ASSESSING CUSTOMER DISCRIMINATION IN

SPORTS TELEVISION VIEWERSHIP

by

BYUNGJU KANG

(Under the Direction of Steven H. Salaga)

ABSTRACT

Becker (1971) first identified the potential sources of labor market discrimination, which is defined as the unequal treatment of equally qualified workers. Sports labor markets serve as an excellent testing ground for discrimination due to the large amount of information that is publicly available on the performance, employment status, and personal characteristics of key individuals over extended periods of time.

This dissertation focuses on customer discrimination by race and asks: “How do consumers respond to a product based on the racial background of the key individuals who represent the product?” It is difficult to empirically address this question due to difficulty in collecting data that captures actual consumer behavior while simultaneously controlling for product quality and characteristics. Therefore, this dissertation empirically tests for potential customer discrimination based on the racial information of key actors (i.e., players and head coaches) in live sport television consumption. This dissertation builds off of existing literature by assessing potential customer discrimination in both National Collegiate Athletic Association (NCAA) men’s college basketball games and

National Basketball Association (NBA) professional games using national and local market television viewership data, respectively, over the same time period.

After controlling for factors capturing contest quality and characteristics, the empirical models produce evidence indicating the race of key individuals is a practically relevant and statistically significant driver of live sport product consumption. A positive impact of minority players on viewership exists, regardless of viewership type, with respect to both the sheer number of roster players by race and actual playing time by race. Furthermore, this positive effect is primarily due to Black players in both collegiate and professional basketball, a result potentially suggesting reverse discrimination against White players. At the managerial level, the results indicate a potential consumption bias against minority head coaches in both settings. Together, the findings suggest a potential bias in consumption against minorities in leadership positions, but preference for minorities when they are competing as athletes in the actual competition.

INDEX WORDS: customer discrimination, racial discrimination, television viewership, college basketball, professional basketball, consumption

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by

BYUNGJU KANG

BA, University of Seoul, Republic of Korea, 2011

MA, University of Michigan, 2014

MA, Clemson University, 2016

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BYUNGJU KANG

Major Professor: Steven H. Salaga
Committee: James J. Zhang
Jepkorir R. Chepyator-Thomson
Brian M. Mills

Electronic Version Approved:

Ron Walcott
Vice Provost for Graduate Education and Dean of the Graduate School
The University of Georgia
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CHAPTER 1

INTRODUCTION

The topic of discrimination has drawn considerable academic attention since Becker (1971) identified three possible sources of labor market discrimination in his publication, *The Economics of Discrimination*. Economic discrimination, which is defined as unequal treatment of employees with equal qualifications, is said to occur when the behavior of one individual (i.e., employer, employee or coworker, and customer) toward the other is not motivated by an objective consideration (Becker, 1971) such as productivity (or performance). Therefore, identifying the prevalence, degree, form, and trends of discrimination, as well as eliminating discrimination in decision-making are critical issues (Romei & Ruggieri, 2013). Such issues have been studied in a multitude of areas, including social, legal, economic, and more recently, computer science. The literature spans a wide range of fields such as labor economics (e.g., Kahn, 1991; Lang & Lehmann, 2012), social profiling (e.g., Tillyer et al., 2010), credit and consumer markets (e.g., Dymski, 2006), and other contexts including education quality (e.g., Carter et al., 2017) and healthcare coverage (e.g., Shavers et al., 2012).

The two most popular types of discrimination studied are taste-based discrimination (Becker, 1971) and statistical discrimination (Arrow, 1971), both of which provide different explanations. While statistical discrimination models imply that discrimination is caused by a lack of information (i.e., informational bias), taste-based discrimination models focus on more elusive and deep-rooted cognitive biases (Pedersen

& Nielsen, 2022). The latter is the focus of the present study which is in line with the majority of past research which has also focused on taste-based discrimination. A deep analysis of the differences between statistical and taste-based discrimination is beyond the scope of the present study.

Identifying and understanding discrimination is particularly important for understanding social inequalities as well as public policy (Lippert-Rasmussen, 2018), given the multicultural and multiethnic nature of society in the United States (U.S.). From a public policy perspective, the impact of antidiscrimination legislation on economic outcomes has been of interest in literature since the Equal Pay Act in 1963 and the Civil Rights Act in 1964 which prohibits discrimination practices on the basis of race, sex, gender, and ethnicity. This leads to discrimination becoming a social issue with respect to gender and racial equity (Kuppuswamy & Younkin, 2020).

However, discrimination and prejudice continue to be concerns that many people face on a daily basis, especially in light of today's complex and covert forms of discrimination (Pager & Shepherd, 2008). For example, approximately 40 percent of respondents believe that discrimination based on race or ethnicity is still a significant issue in the United States, with Black and Hispanic respondents more likely to consider discrimination as at least a somewhat serious problem in comparison to White respondents (Wike et al., 2021). Additionally, there was the rise in discrimination and violence against Asian Americans during the Coronavirus outbreak as one-third of survey respondents stated they were physically afraid of someone (Ruiz et al., 2021). Despite the fact that it may be becoming less visible, discrimination is still a social concern posing challenges in conceptualization and assessment (Pager & Shepherd, 2008). As a result, discrimination is generally viewed as socially reprehensible, normatively unacceptable, or illegitimate (Pedersen & Nielsen, 2022).

The majority of research has focused on how discrimination manifests itself in various labor markets, and substantial progress has been achieved in assessing various aspects of racial disparities in labor market outcomes (Lang & Lehmann, 2012). Discrimination research has typically focused on the role of discrimination in generating wage differentials between groups in question using a regression-based decomposition approach. Wages are regressed on a race indicator variable after controlling for other factors relevant to performance (or productivity). However, empirically assessing discrimination is difficult because controlling for differences in worker productivity is challenging, primarily due to the fact that productivity is driven by a variety of factors (Kahn, 1991). It is difficult to find industries where all relevant data is publicly available, which may result in unadjusted differences between the groups in question (Neumark, 2018).

Becker (1971) first proposed that wage disparity between workers is caused mostly by three domains of discrimination: employer, coworker, or customer-based discrimination. In other words, discrimination is to occur when employers prefer to hire a specific group of workers (i.e., employer discrimination), when a particular group of workers needs to be paid more to work alongside others (i.e., employee or coworker discrimination), or when customers prefer to interact with a certain group of workers in market transaction (i.e., customer discrimination), all of which are motivated by a taste for discrimination. However, Becker (1971) also suggested that discovering and isolating the actual source(s) of discrimination among the three domains is challenging because discrimination might originate in one, two, or all three domains (Depken II & Ford, 2006). A significant issue may arise when addressing the implications for public policy targeted at decreasing the impacts of racial discrimination if findings are produced without identifying the source(s) of discrimination.

In light of these issues, sports labor markets provide an excellent testing ground for labor economics theories (Holmes, 2011; Kahn, 2009) due to the granular nature and uniqueness of its data. Unlike other industries, it is replete with extensive, publicly available data covering performance, employment status including compensation, and personal characteristics of athletes and coaches over extended periods of observation. In addition to data quality, the increased diversity of participants in sports provides a natural experiment to study the extent of discrimination (Kahn, 2000) including discriminatory decision making, the nature of discrimination, and behaviors that lead to discriminatory outcomes. Notably, discrimination based on demographic characteristics such as race, sex, gender, and ethnicity has been one of the most documented parts of the dark side of sports in sport economic literature (Andreff, 2019) and considerable attention has been paid to the theory and empirical analysis of sports labor market discrimination in a variety of settings (Kahn, 2009).

Numerous studies have investigated discrimination in sports and Kahn (1991) first categorized four primary manifestations of discrimination in professional sports as salary discrimination, positional discrimination, hiring discrimination, and customer discrimination. Among these manifestations, customer discrimination is the focus of this study. The theory of customer discrimination explains discriminatory hiring in that it might be economically efficient given the pressures from the demand side (Kuppuswamy

& Younkin, 2020). In other words, the literature suggests that consumers desire to see employees who look like them (i.e., homophily or in-group favoritism), and likewise the assumption that consumers dislike seeing people of a different race has been used to explain why discriminatory hiring practices continue to exist across a wider range of occupations.

However, identifying and understanding customer discrimination is challenging both theoretically and empirically, even in the context of sports. The previously stated assumption that people prefer their own race and/or ethnicity is called into question by recent evidence of consumer preference for diversity (Aldrich et al., 2005) and changes in national demographic composition brought on by the population growth of minorities (U.S. Census Bureau, 2019). Furthermore, the empirical challenge of quantifying customer discrimination has been hampered by the fact that unlike other forms of discrimination, discrimination practices based on customers' preference is less likely to be eliminated in perfectly competitive markets since in some cases, it can increase profits (Kahn, 1991). This leads to difficultly in isolating customer-related discrimination from other sources of discrimination since customer discrimination may potentially be an explanation for the persistence of discriminatory employment practices (Nardinelli & Simon, 1990).

Meanwhile, customer discrimination in sports is alleged to occur when fans have a strong preference for certain traits of athletes including race (Kahn, 1992) in which fans prefer to avoid coming into contact with members of other racial groups to consume their favorite sport products (Holmes, 2011). Given the diversity of consumer preferences, the sport industry is a customer-based service sector (Kahn, 2000) making customer discrimination more likely to be an empirical concern. Sports labor markets, where the race of key actors is visible but the consumer is physically distant, provide a unique testing ground for customer discrimination analysis. Hence, studies of customer discrimination in sport examine how fans respond to traits of athletes including race in order to discover potential sources of discrimination in consumer behavior. Accordingly, this body of work has the ability to provide practical implications to sport teams, leagues, managers, and society as a whole with respect to how consumers respond to product characteristics.

With this in mind and utilizing the framework of economic discrimination, the present study examines potential biases among consumers of basketball at the professional (National Basketball Association; NBA) and collegiate (National Collegiate Athletic Association; NCAAB) levels by analyzing game-level television viewership figures during 2013-14 and 2014-15 seasons. Unlike studies using game day attendance data, assessing customer discrimination via television viewership is preferred as it is a relatively costless way to reflect one's preferences (Depken II & Ford, 2006). In other words, once the cable television package is paid for, deciding whether to turn in to a given program or not is essentially effortless. Utilizing television ratings, therefore, is beneficial in that it also avoids supply constraints, one of the most prevalent issues when using stadium attendance data to analyze preferences.

Contextual Background

The United States is a unique society in terms of cultural diversity due to the blending of cultural backgrounds and ethnicities. According to U.S. census Bureau's race-ethnic population estimates in advance of the 2020 census, the national headcount revealed a more diverse nation that was previously calculated (U.S. Census Bureau, 2019). Nearly 30 percent of Americans identified with a race or ethnic group other than White. Furthermore, non-Whites made up to 23 percent of the labor force in 2020 (U.S. Bureau of Labor Statistics, 2021). So, it is fairly reasonable to consider that the demographic composition of sports organizations should correspond to the percentages of various groups in the general population.

