interpreting these findings. First, I provide a thorough discussion of the analysis of outcomes reported in Chapter 4. Next, theoretical contributions as well as practical implications of the findings are discussed.

5.1 DISCUSSION

The present dissertation examining the impact of consumer perceptions of tanking on demand for NBA games has a few important findings. First, the estimation results in Table 4.3, Column (2) suggest that the short-term volume of tanking tweets for home teams is negatively related to attendance in the NBA. Recall that the short-term variable quantifies the intensity of tanking discussions within 31 days before the tipoff of an NBA game. Hence, this result provides evidence that when fans become more aware of tanking for home teams prior to a match, they tend to have lower demand for NBA games. This finding is not surprising, considering the fact that tanking teams purposely losing games jeopardizes the spirit of sports competition, which requires participants to exert the best effort in sporting contests (Tayade, Bhamare, Kamble, & Jadhav, 2013). Therefore, when fans perceive the existence of tanking, they may lose interest in attending these games.

The above conclusion is also slightly different from the observation provided by Preston and Szymanski (2003) that cheating behavior in sport may not significantly

undermine consumer interest in sport. Preston and Szymanski (2003) listed some anecdotal evidence that betting-related match fixing in MLB and the English Premier League (EPL) did not seem to hurt demand for sport as the popularity of these sports leagues continued to grow after gambling scandals. While tanking is distinct from other match-fixing behaviors in that it is not strictly prohibited by league rules (Lenten et al., 2018), empirical evidence from this dissertation shows that perceived tanking behavior does negatively affect consumer demand for sport.

Another important finding from this dissertation is the long-term volume of tanking tweets for home teams is negatively related to NBA attendance. Recall that the long-term variable gauges the intensity of tanking discussions from the previous season. This conclusion implies that tanking discussions from the past has a persistent influence on present attendance decisions. In other words, teams with a tradition of tanking may not only suffer from lower attendance in the current season but also in the future seasons due to perceived tanking behavior.

The above findings that the increasing awareness of tanking undermines consumer interest in both the short term and long term are worth further discussion. The prior studies of tanking noted that tanking behavior in sport damaged the quality of sports competitions, which generally encompasses the quality of sports teams and game uncertainty (McManus, 2019; Price et al., 2010; Soebbing & Mason, 2009; Vamplew, 2018). The current dissertation offers additional evidence of the adverse impact of perceived tanking on consumer demand for sport. Considering teams do not publicly admit tanking, fans may not always correctly recognize tanking behavior from poor team performance (Paxton, 2018). Thus, how fans perceive the idea of tanking may become a

critical factor in their attendance decisions. The findings from the regression analysis draw upon the previous research of demand for sport and offer evidence that the more fans are aware of the existence of tanking, the lower demand for sport will appear.

Second, my models conclude that neither the short-term nor long term sentiment of tanking tweets for home teams has an impact on attendance in the NBA. Recall that sentiment variables measure the fan attitudes toward the idea of tanking. These findings suggest that even if fans hold more positive attitudes toward tanking for home teams, game attendance will remain the same. Similarly, fans with more negative attitudes on tanking for home teams do not seem to lower game attendance. This finding seems surprising as numerous studies concluded that consumer sentiment is a key predictor of purchase behavior (Huth, Eppright, & Taube, 1994; Nguyen & Claus, 2013). One possibility is that some fans develop habit to attend sporting events even they hold negative sentiment on tanking behavior (Ge, Humphreys, & Zhou, 2020). Another possible explanation of this result is that fans may not be interested in attending games featuring tanking teams, despite their support of the idea of tanking for home teams. For instance, fans may root for home teams to deliberately lose games for draft picks which can help regain competitiveness in the near future (Wade, 2013). Yet, such positive views on tanking do not create more incentives for fans to attend games in the current and next season.

Finally, this dissertation concludes that consumer perceptions of tanking for visiting teams will affect attendance decisions. Specifically, the data analysis reveals that there is a statistically positive relationship between the short-term sentiment of tanking tweets for visiting teams and demand for NBA games. There were concerns that tanking

teams may create negative externalities when they play road games (Whitney, 2005). That is, tanking teams undermining consumer interest in NBA games may incur additional costs to the rest of the league without being penalized (Humphreys & Nowak, 2017). Both positive and negative externalities are common in the sport industry (Downward & Rasciute, 2011). For instance, Humphreys and Johnson (2020) noted that NBA super stars such as Michael Jordan, Magic Johnson, and Larry Bird could produce significant positive externalities to the rest of the league. When NBA star players play road games, the number of tickets sold in opponents' arenas are expected to spike. Yet, opponents benefiting from more ticket sales do not pay salaries for these star players (Humphreys & Johnson, 2020). Similarly, the current dissertation finds evidence of negative externalities of perceived tanking behavior related to visiting teams. If local fans have strong negative views toward the opponent's tanking strategy prior to an NBA match, then attendance will be lower even though tanking is not directly linked to home teams.