However, the representation of people of color (or minorities) in North American sports tells us a different story. Figure 1.1 displays the representation of the Opening Day rosters for the major North American leagues in 2021, including players, head coaches, and all coaches. With the exception of baseball, racial minorities dominate the composition of players in all leagues.[1] Particularly, in basketball (i.e., NCAAB, NBA, and Women's National Basketball Association; WNBA), players who identify as a racial minority represent roughly 80 percent of the sample population, with African American players making up more than 70 percent of the total population in professional basketball leagues (i.e., NBA and WNBA). This implies that basketball in the U.S. is an important part of Black culture (Ogden & Hilt, 2003).

Additionally, Figure 1.1 provides evidence that the proportion of racial minority head coaches is far lower than that of racial minority players in all sport leagues. This pattern signals that racial minorities have substantial opportunities on the court or field, but not in positions of leadership (Cunningham, 2020). Some view this as incompatible given the fact that most coaches were former players (Cunningham & Sagas, 2002), which represents a large pool of potential coaches (Nesseler et al., 2020). Becker's (1971)

[1] Racial minorities represent non-White individuals including African American, Hispanic, Asian, American Indian or Alaska Native, and one with two or more races, as well as voluntary nondisclosure.

concept of racial discrimination by customers is embodied by the assumption that fans prefer to watch players of their own race. Therefore, a relevant question in sport economics is to ask whether sport fans engage in any discriminatory practices based on the race of key actors, such as players or coaches.

Basketball is seen by many as an oasis of financial potential for talented African American athletes (Kahn, 2006). Specific to the sport of basketball, African Americans have historically outnumbered White players in player population by raw numbers. Figure 1.2 depicts the representation of racial minority players in both collegiate and professional basketball for a decade beginning with the 2011-12 campaign. There is a clear and persistent pattern in professional basketball (i.e., NBA and WNBA) that racial minorities have been a dominant group in terms of raw numbers and have gradually increased proportionately, especially in the NBA. We can observe a similar pattern in college basketball though the rate is lower relative to professional basketball. We can also find evidence that Black players are still dominating the league from other perspectives. In the NBA, for example, 27 of the 30 highest-paid players at the start of the 2020-21 season were Black. Furthermore, only three White players (Steve Nash, Dirk Nowitzki, and Nikola Jokić) won the league's Most Valuable Player (MVP) Award since the 1985-1986 season after Larry Bird won it three years in a row.

Black success in basketball has also progressed to the coaching positions; at the start of the 2020-21 season, nine of the NBA's 30 head coaches (30%) were minorities with seven of them being Black. Figure 1.3 provides the representation of racial minority head coaches in both collegiate and professional basketball for a decade beginning with the 2011-12 season. Black head coach representation at elite levels of basketball is found at a much higher percentage than in football or baseball. For example, in the National Football League (NFL) in the 2020-21 season, only five of 32 head coaches (15.6%) were minorities with only three being Black, and in MLB in the 2020-21 season, only six of 30 head coaches (20%) were either Black or Hispanic. This is an intriguing result, especially in the NFL, as the league initiated the “Rooney Rule” which requires NFL teams to interview at least one minority candidate for head coaching vacancies (DuBois, 2015).

Despite the clear evidence of success on the court, the question of discrimination against racial minorities still remains salient in basketball. It is pertinent to explore whether sport consumers display any discriminatory behavior in relation to the race of players given that basketball has by far the greatest proportion of Black participation among the major North American sports leagues at both collegiate and professional levels (Berri, 2017). This is also an important topic in basketball given there has been an influx of White international players from European and South American countries (e.g., Hill & Groothuis, 2017; Yang & Lin, 2012). Furthermore, a recent study has found possible reverse discrimination against White players in terms of pay discrimination (Groothuis & Hill, 2013).

Moreover, given the effort leading sports organizations have placed on promoting diversity in leadership positions (Salaga & Juravich, 2020), there is relevance in estimating how the race of leaders is related to consumption. While researchers have investigated racial discrimination at the managerial levels in a variety of settings with respect to entry, compensation, retention, and dismissal (e.g., Braddock et al., 2012; Humphreys et al., 2016; Kahn, 2006; Madden, 2004; Malone et al., 2008; Mixon & Trevino, 2004; Salaga & Juravich, 2020), very little empirical analysis (Avery et al.,

2015) has directly examined potential customer discrimination specific to the position of power (i.e., managers or head coaches) based on race. Missing from the literature is empirical analysis using television viewership as the previous study used the average regular season home game attendance as the dependent variable. Therefore, further investigation is required to evaluate whether or not head coach race impacts customer behavior reflected in television ratings.

Purpose of the Present Study

Despite the importance of understanding the existence of customer discrimination in sports labor markets, studies using television ratings are relatively scant when compared to those using stadium attendance. Therefore, the present study incorporates television viewership data to investigate potential customer discrimination in the context of basketball. Particularly, this study merges the discrimination and consumer demand literatures by focusing on both player and managerial levels of the organization and assessing whether the race of key actors is a practically relevant and statistically significant driver of consumption.

Accordingly, the purpose of the present study is twofold. The first goal of this study is to empirically examine how the race of players is related to television viewership. Expanding on Kanazawa and Funk (2001), this study quantifies player race in two different ways – the racial composition of the competing team rosters and the actual minutes played by race in a given contest. Racial composition of the team roster is a relevant factor in the structure of the team roster (Morse et al., 2007), particularly because in basketball, frequent roster turnover leads to changes in team composition. Moreover, the inclusion of minutes played accounts for the possibility that star players may have a greater effect on television viewership than marginal players or players who do not play at all (Kanazawa & Funk, 2001).

The second goal of this study is to empirically investigate potential customer discrimination in television viewership based on the organizational leader (head coach) of the competing entities. Recent studies have advanced the literature by examining discrimination not only on the player-level but also on the managerial level, in particular with respect to head coaches (Kahn, 2006). However, discrimination research specific to head coach race in sports has mostly focused on the supply side of the market such as entry, compensation, retention, and dismissal (e.g., Braddock et al., 2012; Humphreys et al., 2016; Kahn, 2006; Madden, 2004; Malone et al., 2008; Mixon & Trevino, 2004; Salaga & Juravich, 2020). To the best of my knowledge, there has been no research specifically focused on team leadership and how personal characteristics such as race of head coaches may influence live television sport product consumption.

Accordingly, this study merges the discrimination and consumer demand literatures by assessing whether the racial demographics of key actors is a practically relevant and statistically significant driver of product consumption. This study builds on the existing literature because it assesses potential customer discrimination at both the professional and collegiate levels over the same time period by focusing not only on the player level, but also on the managerial level. It also assesses national television viewership (NCAAB) and local market television viewership (NBA) to test whether customers exhibit different (or similar) patterns of discriminatory preferences dependent on the different quality levels of competition within the same sport (product) context, given the assumption that audience composition may differ between the two. Further, the size of the data set utilized is more robust in comparison to previous research. Additionally, substantial time has passed since previous work has analyzed this topic in different settings. As a result, it is possible changing racial attitudes may lead to different consumer preferences related to race.

Accordingly, this dissertation contributes to customer discrimination and consumer demand literatures by addressing the following research questions:

RQ1 Does game-level consumption differ based on the number of players by race for the competing teams?

RQ2 Does game-level consumption differ based on the minutes played by player race for the competing teams?

RQ3 Does game-level consumption differ based on the race of head coaches leading the competing teams?

To preface the findings, in contrast to the customer discrimination hypothesis, this study finds evidence that the racial information of key actors is a practically relevant and statistically significant driver of consumption after controlling for other relevant factors. The results indicate potential customer discrimination in favor of minority players in terms of both the sheer number of players on the combined active roster and the actual playing minutes by race both in collegiate and professional basketball.[2] That is, minority players taking up more roster places and playing more minutes relative to White players have a positive effect on viewership in basketball. Further, there is also clear evidence that a positive impact of minority players is due to Black players in relation to White

[2] The regression coefficients which represent both the sheer number of minority players and the actual playing time contributed by minorities in college basketball just miss statistical significance at ten percent level.

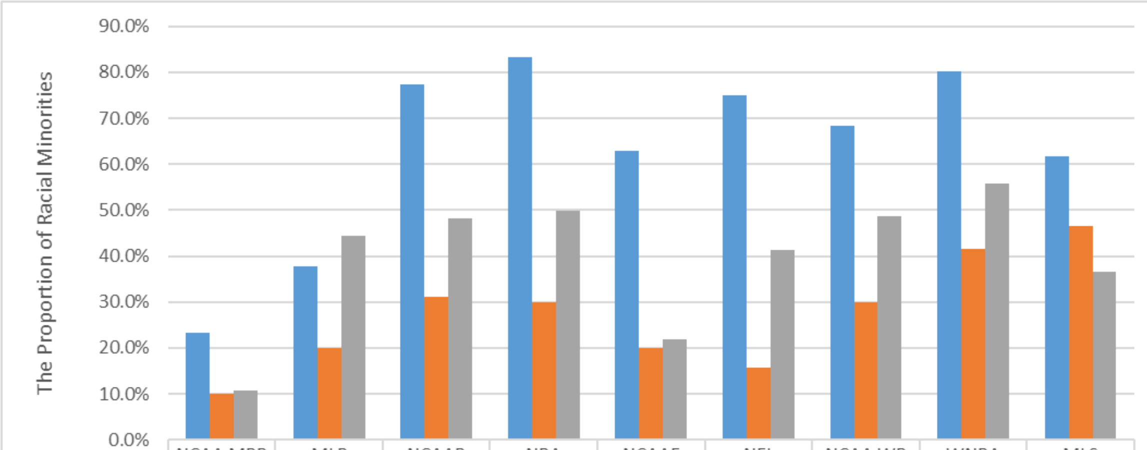
players in both collegiate and professional basketball[3], a result signifying potential reverse customer discrimination against White players. These results stand in stark contrast to research by Kanazawa and Funk (2001), who found professional basketball teams with more White players produced significantly higher local television ratings.

Conversely, this dissertation uncovers evidence of customer discrimination against minority head coaches after controlling for the race of players and other factors influencing viewership. At the managerial level, consumers respond negatively to minority head coaches, holding all other factors constant, in both collegiate and professional basketball. These findings suggest that fans are conscious of the racial background of head coaches and prefer watching games with fewer minority head coaches. Together with the results of player race specifications, these findings suggest a potential consumption bias against minorities in leadership roles, but not against minorities competing as athletes in the actual contest.

The remainder of the document is structured as follows: Chapter 2 reviews previous literature on discrimination in sport, with a specific emphasis on customer discrimination. Chapters 3 and 4 provide a description of the data, empirical modeling, and results specific to customer discrimination in NCAA basketball and in NBA, respectively. Chapter 5 offers discussion and highlights implications based on the findings from both contexts. Lastly, the final section offers concluding remarks and directions for future research.

[3] Also, the regression coefficient of Black in terms of the sheer number of roster players in relation to the White baseline just misses statistical significance in collegiate basketball.

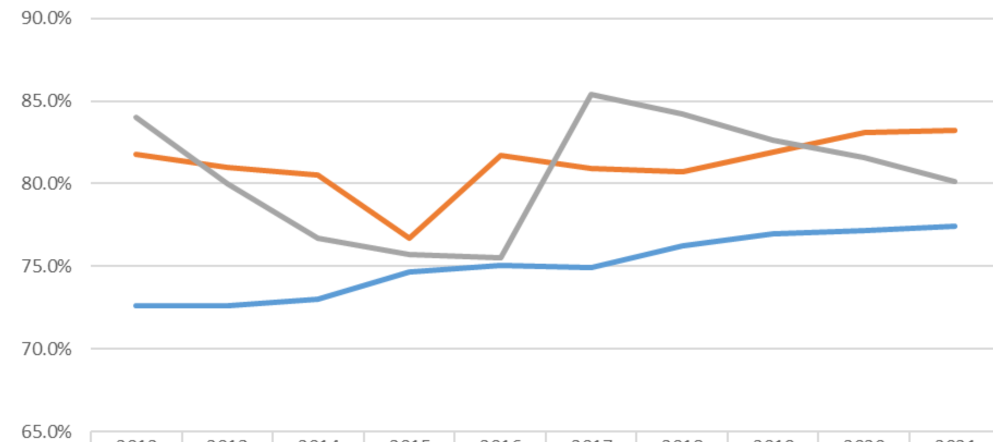
Figure 1.1 Representation of Racial Minority Coaches and Players in North American Sports



	NCAA MBB	MLB	NCAAB	NBA	NCAAF	NFL	NCAA WB	WNBA	MLS
Players	23.4%	37.7%	77.4%	83.2%	63.0%	75.0%	68.4%	80.1%	61.7%
Head Coach	10.1%	20.0%	31.2%	30.0%	19.9%	15.6%	29.8%	41.7%	46.4%
All Coaches	10.7%	44.4%	48.2%	49.8%	21.9%	41.3%	48.7%	55.8%	36.6%

Note. Opening-Day roster data for North American sports leagues in 2020-21 season. Data collected from The Institute for Diversity and Ethics in Sport (www.tidesport.org) and NCAA Diversity Research (https://www.ncaa.org/sports/2013/11/20/diversity-research.aspx). NCAA MBB = National Collegiate Athletic Association (NCAA) Men's Division I Baseball. MLB = Major League Baseball. NCAAB = NCAA Men's Division I Basketball. NBA = National Basketball Association. NCAAF = NCAA Men's Division I Football. NFL = National Football League. NCAA WB = NCAA Women's Division I Basketball. WNBA = Women's National Basketball Association. MLS = Major League Soccer.

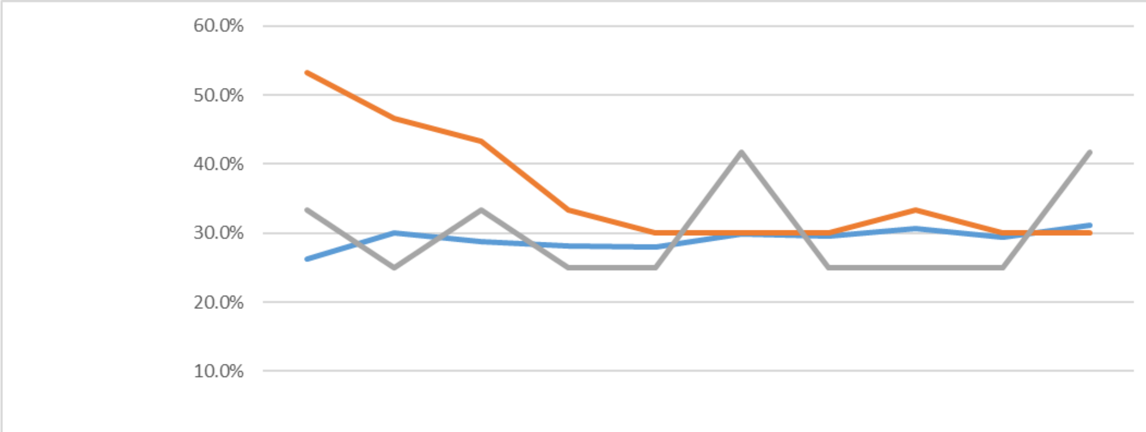
Figure 1.2 Representation of Racial Minority Players in Basketball



	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Players NCAAB	72.6%	72.6%	73.0%	74.7%	75.0%	74.9%	76.2%	77.0%	77.1%	77.4%
Players NBA	81.8%	81.0%	80.5%	76.7%	81.7%	80.9%	80.7%	81.9%	83.1%	83.2%
Players WNBA	84.0%	80.0%	76.7%	75.7%	75.5%	85.4%	84.2%	82.6%	81.6%	80.1%

Note. Opening-Day roster data for North American sports leagues beginning with the 2011-12 season (listed as 2012 for brevity). Data collected from The Institute for Diversity and Ethics in Sport (www.tidesport.org) and NCAA Diversity Research (https://www.ncaa.org/sports/2013/11/20/diversity-research.aspx). NCAAB = NCAA Men's Division I Basketball. NBA = National Basketball Association. WNBA = Women's National Basketball Association.

Figure 1.3 Representation of Racial Minority Head Coaches in Basketball



	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Head Coach NCAAB	26.2%	30.1%	28.8%	28.2%	28.0%	29.9%	29.6%	30.6%	29.4%	31.2%
Head Coach NBA	53.3%	46.7%	43.3%	33.3%	30.0%	30.0%	30.0%	33.3%	30.0%	30.0%
Head Coach WNBA	33.3%	25.0%	33.3%	25.0%	25.0%	41.7%	25.0%	25.0%	25.0%	41.7%

Note. Opening-Day roster data for North American sports leagues beginning with the 2011-12 season (listed as 2012 for brevity). Data collected from The Institute for Diversity and Ethics in Sport (www.tidesport.org) and NCAA Diversity Research (https://www.ncaa.org/sports/2013/11/20/diversity-research.aspx). NCAAB = NCAA Men's Division I Basketball. NBA = National Basketball Association. WNBA = Women's National Basketball Association.

CHAPTER 2

LITERATURE REVIEW

Chapter 1 highlighted the importance of understanding customer discrimination in sports labor markets because it is socially relevant topic not only in sports, but also in the management and economic literatures (Salaga & Juravich, 2020). This chapter introduces a comprehensive overview of three lines of literature relevant to the study of customer discrimination. The first section provides an overview of discrimination theory in labor economics which includes a thorough review of the discrimination literature in sports focusing primarily on customer discrimination at the player and the managerial levels of the organization. This work assesses whether a race is a practically relevant and statistically significant driver of consumption. This is important particularly because research on taste-based customer discrimination has developed out of discrimination research in labor economics. The second section is devoted to a discussion of consumer demand theory as this study combines the literatures on discrimination and consumer demand, and measures the factors that influence the consumption of live events in light of the racial composition of key actors (i.e., players and head coaches) on the competing teams. The third section includes a review of literature relative to the uncertainty of outcome hypothesis (UOH), one of the hypothesized drivers (factors) for fans to consume the live sport product.

Theory of Discrimination

The theory of discrimination in labor economics dates back to Gary Becker's 1957 book, *The Economics of Discrimination*. Since then, understanding whether discrimination results in inferior market outcomes have drawn substantial attention in labor economics. Discrimination is defined as unequal treatment of employees with equivalent qualifications. In other words, discrimination is said to occur when the behavior of one individual toward the other is not motivated by an objective consideration since the individual has a 'taste for discrimination' (Becker, 1971), and objective behavior is based on productivity (or performance) considerations. Therefore, the primary concern in this line of study is to empirically assess whether discrimination in specific labor markets produces market outcomes that differ from those of relatively competitive markets for many groups.

Economists have paid considerable attention to the theory and empirical analysis of labor market discrimination in a variety of settings (Kahn, 2009). Statistical and taste-based discrimination have generally been recognized as the two major theoretical models of economic discrimination in the literature. Becker (1971) first proposed that discrimination occurs because an individual has a taste for certain demographic characteristics of others including race. As a result, the behavior of that individual reflects prejudice against or preference for a certain characteristic of a group. This type of discrimination may also be the result of invalid statistical inference. For instance, the general managers (GMs) of sport teams may prefer to recruit Black players over those of other races because of their bias (or preference) for Black players, who they may see as being more athletic than other players. This prejudice is relatively independent from rational or economic considerations.

Statistical discrimination is based on a valid statistical inference (i.e., inaccurate assessment) as was first developed in the pioneering works of Arrow (1971) and Phelps (1972). In other words, discrimination is said to occur due to limited information on the abilities of individuals. It is not tied to prejudice, but heavily relies on stereotypes based on assumed group averages due to imperfect information about individuals. As a result, when a characteristic such as race is correlated with unobserved or imperfect information, people may utilize that characteristic to update their prior estimates. Therefore, the role of information is particularly salient. To illustrate, using the same example as before, GMs may prefer to recruit Black players because they believe that players of other races are less athletic due to inaccurate information about their productivity (or performance) based on their past experience. This type of discrimination persists until information is updated. However, the remainder of this section concentrates on taste-based discrimination because the majority of previous studies have largely focused on taste-based biases.

Becker (1971) identified three models of discrimination in labor markets by the discriminatory tastes of three different types of agents – employers, employees, and customers. These categories encompass nearly all of the existing literature in labor market discrimination. The first type of discrimination, employer discrimination, is said to occur when a particular group of workers, such as Blacks whose marginal value product is greater than their marginal cost, are not hired due to an employer's subjective taste (or preference). Assuming that each individual worker has identical productivity (i.e., perfect substitutes), this form of discrimination arises because the employer simply prefers association with one group instead of others (Neumark, 2018). If there are enough employers with a taste for discrimination, certain groups of workers may be out of work or earn a wage lower than their marginal revenue product. As a result, this would increase the wages for favored workers, increase the cost of production, and eventually reduce the profitability of the discriminatory employers. Therefore, in the competitive labor and product markets, discriminating employers will eventually be driven out of the market (Szymanski, 2000), resulting in the disappearance of discrimination.

Employee (or coworker) discrimination is the second form of discrimination identified by Becker (1971). In employee discrimination models, a particular group of workers require a higher wage (i.e., wage premium) in order to work alongside others because of their discriminatory taste (or preference). This might occur if there is a relatively incomplete segregation of workforces where one particular group of workers are predominant (Arrow, 1971). As a result, minorities or the non-favored group of workers earn lower wages and have inferior job opportunities even if they are perfect substitutes. For the same reasoning as employer discrimination, employee discrimination cannot persist in the competitive labor and product markets in the long run as owners associated with discriminating workers will eventually be forced out of business.