In addition to the two variables of interest, this dissertation reveals important findings in control variables that are worth discussion. First, despite some variations in results showing the impact of facility age on NBA attendance, the general trend suggests that consumer interest in NBA games declines as sports facilities age. In particular, the full model utilizing the entire dataset of NBA games ranging from the 2013-14 to 2017-2018 seasons shows the positive estimator on the linear term of facility age and the insignificant coefficient on the quadratic term (Leadley & Zygmont, 2005). This finding shows NBA attendance will fall as NBA arenas becomes older, which is similar to what Coates and Humpreys (2005) estimated. Second, most models in this dissertation show

the estimated coefficients on the quadratic term of point spreads are positive and significant and are insignificant on the linear term. Such results suggest a convex relationship between game uncertainty and demand for NBA games. In other words, this conclusion indicates that local fans may like predictable games more than unpredictable matches, which is consistent with what Coates et al. (2014) and Demmert (1973) suggested but does not support the UOH. Third, the market competition, quantified by the number of MLB, NFL, and NHL teams in the same market as an NBA team, does not show a significant relationship with NBA attendance in most models. On the contrary, the full model reveals a negative link, which is consistent with the conclusion drawn from many prior studies (e.g., Demmert, 1973; Whitney, 2005). The different estimation outcomes may arise from the fact that some models in this dissertation use subsets of NBA games. Considering that the market competition variable does not change significantly across the seasons, these models using subsets of data may not contain sufficient variations in the market competition variable, and thus produce insignificant estimators. Nevertheless, the results in the full model offer similar findings as preceding research that market competition may limit consumer interest in NBA games (Morse, Shapiro, McEvoy, & Rascher, 2007). Fourth, this inquiry finds control variables such as team quality, population, economic conditions, and holiday games largely have positive relationships with consumer demand in the NBA. These findings have similar conclusions as previous studies (Hansen & Gauthier, 1989; Jane, 2016; Leadley & Zygmont, 2005).

5.2 THEORETICAL CONTRIBUTIONS

This dissertation makes several theoretical contributions. First, it contributes to the literature of demand for sport by exploring the impact of tanking in sport, behavior that may undermine the integrity of competition (Borland & MacDonald, 2003; Villar & Guerrero, 2009). While prior studies noted the importance of understanding the effect of unethical team behavior such as tanking and match-fixing on consumer demand (McManus, 2019; Preston & Szymanski, 2003), none of them attempted to quantitatively measure such impacts. The controversial but prevailing topic tanking serves as a great means to understand how sports fans will respond to unethical behavior in sport (Howman, 2012; Wolfers, 2006). Hence, the current dissertation develops a new set of factors estimating perceptions of tanking and uses the NBA as a context to systematically analyze how these variables may affect NBA attendance. As such, the findings from the current disseratation strengthen the theoretical understanding of demand for sport in relation to unethical team behavior.

Second, the current dissertation extends previous examinations of demand for NBA attendance (Hausman & Leonard, 1997; Leadley & Zygmont, 2005; Mills & Fort, 2014). Despite research interests in understanding factors that affect consumer demand for sport, the recent studies of demand for NBA attendance seem scant. This dissertation employs the attendance data from five recent NBA seasons between 2013-2014 to 2017-18 and re-examines a wide range of variables that are deemed as key determinants of NBA attendance. The findings suggest that variables such as facility age quality, game uncertainty, team quality, population, economic conditions, and holiday games are significant predictors of attendance decisions for NBA games, largely echoing previous

test results (Hansen & Gauthier, 1989; Morse et al., 2007). As such, the present dissertation advances the literature of NBA attendance by examining key determinants of demand for NBA games with more recent data.

Third, this dissertation provides theoretical contributions in understanding tanking behavior in sport. Prior tanking research primarily focused on developing evidence of tanking in sport (Fornwagner, 2019; Price et al., 2010; Soebbing & Humphreys, 2013; Taylor & Trogdon, 2002). For instance, the seminal tanking study conducted by Taylor and Trogdon (2002) concluded NBA teams would attempt to purposely lose games after being removed from playoff contention. Despite the extensive examinations of tanking in sport, none of the earlier research studies how consumers may respond to the idea of tanking (Borland et al., 2009; Price et al., 2010; Soebbing & Humphreys, 2013; Taylor & Trogdon, 2002). The present dissertation explores the relationship between perceptions of tanking and consumer interest in sport and is the first one to quantitatively explore consumer reaction to tanking behavior in sport. As such, this dissertation adds significant theoretical contributions to the tanking literature.