Customer discrimination, often known as customer-based discrimination, is the third form of discrimination. In general, customer discrimination is said to occur when customers discriminate against a certain group of workers and receive lower utility (i.e., disutility) from trading with them. As a result, this will lower the wage of discriminated workers working in jobs with customer contact. In the context of sports, customers (or fans in sports) have a strong preference for their favorite sport products and this is manifested by the premium that they are willing to pay over the market price to consume such products. For example, if fans love a certain race of players, they may be more willing to pay to consume products these favored players are associated with. In order to meet customer demand, teams hire such players at a salary premium, which eventually leads to a wage differential between favored and non-favored players by fans.

It is important to note that discrimination attributable to employer's and employee's prejudice will not persist over time in competitive labor and product markets in the long run. Employer discrimination will result in equally segregated firms with equal pay for equal work as non-discriminating employers push discriminatory employers out of business (Kahn, 2000). However, wage differentials between equally-qualified workers due to customers' prejudice is not likely to be eliminated by market forces. For example, an employer that pays the premium to hire a certain type of worker whom customers prefer is likely to be rewarded by the market (Kahn, 1991). Conversely, non-preferred workers who still possess a personal comparative advantage need to accept lower compensation if they want to remain in the customer sector, or shift to the non-customer sector where their comparative advantage is lost (Kahn, 2000). This indicates that discrimination based on customer prejudice is less likely to be eliminated by competitive market forces than discrimination based on employer or employee prejudice.

Moreover, customer discrimination is the most likely cause of other forms of discrimination. Even though employers may adopt race-neutral hiring practices, they might not generate increased revenue and hence profits if customers do not want to those practices (Burdekin et al., 2005). This suggests that it is still challenging to isolate customer-related discrimination from other sources of discrimination (e.g., employers or co-workers). Therefore, Nardinelli and Simon (1990) drew the conclusion that any persistent discrimination in the labor market is most likely the outcome of customer prejudice. And, of course, the sport industry is a customer-based service sector (Kahn, 2000) where customer discrimination is more likely to be an empirical question given heterogeneous customer preferences.

Meanwhile, the outcome of all the aforementioned forms of discrimination is the wage differential between favored (or dominant) group of workers and non-favored (or minority) groups of workers. So, the simplest way to identify discrimination is to quantify the existence of unequal pay for equal work. Thus, studies in labor market discrimination largely begin with a regression-based decomposition approach where wage is the dependent variable, while the independent variables include performance-related factors along with an indicator variable of unequal treatment (e.g., race, sex, or age). By controlling for productivity-related differences between groups in question, this approach allows us to assess the '*ceteris paribus*' impact of discrimination on salary difference.

However, the difficulties of objectively measuring productivity of workers poses a significant challenge for studies on discrimination in labor markets. By the definition of discrimination, a key assumption is that two groups of employees in question – favored and non-favored groups – should be equally productive by using the same standards. That is, two groups of employees should be perfect substitutes in production. Otherwise, it would be impossible to determine whether the difference in productivity is attributable to the effect of discrimination or that of different ability between workers (Nardinelli &

Simon, 1990). However, the challenge is that, in reality, the groups in question differ in numerous characteristics that lead to unadjusted differences in productivity (Neumark, 2018). This implies that these unmeasured productivity-related factors may cause unexplained wage inequalities between workers rather than discrimination even though regression can account for these differences.

A second problem with the regression approach is that the regression controls might affect responses to discrimination (i.e., variable of interest), and consequently lead to multi-collinearity issues. In practice, education and experience are typically used as a proxy for qualifications or productivity. However, such variables are likely to be correlated with the independent variable(s) of primary interest such as race (Kahn, 1991). For instance, discrimination may result in Blacks and Whites having different educational opportunities. Another shortcoming of typical regression approaches lies in the problem of unobserved productivity variables (i.e., omitted variables), such as the quality of education or the quality of previous work experience (Hoang & Rascher, 1999a, 1999b). Such factors might result from the differential effect of race, but are sometimes difficult to measure. Therefore, adopting a regression technique could potentially lead to biased estimates and hence inappropriate conclusions regarding the extent of labor market discrimination (Kahn, 2009).

In light of these issues, sport economists have argued that labor markets in sports provide a unique setting for empirical analysis (Holmes, 2011; Kahn, 2009). A particular advantage of using sports data is that it generally provides extensive, publicly available data regarding the performance and compensation of athletes and coaches, which is not traditionally found in other industries. For example, in baseball, detailed information on player performance, such as batting average (BA) for hitters, earned run average (ERA) for pitchers, errors (E) for fielders, and many more, are supplied by various sources. Such data are generally sufficient to account for qualifications or productivity which allows for the ability to eliminate potential challenges that may arise from employing regression techniques.

Moreover, sports data also generally contains additional information about the firm each player works for (e.g., team), the identity and performance of each player's co-workers (i.e., teammates), the player's supervisors (i.e., coaches), and customers (i.e., fans) who are willing to attend or watch games. The uniqueness of sports data allows us to examine all sources of discrimination in Becker's terms. Furthermore, information regarding players' compensation packages (i.e., contracts) and employment circumstances surrounding a player's exit from a team (e.g., trades and releases) is readily accessible, allowing us to study other forms of discrimination such as hiring and retention discrimination (Kahn, 2009). Therefore, economists have turned to labor markets in sports because sports provide a prime setting to study the extent of discrimination including discriminatory decision making, the nature of discrimination, and behaviors that lead to discriminatory outcomes.

Discrimination in Sports

Discrimination has been a thoroughly investigated topic in professional sports and numerous studies have investigated various forms of discrimination in sports labor markets.[4] In his survey of the literature, Kahn (1991) first proposed four primary

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[4] As Becker (1971) argued, labor market discrimination could result from employer prejudice, co-worker discrimination, or customer preferences. Just as discrimination can have several sources, so as can it take various forms.

manifestations of discrimination in professional sports. These include salary discrimination (unequal pay for equal work), hiring discrimination (entry and retention discrimination), positional segregation (disproportionate representation at positions), and customer discrimination. There also exist other forms of discrimination against minorities in professional sports including limited endorsement opportunities (Lipman, 1988), exclusion from managerial and executive positions (e.g., Braddock et al., 2012), as well as limited speaking engagements (Lapchick, 1991). This section, however, concentrates on the four manifestations of discrimination, placing more emphasis on customer discrimination in sports.

Salary discrimination

Salary discrimination is the most extensively studied issue in sports labor markets since it is the simplest form to test discrimination (Kahn, 1991). Accordingly, a large portion of the literature has examined salary differences between equally qualified players based on race. A typical research design for this line of research is a regression in which salary (or log salary) is the dependent variable and a series of performance indicators, team characteristics, and market characteristics are the independent variables, with an indicator variable for race being the variable of primary interest. The significant regression coefficient of the race indicator implies potential evidence of discrimination on the basis of race.

This form of discrimination has been studied in all four major leagues in the U.S. (e.g., Curme & Daugherty, 2004; Gius & Johnson, 2000; Groothuis & Hill, 2013; Kahn & Sherer, 1988; Palmer & King, 2006) as well as Major League Soccer (e.g., Kerr, 2019), while studies on baseball and basketball have been prevalent. The results of renowned studies on salary discrimination have been contradictory. Some have discovered evidence of salary discrimination against Black workers (e.g., Berri & Simmons, 2009; Palmer & King, 2006), while others found evidence of salary discrimination against White workers (e.g., Gius & Johnson, 2000).

In professional baseball, Palmer and King (2006) found evidence of salary discrimination against Black and Hispanic players in Major League Baseball. They categorized the players into three groups: Blacks, Whites, and Hispanics, and computed separate regressions for players with low, medium, and high salary distributions to reveal discrimination at different levels of compensation. They found evidence of discrimination against Black and Hispanic players in the lower range of the salary distribution, even though this was not apparent in the middle- or high-level salary groups.

In profession football, Gius and Johnson (2000) used a data set of 938 NFL players from the 1995 season and found evidence of reverse salary discrimination, as Black players earned more than White players by 10%, even after controlling for player position. However, their analysis used a sample of players from multiple positions and in the NFL, players are valued on a position-specific basis. Since it is empirically challenging to account for individual performance when analyzing numerous positions, subsequent studies on salary discrimination in football have varied by position (e.g., Burnett & Van Scyoc, 2015; Keefer, 2013). While Keefer (2013) found evidence of a 10% pay premium for White linebackers in football, Burnett and Van Scyoc (2015) found no pay premium for linebackers or offensive linemen using rookie data.

In professional basketball, Bodvarsson and Brastow (1998) utilized regression to test for potential salary discrimination using a sample of 151 players from the 1990-91

NBA season. They found no evidence of racial discrimination suggesting that salary discrimination had disappeared by the mid-1990s, a result of a decrease in owner monopsony due to the negotiation of a new NBA collective bargaining agreement between the owners and players in 1988. Overall, the general finding from existing literature indicates salary discrimination against athletes by race has decreased in North American professional sports labor markets.

Hiring discrimination

Even if there were equal pay for equal work, it is still likely that Black players would have to meet higher standards than equally performing White players to enter (i.e., hiring discrimination) and have a lesser probabilities of being retained (i.e., retention discrimination) in professional sports (Kahn, 2009). In hiring discrimination, the non-preferred group faces barriers resulting in the group being underrepresented in the market (Longley, 2006). Accordingly, one way to look at hiring discrimination is to compare the performance of Black and White incumbents given the assumption that the Blacks should outperform the Whites if they faced racial entry barriers to some extent. One potential problem with such research is that it does not provide direct evidence of hiring discrimination (Kahn, 1991).

Hiring discrimination had been studied in a variety of settings (e.g., Gwartney & Haworth, 1974; Hoang & Rascher, 1999b; Jiobu, 1988; Kahn & Sherer, 1988) and some of the earlier studies on baseball found evidence of entry discrimination. For example, Gwartney and Haworth (1974) used data from the early 1950s and found a positive correlation between the number of Black players on a team and the winning percentage of those teams. This indicates that teams with greater integration had greater success.

An alternative way of examining entry discrimination is to access player draft data on the basis of race. In professional hockey, Lavoie (2003) used draft data from players in the 1993-94 season and divided the league's teams into two groups: teams located in Canada and teams in the U.S. The study found that English-Canadian teams discriminated against the Europeans but not French-Canadians, whereas U.S. teams discriminated against the French-Canadians. The findings illustrated that the French-Canadians still experienced some entry discrimination at the time of the draft, despite the fact that no league-level discrimination was apparent.

Recent studies have focused more heavily on employee treatment with regard to layoffs or discharges (i.e., retention or exit discrimination) using survival analysis (e.g., Salaga & Juravich, 2020), due to the aforementioned methodological limitations of entry discrimination research. In research on entry discrimination, determinants of where players are drafted are estimated by the function of previous-level experience, such as college performance (Kahn, 2009). For example, Volz (2017) examined the data of quarterbacks from the 2001 to 2009 seasons in the NFL and found evidence of discrimination against Black players. Controlling for performance-related measures including injury, age, experience, and many more, the study found that Black quarterbacks were approximately twice as likely to be benched the next game than observationally equivalent White quarterbacks. However, such analysis requires identifying the pool of all players who wish to be drafted (Volz, 2017). Additionally, it is nearly impossible to control for college statistics between players given the variation in quality levels in college sports.

Positional segregation

Positional segregation occurs when players of a certain race are disproportionately underrepresented or overrepresented in certain positions due to the belief that these players are not competent to carry out the responsibility of a given position. For example, in professional baseball, Blacks had long been over-represented at what have been known as the “peripheral” or “less central” playing positions (Curtis & Loy, 1978) such as outfielders, while Whites had been over-represented at central positions such as pitchers, catchers, and infield positions. Similarly, in professional football, Blacks were underrepresented at quarterback, kicker, and linebacker positions.

One explanation of the Black underrepresentation in central positions is the result of discrimination based on negative stereotypes about Black players (Medoff, 1986; Scully, 1974). Black players have been accused of being kept out of the central positions because it was thought that they were less intelligent or have lower leadership abilities than White players. This implies that this line of reasoning is also consistent with the existence of co-worker discrimination as White players may resist taking orders from Black players (Kahn, 1991). On the other hand, discrimination in training opportunities prior to the entry into professional sports may be the cause of the Black underrepresentation in central positions. According to this argument, such central positions require more training and equipment than other positions which lead Black players to choose non-central positions (Medoff, 1986).

Positional segregation in sports was extensively studied in earlier decades from the 1960s to 1980s, but work in this field has declined because the sports labor market has witnessed an overall reduction in positional segregation by race with respect to players (Day, 2015). Early studies in this area simply calculated the percentage of Black players in each position to assess whether they were either underrepresented or overrepresented. In professional football, for example, Scully (1973) found evidence that Black players in the 1960s and 1970s were underrepresented in quarterback, kicker, and linebacker positions, while being overrepresented in defensive back, running back, and wide receiver positions. However, compared to other discrimination forms, positional segregation has been found to be less significant in the empirical literature. Recent studies, for example, have examined the relationship between job segregation (or promotion) and race within the coaching profession (Day, 2015).

Customer discrimination

Customer preferences, which can range from a distaste of dealing with people of a different race to a general dislike of seeing people of a different race, are another source of discrimination (Kuppuswamy & Younkin, 2020). Customer discrimination argues discriminatory hiring is not driven by employers but by the preferences of their customers. Customer discrimination in sports is said to occur when sports fans prefer sport products or services that are sold or provided by members of their own group (Aldrich et al., 2005) because they have personal prejudices against certain traits of athletes including race. Hence, customer discrimination in the context of professional sports is also known as fan discrimination. This line of study primarily focuses on how fans respond to those traits of athletes such as a player's racial category in order to identify potential sources of discrimination within the behaviors of sport consumers.

As previously explained, testing for the existence of customer discrimination is important because, unlike employer and employee discrimination, customer discrimination cannot be eliminated by market competition (Kahn, 1991), so it might be insidious in professional sports. Non-discriminating employers can earn higher profits by hiring workers on the basis of their productivity in the long run, and in a competitive market, discriminating employers will be driven out of business, resulting in the disappearance of discrimination (Romei & Ruggieri, 2013). However, to the extent that customer prejudice exists, there could be a case where an employer pays more to players that customers prefer and is rewarded by the market (Kahn, 2009).

Moreover, it remains difficult to isolate customer-related discrimination from employer or employee discrimination using salary data. Thus, sport economists have analyzed customer discrimination in sports labor markets through alternative settings (Depken II & Ford, 2006). Mainly, the literature has studied customer discrimination in three primary settings in order to address this subject: sports memorabilia trading markets (e.g., Nardinelli & Simon, 1990), fan voting for all-stars (e.g., Depken II & Ford, 2006; Hanssen & Andersen, 1999), and attendance or television viewership (e.g., Brown et al., 1991; Kanazawa & Funk, 2001).

The research studying the sports memorabilia trading market provides the ability to examine how fans demand products of an individual player through the price of that player's card on the secondary market without considering employer or employee discrimination (Watanabe et al., 2017). This allows sport economists to examine whether certain player characteristics including race may be significant factors in determining the price of cards and the purchasing behavior made by fans.

In a review of this line of study, some found evidence that consumer preferences for cards featuring White players are higher than their non-White counterparts (Andersen & Croix, 1991; Fort & Gill, 2000; Gabriel et al., 1999; Nardinelli & Simon, 1990), a result illustrating potential consumer prejudice based on the racial characteristics of athletes. For instance, Nardinelli and Simon (1990) examined the market for collectible baseball cards to see whether race directly affects the value of a player's card. To solve the common player problem,[5] they assumed that the dollar price of a baseball card is equal to the common player price and the value related to a player's performance and characteristics including race. They found evidence that Hispanic hitters and Black pitchers had significantly lower card prices when holding an extensive set of player performance variables constant, as the cards for White players sold for premiums approximately 10% higher in 1989 than those for non-White counterparts. This implies that a player's race influences the value that fans place on a card. In other words, there exists a significantly lower demand for the baseball memorabilia of non-White players, demonstrating the preference of the customers for White players.

However, there appears to be an apparent contradiction in the literature because other studies found non-significant results illustrating that the racial characteristics of athletes does not affect the value (price) of trading cards (Broyles & Keen, 2010; McGarrity et al., 1999). For example, McGarrity et al. (1999) questioned the data collection methodology from previous studies given that the card price is a function of players' lifetime performance by the time the card is traded. The inclusion of active players may lead to serious measurement error due to the variation in card supply. Thus, they proposed a refined approach using the 1994 prices of 1974 Topps cards in order to

[5] Most baseball cards sell at what is called the "common player" price, which is the minimum value a card can take but is unrelated to the performance of the player. Even the worst performed player's card had a positive price because it has a common player price which represents its intrinsic value as a card.

focus on the prices of cards of retired players. Contrary to Nardinelli and Simon (1990), they found little evidence of racial discrimination against Black and Hispanic players.

As previously mentioned, discrimination studies that factor in the price of player cards can be associated with methodological problems because of a different set of supply-side influences. Two specific problems include determining confounding factors such as the scarcity of a player card (McGarrity et al., 1999) and the problem of time lag between when the card is released and when the card is traded (Depken II & Ford, 2006). First, the prices of cards heavily rely on the supply of such cards in the market, but the scarcity of a player card may play a significant role in determining the price, not actual discrimination by fans due to the lack of information on the size of the market and the number of cards that are actively traded for each player (Watanabe et al., 2017). Second, even though one study found evidence of customer discrimination, the lag in time leads to uncertainty of "what portion of the population is being modeled" (Depken II & Ford, 2006, p. 1063). Using the current price of player cards previously issued for individual players, therefore, restricts the sample of the population whose preferences are being modeled. These issues may yield markedly different empirical results in customer discrimination findings and therefore require alternative measures of customer preference which eliminate supply-side influences.

Due to the above issues, economists have turned to alternative methods to investigate customer discrimination in sports. One approach is to examine ballots for All-Stars or Hall of Fame voting to directly measure fan preferences. This approach allows for the ability to see a purely unbiased voting preference of fans for their favorite players who appear on the ballot. One benefit of this approach is that it allows for the ability to measure consumer preference of larger fan populations due to the fact that voting (especially online voting) requires lower costs than purchasing memorabilia or tickets to a sporting event (Watanabe et al., 2017). So, the ballots reveal preferences in a more straightforward manner (Depken II & Ford, 2006).

According to this line of inquiry, voting for All-Stars by fans has shown that discrimination toward Black players has declined over time (Hanssen & Andersen, 1999), especially during the 1990s when Hispanic and Black players outperformed White players (Depken II & Ford, 2006). Hanssen and Andersen (1999) first published a study employing All-Star voting in Major League Baseball as a method to test whether consumer-based bias exists. They used balloting data from 1970 to 1996 and discovered that Black players received substantially fewer All-Star votes by fans than observationally equivalent White players in the 1970s. More importantly, however, they found evidence that such customer-based discriminatory attitudes in voting had diminished over time and even become statistically insignificant after 1989.

Depken II and Ford (2006) extended the analysis of Hanssen and Andersen (1999) utilizing All-Star voting data from 1990 to 2000 to investigate customer discrimination in Major League Baseball. They included a series of indicator variables representing various regions of the United States in order to test whether fans in different areas had different voting patterns with respect to players' traits. After controlling for player and team characteristics, they found no evidence of customer discrimination against Black and Hispanic players during the 1990s based on perceived race by players' first initial and surname (Hanssen & Andersen, 1999). However, they found evidence that there was voting preference in favor of Black and Hispanic players during the 1990s, which indicated reverse customer discrimination against White players.

Another possibility to examine potential customer discrimination is to look at whether the racial composition of a team roster influences fans' willingness to attend or watch sporting events by considering game-day attendance or television ratings. This body of literature was initially revealed by testing the fans' willingness to pay at the gate (i.e., game-day attendance), and whether the admission fee that spectators accept to pay depends on the players' race (Andreff, 2019). Previous research has generally focused on assessing customer discrimination by demonstrating that hiring practices often mirror local demographics (Holzer & Ihlanfeldt, 1998) or that White workers in areas with large White populations earn more than Black employees (Hamilton, 1997; Kahn, 1992). This implies that professional sports fans have some degree of 'in-group favoritism' (Wang et al., 2021) – a preference for watching athletes of their own race, ethnicity, or nationality. This allows the franchise owners to be willing to pay higher salaries to players who bring in more fans and hence generate greater revenue (Andreff, 2019).

This line of literature has largely been confined to baseball and basketball (Kahn, 1991) since players in basketball, for instance, are more visible to fans both on the court and on the bench than players in other sports (Kahn & Sherer, 1988), especially where White players are relatively scarce. Baseball is also highly relevant in this context because teams typically utilize a rotation of five starting pitchers, and fans readily know whether their favored pitchers start in advance through announcements days before a given game begins (Nutting, 2012). Moreover, the size of the team roster plays a key role while conducting this type of research because it is relatively easy to identify a player's race or ethnicity by looking at their image (Foley & Smith, 2007).[6] This allows for the ability to empirically test if customer discrimination is prevalent given that players possess characteristics that may be appealing or not appealing to customers.

In baseball, Scully (1974) started the work in this line of study by examining the average home attendance data for 57 National League starting pitchers in the 1967 MLB season and found evidence that Black starting pitchers drew significantly fewer fans (1,969 fans) per game than White starting pitchers, a result suggesting the presence of customer-based discrimination in the 1960s. However, Gwartney and Haworth (1974) found evidence that the presence of Black players on a team roster had a positive and statistically significant impact on the annual home attendance (55,000 – 60,000 additional attendees per season per additional Black player). Using decade attendance data in the 1950s, this finding might be attributable to the fact that the inclusion of Black players increased team quality (measured by games won), which in turn attracted additional fans to attend the game (Tainsky & Winfree, 2010). This finding implies that Black players actually raised home attendance in the 1950s. Foley and Smith (2007) used more recent attendance data to confirm that customer discrimination against Hispanic players persisted in the MLB in the 1990s as they found evidence that home attendance decreased when teams in Boston, Cleveland, Houston, San Diego, and Saint Louis added Hispanic players to the roster.