Fourth, this dissertation advances sport management research of sentiment analysis on social media. With the increased use of social media, a range of sports research have begun to examine content from social media such as Twitter, Facebook, and Instagram, in order to form a better understanding of consumer sentiment (Abeza, O'Reilly, & Reid, 2013; Filo et al., 2015; Yan, Pegoraro, & Watanabe, 2018; Yan, Watanabe, Shapiro, Naraine, & Hull, 2019). Unlike previous sport social media studies that predominately use lexicon-based methods to estimate sentiments from social media posts, this dissertation adopts machine learning models to extract sentiments from social

media content (Chang, 2019). Using social media Twitter combined with sentiment analysis techniques, my work reveals the change of consumer perceptions of tanking over time, and offers a rigorous measure of fans' reactions to underperformance in sport.

5.3 PRACTICAL IMPLICATIONS

Through constructing short-term and long-term variables quantifying consumer perceptions of tanking, this dissertation develops robust evidence regarding how consumer interest in sport will be affected by perceived tanking behavior. Such evidence may provide several important practical implications for policymakers. First, my work indicates that both the increasing awareness of tanking for home teams and negative attitudes toward tanking related to visiting teams can significantly undermine consumer interest in attending sporting events. Furthermore, it is evident that not only does the extensive discussion of tanking prior to NBA matches damage fan interest, but also the tanking discussions from the last season damage interest too. This finding suggests the widespread discussion of tanking around the league can produce both instant and persistent negative impacts on demand for sport. To maintain consumer interest in sporting contests, it is, therefore, critical for policy makers to restrain the speculation of tanking and retain a less negative image of tanking around the league. For instance, the NBA fined the Dallas Mavericks owner Mark Cuban $600,000 for publicly admitting tanking in the 2017-2018 NBA season (NBA, 2018). Such penalizations may effectively reduce the broad discussion of tanking among fans and create a more positive league image, and thus can help avoid a drastic falloff of demand for NBA games due to perceived tanking behavior (Paxton, 2018).

Second, this dissertation offers a tool for practitioners to monitor consumer perceptions of tanking. Using social media platform Twitter, my work concludes that fans in general hold negative views toward tanking and the sentiment seems to improve over the seasons. Additionally, compared to other NBA seasons included in the dataset, the 2013-2014 and 2017-2018 NBA seasons witnessed the extensive discussion of tanking. The above conclusions show Twitter could be considered as an effective medium to understand how fans perceive the concept of tanking (Yu & Wang, 2015). Furthermore, my work also provides detailed steps of calculating the volume of tanking tweets as well as the process of using machine learning models to extract sentiments from Twitter posts (Schuckert, Liu, & Law, 2015; Xiang, Du, Ma, & Fan, 2017). Taking the volume and sentiment of tanking tweets together, practitioners can form a holistic view of consumer perceptions of tanking that may help improve decision makings related to tanking behavior in sport.

CHAPTER 6

CONCLUSION

6.1 SUMMARY

This dissertation centers on examining the behavior of sports teams tanking for draft picks and thoroughly analyzes the impact of consumer perceptions of tanking on demand for sport. To successfully measure perceptions of tanking, the current dissertation used social media posts from Twitter, an online platform where people express thoughts and opinions on various topics (Morstatter, Pfeffer, Liu, & Carley, 2013). By analyzing tanking-related Twitter posts, the two variables are proposed to represent consumer perceptions of tanking, the volume and sentiment of tanking tweets. Notably, the volume of tanking tweets reflects the fans' awareness of tanking and is calculated by counting the number of tanking tweets posted over a period of time. The data analysis of this variable indicates the 2013-2014 and 2017-2018 NBA seasons contained considerately more tanking discussions on Twitter than other seasons examined within this dissertation. This observation signals that fans are well aware of the existence of tanking in these two NBA seasons.

The second variable, the sentiment of tanking tweets, represents consumer sentiment on tanking and is quantified by calculating the average sentiment expressed in tanking tweets. Sentiment analysis with machine learning models is performed to classify each tanking tweet into one of the sentiment classes, positive, neutral, and negative (Kouloumpis, Wilson, & Moore, 2011). The sentiment variable then counts the average

sentiment from tanking tweets posted within a particular period of time. Overall, the Twitter data suggests that a considerable portion of tanking tweets contain negative sentiments, meaning fans in general hold negative views toward tanking. Additionally, the season average sentiment on tanking shows continues improvement, implying that fans become more acceptable to the idea of tanking over the years.

After building two variables measuring consumer perceptions of tanking, I estimate their relationship with NBA attendance. The regression analysis offers clear evidence that the short-term volume of tanking tweets for home teams prior to an NBA game is negatively related to attendance decisions. This evidence suggests the extensive discussion of tanking related to home teams significantly affect ticket sales in the short run. This dissertation also finds a lasting effect of the volume of tanking discussions for home teams on demand for NBA games. Specifically, the results conclude that the broad discussion of tanking related to home teams from the prior NBA season can significantly reduce consumer demand for games in the current season, indicating that the adverse effect of the volume of tanking discussions on attendance can persist for a while.