In basketball, although the racial composition of a team had no statistically significant impact on attendance (e.g., Schollaert & Smith, 1987) in the 1960s and 1970s, Kahn and Sherer (1988) discovered that, all else being equal, attendance was significantly

[6] In the NBA and MLB, only 15 players and 26 rostered players per club, respectively, are involved in determining the race of the players. When it comes to football, the number rises to 53 players.

higher for NBA teams fielding more White players during the 1980-86 period. This is equivalent to approximately 13,000 additional fans per year. This implies that fans may have made their spectating decisions in part on the basis of the racial composition of a team in the 1980s. In opposition, Brown et al. (1991) used a different measure of racial composition of a team roster using 1983-84 season attendance data and found no evidence of customer discrimination. They included the percent of playing time contributed by each players' race and found evidence that the percent of playing time by Black players had a negative, but statistically insignificant impact on attendance.

Meanwhile, Burdekin and Idson (1991) provided evidence of the aforementioned in-group favoritism in the NBA in the 1980s as they found evidence that the racial makeup match between team roster and the metropolitan market where the team is located improves game attendance. This indicates that metropolitan areas with a smaller percentage of minorities were more likely to field teams with more White players. A similar relationship was found in the 1990s (Burdekin et al., 2005), with accompanying revenue gains found from the inclusion of additional White players on teams located in areas with a larger percentage of White residents. In particular, their finding suggests a tendency for more skilled White players to be employed in cities with larger White populations in the 1990s.

Due to stadium capacity constraints, early studies of customer discrimination looking at the relationship between the racial composition of a team roster and match attendance may provide difficulties (Goddard & Wilson, 2009). That is, the majority of games, especially in the NFL and NBA, are sold out and this causes a divergence between attendance and the underlying level of consumer demand (Berri et al., 2004) where desired attendance is different from stadium capacity (Borland & MacDonald, 2003). However, accounting for the truncation of the data, Berri et al. (2004) employed gate revenue data for four consecutive seasons beginning with the 1992-93 season and found a lack of evidence of a racial match between the team and host city. Thus, this suggests racial discrimination by customers was widely prevalent in the NBA in the 1980s, but was not evident later in time.

The enduring use of attendance data as a proxy for demand requires a need to elaborate on previous findings with respect to customer discrimination through the analysis of other sources (Tainsky, 2010) because fan preferences for a professional team may be manifested in other ways. Given that media is the largest source of revenue in North American professional sports market (Broughton, 2019), the use of television ratings, in particular, is preferable. One rationale for utilizing television ratings is to circumvent supply constraints is due to the relatively low cost of watching contests on television (Depken II & Ford, 2006) and the widespread availability of television with large viewership (Watanabe et al., 2017). Additionally, compared to highly informed fans who make the effort to attend games, television viewers may account for a more diverse body of consumers encompassing both home and visiting team supporters as well as casual fans. This allows for the ability to identify consumer preference for both *ex ante* factors and in-contest product quality characteristics (Chung et al., 2016; Paul & Weinbach, 2007). After controlling for factors with respect to game and team characteristics, a viewership decline brought on by an increase in members of underrepresented groups on team rosters may be viewed as customer discrimination.

However, compared to studies employing stadium attendance, the number of customer discrimination studies using television ratings are relatively scant. To the best of my knowledge, only a few studies have looked at customer discrimination using television ratings (Aldrich et al., 2005; Jane, 2014; Kanazawa & Funk, 2001; Meier & Leinwather, 2013), primarily due to limited data availability. Among these, Kanazawa and Funk (2001) examined racial team composition using Nielsen television ratings of locally televised games in the 1996–97 season to explore customer–based discrimination in relation to television viewership in basketball. They developed two dichotomous variables to indicate the number of White players and the percentage of the total minutes of playing time contributed by White players for both the home and visiting teams, respectively, in order to investigate the existence of discrimination. Their findings suggested the presence of customer discrimination as they uncovered evidence of increased viewership when there was greater participation by White players.

Aldrich et al. (2005) examined the impact of Black quarterbacks on demand in the NFL by combining television ratings for ABC's Monday Night Football with data from the General Social Survey (GSS) on racial views. They added two quarterback performance metrics of passer rating and rushing yards. Their findings indicated that quarterbacks who pass the ball enhance TV viewership while quarterbacks who run the ball lower it. Moreover, they discover evidence showing that in 1998, Monday Night Football games with at least one Black quarterback attracted more than two million additional viewers per game, demonstrating a preference for diversity.

One of the issues while assessing the racial composition of the team roster in relation to television ratings is the dynamic nature of sport (Watanabe et al., 2017). That is, in-game outcome uncertainty (i.e., score differential at time *t*) between two competing teams may have an ongoing impact on the change in television ratings during the course of the game (Jane, 2014). However, it is difficult to measure exactly how many and how long players of certain races have appeared because players are substituted in and out of a game frequently. In order to avoid this problem, Jane (2014) utilized minute-by-minute television viewership figures of Taiwanese viewers for World Baseball Classic (WBC) games. After controlling for on-field performance of players, he found that viewership increased when Taiwanese and Asian players played, illustrating that Taiwanese viewers exhibited discrimination favoring Taiwanese and Asian players.

Race of Head Coaches

While there is a large body of study analyzing discrimination in sports labor markets, the majority of this literature has routinely looked into potential discrimination on the basis of race, sex, gender, and ethnicity of players. A relatively small subset of literature has studied potential discrimination at the leadership level despite the fact that personal characteristics (e.g., Hambrick, 1995) and production (Bandiera et al., 2020) of leaders are highly associated with organizational performance (Salaga & Juravich, 2020). According to implicit leadership theory (ILT), race is one of the implicit characteristics for many people when considering a leader, which postulates that individuals may cognitively structure a leadership prototype representing the traits and behaviors that leaders should possess (e.g., Junker & Van Dick, 2014). However, there has long been a belief that White people are more frequently associated with leadership than non-White people (Avery et al., 2015). Particularly, labor market discrimination at the managerial level is a highly contentious topic, especially in North America (Kahn, 2006), given that

Black athlete participation rates far outweigh the percentage of Black people working in front office or coaching positions in professional sports. In light of the fact that managers and leaders are crucial to an organization's success (Nesseler et al., 2020), it is crucial for research to look at the relationship between a leader's race and relevant industry-specific outcomes, such as consumption.

Similar to other industries, head coaches are considered analogous to chief executive officers (Foreman & Soebbing, 2015; Ndofor et al., 2009) as they hold a visible and influential position in team sports (Nesseler et al., 2020). Like star players, head coaches have a prominent role in representing their teams (Nesseler et al., 2020) and under this assumption, researchers have investigated racial discrimination at the managerial level in a variety of settings, with the majority of research in football and basketball examining entry, compensation, retention, and dismissal (e.g., Braddock et al., 2012; Humphreys et al., 2016; Kahn, 2006; Madden, 2004; Malone et al., 2008; Mixon & Trevino, 2004; Salaga & Juravich, 2020).

For instance, Salaga and Juravich (2020) looked at all tenures of permanent NFL head coaches from the 1985 to 2018 seasons. They did not find any indication that the race of head coach was related to performance or that firing rates were different for head coaches of different races after controlling for relevant factors such as coaching experience, playing experience, age, and so on. However, they found evidence that non-White head coaches had longer tenures than White coaches in the Rooney Rule era suggesting a potential retention discrimination against White coaches. In basketball, Kahn (2006) used a hazard modeling approach to analyze racial differences in terms of retention probability, pay, and performance for NBA coaches from the 1996 to 2003 seasons, and found small and statistically insignificant racial effects after controlling for team and coaching qualities. The findings imply that Black coaches in the NBA were not subject to racial discrimination.

Meanwhile, Avery et al. (2015) first investigated customer racial preferences specific to the head coaches using average regular season home game attendance data in both NFL and NBA in order to assess whether Black leaders correlate with less favorable consumer purchasing behavior. Their findings provide no impact of leader race on consumer purchasing behavior except for when organizational performance was low. Missing from the literature, however, is an empirical analysis directly examining potential customer discrimination specific to the position of power (i.e., managers or head coaches) based on race using television viewership data. To my knowledge, there has been no research specifically focused on team leadership and how personal characteristics such as the race of head coaches may influence live television sport product consumption. In other words, despite the fact that the role of racial minorities in leading positions has evolved in recent decades (Cunningham, 2020), there is a paucity of research that specifically evaluates whether fans prefer (or do not prefer) to watch contests with minority coaches. In light of the aforementioned concerns, the present study advances the literature by evaluating how the race of head coaches affects customer behavior through television ratings. Following a systematic review of the literature, it is evident the television viewing habits of sports consumers, as reflected in television ratings, have not been studied by economists who are looking for evidence of racial discrimination at the leadership level in sports.

Theory of Consumer Demand

While customer discrimination is the primary focus, this dissertation is also intertwined with two other strands of literature in sports economics research: work estimating the determinants of television viewership in sport (Borland & MacDonald, 2003), and work testing the uncertainty outcome hypothesis (UOH: Rottenberg, 1956). Accordingly, the following two sections will provide a brief overview of those two research lines, respectively.

First, the current study links to previous literature estimating determinants of sport in general by using television viewership data for a specific contest as the dependent variable in order to evaluate the impact of the race of key actors (i.e., athletes and head coaches) on viewership levels. Estimating demand for live sport is a cornerstone area of investigation in sports economics and stemmed from the pioneering works of Rottenberg (1956), Neale (1964), and Noll (1974). Since then, there have been numerous empirical studies assessing the demand for sport (e.g., Borland & MacDonald, 2003; Fizel, 2017; Schreyer & Ansari, 2021, 2022). Given that the ultimate objective of sporting teams or leagues is to maximize fan interest (Borland & MacDonald, 2003), it is empirically important to understand the determinants of demand for sporting events.

The early sport demand literature primarily used game day attendance as a proxy of demand partially due to data accessibility and the fact that stadium attendance was an important topic since attendance-related revenues were the largest revenue source for teams. For years, relatively little was known about the demand for sport television viewership (Mongeon & Winfree, 2012), and recently there has been a growing occurrence of sport demand studies using television viewership data. One of the reasons is that broadcast revenue has increased steadily over time and has become a major revenue source for both sport organizations and media outlets (Coakley, 2009). Early work in this line of literature focused on whether attendance and television viewership might potentially substitute for one another, but there was no universal agreement on the nature of the relationship (e.g., Allan & Roy, 2008; Buraimo, 2008; McEvoy & Morse, 2007; Mongeon & Winfree, 2012).

Data capturing television viewership are preferred over game-day attendance for a number of reasons. First, television viewership is more likely to reflect the interests of a wider range of customers including fans of both home and visiting teams as well as casual sports fans (Brown & Salaga, 2018), as opposed to game day attendance data, which is likely to capture preferences of home team supporters due to economic factors such as travel costs (Borland & MacDonald, 2003). Second, in contrast to game-day attendance data where the decision to purchase a ticket occurs in advance before the actual game is played (Salaga & Tainsky, 2015), there is no potential issue tied to the timing of measuring the determinants of demand since the decision to watch and the actual game occur at the same time. Third, since television viewership has no capacity restrictions, there is no difference between the actual level of demand and television viewership consumption. Alternatively, the capacity of the stadium plays a key role in game attendance (Goddard & Wilson, 2009) because in many leagues, the majority of games are sold out, which creates a divergence between actual attendance and inherent demand (Berri et al., 2004) where desired attendance is different from the actual stadium capacity (Borland & MacDonald, 2003).

For the reasons listed above, scholars have turned their attention to television viewership as a proxy of demand and have estimated the impact of demand determinants in a wide array of leagues and sports. Thus, this line of literature is expanding but is still relatively limited compared to that using attendance data, primarily due to data availability constraints. The majority of this literature has estimated television demand for European football (Alavy et al., 2010; Bond & Addesa, 2019; Buraimo, 2008; Buraimo & Simmons, 2009; Feddersen & Rott, 2011; Forrest et al., 2005; García & Rodríguez, 2002; Johnsen & Solvoll, 2007; Pawlowski & Budzinski, 2012; Pérez Carcedo et al., 2017; Wills et al., 2022), North American major league sports (Aldrich et al., 2005; Bruggink & Eaton, 1996; Chung et al., 2016; Cisyk, 2020; Grimshaw & Burwell, 2014; Grimshaw & Larson, 2021; Hausman & Leonard, 1997; Kanazawa & Funk, 2001; Mongeon & Winfree, 2012; Paul & Weinbach, 2007; Sung et al., 2019; Tainsky & McEvoy, 2012; Tainsky & Winfree, 2010; Xu et al., 2015), collegiate sport (e.g., Brown & Salaga, 2018; Grimshaw et al., 2013; Kang et al., 2018; Salaga & Tainsky, 2015; Tainsky et al., 2014), individual sports, such as mixed martial arts (Tainsky et al., 2012; Watanabe, 2015), auto racing (Berkowitz et al., 2011; Schreyer & Torgler, 2018), road cycling (Van Reeth, 2013), and tennis (Konjer et al., 2017; Meier & Konjer, 2015).

There has yet been any comprehensive framework for classifying the determinants of television viewership for sports due to the variation in uniqueness and cultures of respective sports. However, in line with consumer demand theory, a careful review of the existing literature suggests that there are some antecedent factors that scholars have taken into consideration when estimating television viewership demand.

These factors can be grouped into five categories: anticipated and actual contest quality, temporal factors, substitution, and consumer availability (Salaga et al., 2020). Each group is further explained in Chapters 3 and 4.

Uncertainty of Outcome

The uncertainty of outcome hypothesis (UOH: Rottenberg, 1956), a topic that is closely intertwined with the demand literature, is also strongly related to the current study. Testing the UOH is a part of almost all demand estimations (Fort, 2005). It has been commonly hypothesized that sport fans prefer to watch highly competitive contests between two quality teams (i.e., degree of closeness), implying that demand for sporting events is heavily reliant on the unpredictable nature of game outcomes. In other words, since the outcome of the match is unknown at the time of decision-making, fans may choose to consume or forgo a live sport product depending on their expectations of it (Coates et al., 2014). The implication of the UOH is closely related to the discussion of competitive balance (Lee & Fort, 2008). Therefore, this hypothesis has been investigated in a large number of empirical studies.

A long line of empirical research has measured *ex ante* consumer preference for anticipated outcome uncertainty on match attendance (Buraimo & Simmons, 2008; Czarnitzki & Stadtmann, 2002; Lee & Fort, 2008; Pawlowski & Anders, 2012) with mixed results (Szymanski, 2009). The mixed results are attributable to the quantification methods of the UOH since it is a latent concept which is difficult to accurately quantify (Manasis et al., 2015). In general, both anticipated pre-game outcome uncertainty and actual outcome uncertainty have historically been employed as two common metrics in in empirical studies. While the former accounts for consumer preference for the outcome expectation prior to the game, the latter captures the actual degree of closeness between the competing teams throughout the course of the game. As discussed above, one downside of testing the UOH using match attendance data is the inability to capture preferences for actual outcome uncertainty, since it has no relevance to consumers' purchase decision (Coates et al., 2014).

As an alternative, the utilization of television viewership enables for the measurement of both anticipated and actual outcome uncertainty since viewership data captures consumer preferences for product characteristics known not only prior to the game, but also during the actual broadcast (Chung et al., 2016; Paul & Weinbach, 2007). Recent television viewership demand studies have found that anticipated contest uncertainty has a positive impact on viewership in professional sports (e.g., Buraimo & Simmons, 2009; Forrest et al., 2005; Grimshaw & Burwell, 2014; Tainsky, 2010; Tainsky & McEvoy, 2012), while Salaga and Tainsky (2015), Brown and Salaga (2018), and Kang et al. (2018) found increased viewership is expected when games are predicted to be more certain in NCAA college football and basketball. Particularly, the latter three studies found clear and consistent support against the hypothesis in terms of anticipated outcome uncertainty, but support for actual outcome uncertainty. This suggests that empirical support for the UOH is context specific.

There have been a variety of studies on the UOH in relation to television viewership and the settings have predominantly centered on European club football (Alavy et al., 2010; Buraimo & Simmons, 2008, 2009; Feddersen & Rott, 2011; Forrest et al., 2005; García & Rodríguez, 2002; Johnsen & Solvoll, 2007), North American major league sports (Aldrich et al., 2005; Chung et al., 2016; Grimshaw & Burwell, 2014;

Hausman & Leonard, 1997; Kanazawa & Funk, 2001; Mongeon & Winfree, 2012; Paul & Weinbach, 2007, 2015; Tainsky, 2010; Tainsky et al., 2014; Tainsky & McEvoy, 2012), and other sports such as NASCAR racing (e.g., Berkowitz et al., 2011). However, the literature on collegiate sports has been somewhat scarce, and to my knowledge, there are only a few studies examining NCAA college football (e.g., Brown & Salaga, 2018; Salaga & Tainsky, 2015; Tainsky et al., 2014), and one on college basketball (Kang et al., 2018).

CHAPTER 3

Study I: ASSESSING CUSTOMER DISCRIMINATION IN NCAA COLLEGE BASKETBALL TELEVISION VIEWERSHIP

Study I empirically investigates potential customer discrimination in the context of college basketball. Specifically, this study assesses the relationship between the racial composition of the competing teams and their leaders in a given contest and television viewership in college basketball.

Data Description

Television viewership figures utilized in this study contain all nationally-televised regular season and post-season conference tournament contests in NCAA Division I men's college basketball in the 2013-14 and 2014-15 seasons. Viewership figures which are provided by the Nielsen Company are collected at SportsMediaWatch.com, and all betting market information was gathered from sportsinsights.com. In total, 1,860 contest-level observations are collected, and all other independent variables included in this study are publicly accessible on websites such as basketball-reference.com and espn.com.

Empirical Modelling

Following in line with the television viewership demand literature (e.g., Hausman & Leonard, 1997; Kanazawa & Funk, 2001), the empirical approach utilized in this study models factors affecting the level of television viewership. This work follows the assumption that viewership levels are related to anticipated and actual contest quality, temporal factors, substitutes, and consumer availability. Contrary to attendance demand (e.g., Borland & MacDonald, 2003), it is noted that television consumption decisions are not significantly influenced by price given the availability of free over-the-air networks and the fact that access prices for paid channels via cable and satellite are frequently comparable across markets. Furthermore, it is challenging to determine the real access price for cable and satellite channels in practice due to the vast variation of pricing schemes used by providers across regions (Salaga et al., 2020). Thus, price is typically not taken into account in this line of literature.

In accordance with consumer demand theory and existing literature examining the determinants of television viewership, this study specifies the consumer decision to view a contest as a function of factors associated with anticipated and actual contest quality, temporal factors, substitutes, and consumer availability as follows:

$$V = f(Racial\ Characteristic, Anticipated\ Contest\ Quality, Actual\ Contest\ Quality, Temporal\ Factors, Substitutes, Consumer\ Avaialbility),$$

where V represents the raw total national viewership of a given contest. It is important to note that the empirical model includes both anticipated (pre-game) and actual (in-game) characteristics as consumers have the ability to adjust their consumption instantly while watching (Chung et al., 2016). Unlike demand for stadium attendance, television viewership is influenced not only by pre-game expectations of contest quality, but also by actual game quality characteristics as the game progresses. In other words, the relationship between television viewership and contest quality is attributable to the dynamic nature of sport television viewership as there appears to be an extremely low (almost zero) cost of switching channels (i.e., low opportunity cost).

This study estimates the hedonic function above using Ordinary Least Squares (OLS) regression with White-corrected standard errors to account for heteroscedasticity. The dependent variable, *Ln(Viewers),* is transformed by taking its natural log because the raw total national viewership of a given contest is count data where the data is truncated from the left at zero and is over-dispersed with a long right tail (Long, 1997). The histogram of raw television viewership (*Viewers*) is displayed in the top panel of Figure 3.1 along with a line representing a normal density curve. It is clear that the game-level viewership count is over-dispersed with a long right tail. Accordingly, the use of OLS regression is not suitable as it produces biased estimates in the presence of over-dispersion (Long & Freese, 2006).

Due to the possibility of producing biased estimates, a common transformation used in the television viewership literature is to transform the value of dependent variable by taking its natural log to create a linear-estimating equation (Kennedy, 2008). The lower panel of Figure 3.1 shows the histogram of log-transformed viewership (*Ln(Viewers)*) along with the line of a normal density curve. In comparison to the upper panel, the distribution of the log-transformed viewership is greatly improved and close to a normal distribution. The log-transformation allows us to circumvent violating the assumption of normally distributed error terms (Long, 1997). Some subsequent issues may arise with this approach including the loss of data due to undefined values that are generated by taking the natural log of zero. However, this approach is acceptable when the dependent variable is live viewership as it is nearly impossible to have zero viewership for a given contest.[7]

Therefore, the general estimating equation follows:

$$\begin{aligned} Ln(Viewers)_{i,t} = {} & \beta_0 + \beta_1 AvePom_{i,t} + \beta_2 AveWin_{i,t} + \beta_3 Spread_{i,t} \\ & + \beta_4 Total_{i,t} + \beta_{5-35} Conference_{i,t} + \beta_{36} PowerOOCGM_{i,t} \\ & + \beta_{37} ConfTourney_{i,t} + \beta_{38} ConfChamp_{i,t} + \beta_{39} HCAvePom_{i,t} \\ & + \beta_{40} CoverDiff_{i,t} + \beta_{41} OUDiff_{i,t} + \beta_{42-52} Race_{i,t} + \beta_{53-54} Season_{i,t} \\ & + \beta_{55-59} Month_{i,t} + \beta_{60-66} DayofWeek_{i,t} + \beta_{67-79} StartTime_{i,t} \\ & + \beta_{80} Substitutes_{i,t} + \beta_{81-90} Channel_{i,t} + \varepsilon_{i,t} \end{aligned}$$

where *i* represents the individual contest and *t* represents the season of observation, respectively. Since the dependent variable is log-transformed, the regression coefficients are exponentiated using the following formula for interpretation.

$$100 \times (e^{b_1} - 1) \approx Percent(\%)\ Change$$

<u>Variable Descriptions</u>

Dependent Variable

The dependent variable in untransformed format is the total number of viewers for a given contest (*Viewers*), which is provided by the Nielsen Company and collected at SportsMediaWatch.com.