While the volume of tanking tweets for home teams has significant impacts on NBA attendance in both the short term and long term, the sentiment of tanking discussions for home teams does not appear to have an effect on demand for NBA games. The results from a number of regression models suggest that neither the short-term nor long-term sentiment of tanking tweets for home teams is statistically related to attendance decisions. Although Twitter data collected in this dissertation shows that fans develop more positive attitudes toward tanking over the seasons, the findings from statistical

models predict that improved sentiment on tanking does not seem to help attract fans to NBA arenas.

This dissertation further analyzes how consumer perceptions of tanking for visiting teams can affect NBA attendance. Specifically, econometric models reveal that only the short-term sentiment of tanking discussions for visiting teams seems to be significant in positively changing demand for NBA matches among all variables examined. That is, local fans who hold more negative views toward visiting teams' tanking behavior prior to an NBA match are less likely to attend games. This suggests that perceived tanking behavior for away teams can produce the adverse impact on demand for home games.

6.2 LIMITATIONS

The current dissertation is not without limitations. First, selection bias may exist in Twitter data (Culotta, 2014). While the number of Twitter users has grown tremendously over the past few years, the cohort may not represent the general population (Bae & Lee, 2012). For instance, it is estimated the Twitter users are overall younger and wealthier than the U.S. public (Wojcik & Hughes, 2019). As such, Twitter posts may not fully reflect consumer perceptions of tanking. Despite this concern, a thorough literature review shows that Twitter posts can effectively gauge consumer sentiment (Daniel, Neves, & Horta, 2017). For instance, a wide range of research studying the stock market revealed that investor sentiment calculated from Twitter posts could successfully predict stock price (McGurk et al., 2019). These inquiries provide evidence that opinions and feelings on social media platforms can as least partially

exhibit market sentiment. Therefore, I strongly believe that tanking posts gathered from Twitter well represent the fans' feelings of tanking.

Second, in performing sentiment analysis, the initial step of manually labeling the sentiment of tanking tweets may involve some subjectivity (Liu, 2010). To ensure the quality of manual classification, a few cautious steps were taken in the labeling process (McGurk et al., 2019). First, I invite an expert with strong domain knowledge to label tanking tweets. Second, the coder is asked to spend at least 30 seconds on labeling each tweet. Third, repeated tweets are randomly assigned to label. Any repeated tweets with inconsistent labels will be removed from the sample. The results show that only 0.4% of tweets are wrongly labeled and thus discarded. Fourth, I asked another coder who does not have a strong background in tanking to label the same set of tweets as the main coder. Comparing labeling results shows that 42% of labels are matched, meaning there is some degree of consensus between two coders on the sentiment of tanking tweets. However, as the expert has more domain knowledge in tanking than the other coder, its labels are eventually used in the training set. Despite these precautions, it is critical to note that some subjectivity may still exist in the labeling process.

6.3 FUTURE STUDIES

There are a number of areas for future research that emerges from the topics in this dissertation. Future study could explore new draft policies that will mitigate tanking issues while reserving their original functions of maintaining competitive balance in sports leagues. The present dissertation develops evidence that consumer perceptions of tanking can hurt attendance. As such, it is crucial for sports leagues to amend existing draft policies to restrain tanking behavior in sport. However, it is equally important to

note that draft systems were initially designed to improve competitive balance in sport, which is a key determinant of consumer demand for sport (Grier & Tollison, 1994; Sanderson & Siegfried, 2003). Therefore, future studies may carefully design new draft systems that can not only serve as a scheme to maintain competitive balance but also discourage tanking behavior in sport.

Future studies may also explore the effectiveness of the new draft policy instituted in 2019. Recall in Figure 1.1, the new NBA draft system reduces the possibility for the worst record teams to receive the No.1 draft pick from 25% to 14%. While the new system intends to diminish tanking incentives in the NBA, it is unclear whether it will work as planned. Therefore, future research may use team performance data to further investigate whether lowering the probability of acquiring the No.1 draft pick will discourage tanking behavior in the NBA.

In addition, future research can follow this dissertation to examine the relationship between league policies designed to discourage tanking behavior and consumer sentiment regarding tanking. For instance, the NBA league office instituted the play rest policy in 2017 and fined Mark Cuban $600,000 for publicly admitting tanking in 2018. Such actions aim to preserve a positive image of the league regarding tanking. Yet, it is unclear whether these efforts are effective in changing fans' minds regarding the league's tanking problem. The present dissertation uses the sentiment of tanking tweets to quantify consumer sentiment toward tanking and can also be used to examine the impact of the league's tanking related policies on fans' sentiment toward tanking.

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