Independent Variables of Interest

The independent variables of interest in this study are twofold. First, I collected racial information of student athletes on team rosters and who played in a given contest in

[7] All possible reasonable empirical alternatives such as (Zero-truncated) negative binomial regression, Poisson regression, zero-inflated regression have been tested and the regression results are almost identical to those from the OLS regression with a log-transformed dependent variable.

order to investigate the existence of general customer discrimination at the player level. Second, this study also collects racial information of head coaches who managed the team in a given contest in order to investigate the existence of discrimination at the managerial level. The inclusion of a variable that accounts for racial information of head coaches is used to test whether customers react differently to the race of head coaches in reference to that of players given the hierarchical structure of team organization.

To test the existence of discrimination by viewers at the player level, I calculated two different sets of variables to represent the racial composition of the competing team rosters based on the sheer number of players and actual playing minutes by race, respectively. In order to measure racial information of players on the team roster, a game log of all individual contests including statistics of individual players was collected. Then, the first step to determine the race of each player was through facial recognition. That is, for each player, I extracted their profile picture from the respective university athletic department websites to determine the racial information of each player. To cross-check, the same process was used from images obtained through Google Image and www.sports-reference.com/cbb/. Then the race of each player was coded as one of four racial categories: Black,[8] White, Hispanic,[9] and other races. Players who are not classified as Black, White, and Hispanic are categorized as "other races" due to the lack of a sufficient number of players to generate additional categories. To further cross-check and in the extremely rare case when a player image was missing, the race of a given

[8] Multiracial players who have mixed ancestry of two or more races are categorized as Black if at least one of their parents fits that category. For example, Aaron Gordon at The University of Arizona is categorized as Black for this study because he is a son of a Black father and a White mother.

[9] Hispanic is not valid in race classification as it does not represent race, but instead ethnicity, which is not mutually exclusive from skin color. However, this dissertation uses this race classification which follows in line with previous discrimination literature (e.g., Cunningham & Sagas, 2005; Tainsky et al., 2015).

player was determined through the identification of their ethnic background. I searched online for the player's ethnic background by their surname (https://www.ancestry.com/). From these methods, four indicator variables were constructed to measure the independent variables of interest.

To quantify differences in the joint racial composition of the competing teams, I created a series of variables according to the formula that the percentage of a certain race of players (e.g., Black) equals the total number of Black players divided by total number of players on the rosters of competing teams. Accordingly, *Black*, *White*, *Hispanic*, and *Others* are variables that represent the percentage of Black, White, Hispanic, and other races relative to the total number of players for the two competing teams, respectively. [10] These variables take on a value between zero and one. This makes it possible to identify the source of potential customer discrimination towards (or against) a certain race of players in detail. *White* is treated as the baseline in the regression models and the following formula illustrates how these variables were calculated:

$$White = \frac{\textit{Total number of White players on the competing teams}}{\textit{Total number of players on the team roster of two competing teams}}$$

Then, I also create the variable *NonWhite*, which represents the combined percentage of the number of minority players, which is the sum of *Black*, *Hispanic*, and *Others*. This variable enables the ability to examine customer discrimination in favor of (or against) minority players by assessing the overall impact of non-White players relative to White players on television viewership.

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[10] While basketball fans may react to players of a certain race both on the home and opposing teams, this study creates combined measures of each variable for a given contest because it is not appropriate to calculate separate variables for both home and opposing teams due to the fact that national television viewership is more likely to represent a diverse range of customers than local television viewership.

In addition to the measurement of the racial composition of the competing teams, I also calculated a series of variables to quantify the minutes contributed by each category of player race for the competing teams. I first calculated the sum of minutes contributed by players of the same race on the rosters of competing teams. Then, I calculated the percentage of total playing time by race of players (e.g., Black) using the formula that the percentage of total minutes played by Black players equals the total game-level minutes contributed by Black players divided by total game-level minutes played by all players on the competing teams. *Min_Black*, *Min_White*, *Min_Hispanic*, and *Min_Others* represent the percentage of the actual minutes played by Black, White, Hispanic, and other races relative to the total playing time of all players on the two competing teams in a given contest, respectively. These variables also take on a value between zero and one. The inclusion of these measures control for the possibility that prominent players of a certain race (i.e., high-quality or star players) may have a greater effect on television viewership than marginal players (Kanazawa & Funk, 2001). Similarly, *Min_NonWhite*, the sum of *Min_Black*, *Min_Hispanic*, and *Min_Others*, was measured to assess the overall impact of minority players on viewership. *Min_White* is treated as the baseline and the following formula illustrates how these variables were calculated:

$$Min\_White = \frac{\text{Total game-level minutes played by White players on the competing teams}}{\text{Total game-level minutes played by all players on the competing teams}}$$

In college basketball, there are always 10 players on the court regardless of the frequency of substitution and each player on the court plays for 40 minutes. Hence, the denominator equals 400 minutes unless the game goes into overtime (20 minutes per half).

The analysis also tests the existence of potential discrimination by viewers at the managerial level. Accordingly, I created a variable which represents the number of minority head coaches in a given contest (*HCMinority*). The inclusion of this variable allows for the ability to compare the impact of minority head coaches against White head coaches, which is a common approach utilized in other work (e.g., Salaga & Juravich, 2020). Given two head coaches exist for the two competing teams, this variable is an ordinal variable with a minimum of zero and a maximum of two. The same approach used to classify player race was used to classify head coach race: facial recognition through their profile picture from the respective university athletic department websites with the usage of Google Image or basketball-reference.com for cross-checking, and an ethnic background check through their surname online for the rare case the image is missing. Then, each head coach is coded as either Black, White, Hispanic, or Others. In team sports, head coaches can be regarded as chief executive officers (Foreman & Soebbing, 2015). Accordingly, the race of the head coach might also be a relevant factor for fans to determine whether or not they will watch a given game. Therefore, the inclusion of this variable tests whether head coach race is a practically relevant and statistically significant driver of consumption, given that head coaches also play a crucial part in representing their teams (Nesseler et al., 2020).

Control Variables

I account for anticipated contest quality using a series of variables to measure game characteristics which are known by consumers prior to its start. In terms of absolute contest quality, this study includes two variables. First, I utilize statistician Ken Pomeroy's power ratings to capture consumer preference for anticipated short-term absolute contest quality.[11] *AvePom* is the average pre-game Pomeroy ratings of the two

[11] Ken Pomeroy has been producing and disseminating college basketball power ratings since 2003. These ratings are commonly referenced in popular media and can be found at http://kenpom.com.

competing teams. Since a low power rating value indicates a higher team quality, there is an inverse relationship between the average Pomeroy rating and the absolute contest quality level. In other words, higher values of *AvePom* indicate a lower level of absolute contest quality. In comparison to simple winning percentages, power ratings are preferable given the considerable variation in competition quality across the spectrum of college programs. Specifically, some programs schedule weaker competition prior to conference play, while others take the opposite approach, and Pomeroy ratings account for these differences. Second, *AveWin* measures the combined winning percentage of the competing teams in the three seasons prior to a given observation, which captures anticipated long-term contest quality. This variable accounts for the possibility that consumer interest could be strong for teams which have been competitive in recent years, but may not be as high quality in the current season. Adding this variable to the model is acceptable with respect to concern regarding potential collinearity (Kutner et al., 2004) as the correlation between *AvePom* and *AveWin* is -0.5622.

Anticipated outcome uncertainty and the anticipated level of scoring are modeled via variables using betting line data.[12] I first measure the absolute value of the pre-game closing line point spread (*Spread*) which captures the relative quality difference between the competing teams at the time of broadcast. This is one of the most commonly used proxies for perceived contest-level outcome uncertainty (Paul et al., 2011). Absolute values are used because these estimate the effect of differences in team quality, not preferences regarding the direction of such differences. In other words, this measures preference for anticipated contest uncertainty (e.g., Forrest et al., 2005; Tainsky &

[12] All pre-game closing line point spread and over/under total data was collected from https://www.sportsinsights.com/.

Jasielec, 2014). Smaller values indicate a contest expected to be more competitive (i.e., increased anticipated outcome uncertainty) because a small difference in expected scoring between two competing teams indicates a higher level of competitiveness expected by the betting market. Therefore, the relationship between this variable and viewership is expected to be negative based on the UOH. Similarly, *Total* measures the pre-game closing line over/under total in order to capture potential consumer preference for the level of expected total scoring (Paul & Weinbach, 2007, 2015). Viewership is expected to increase as the anticipated level of scoring increases (e.g., Buraimo & Simmons, 2009; Forrest et al., 2005; Grimshaw & Burwell, 2014; Tainsky, 2010; Tainsky & McEvoy, 2012).

Consumers may react to conference affiliation given the considerable degree of quality variation across the spectrum of college programs. Accordingly, *Conference* is a series of indicator variables which are equal to unity when the game played was between teams in the same conference.[13] Moreover, in college basketball, there have been traditionally powerful conferences which are commonly referred to as "power conferences" (i.e., ACC, Big East, Big 10, Big 12, SEC, and Pac 12). It is possible that contests between teams in these conferences are more preferable to watch by fans. Accordingly, *PowerOOCGm* is an indicator variable representing an out-of-conference game between teams in power conferences. *ConfTourney* and *ConfChamp* are indicator variables specifying whether the game played was a conference tournament game and a conference tournament championship game, respectively. The inclusion of these

[13] Patriot League and Independents are omitted due to the lack of sufficient number of observations.

indicators captures the potential increased interest attributable to relative contest importance related to access to postseason play.

In the second part of the study only, which examines potential customer discrimination at the managerial level, I also incorporate a variable that takes into consideration the race of head coaches and the average Ken Pomeroy power ratings of the two competing teams. *HCAvePom* is an interaction term which refers to the product of *HCMinority* and *AvePom*. By including this interaction term, it is possible to examine if absolute contest quality, measured by *AvePom*, is related to how customers react to the head coach's race, when one or both head coaches are a member of minority group (*HCMinority*). This allows for the ability to measure if customers' reaction to non-White head coaches vary depending on the quality of the teams they are in charge of. Since *HCMinority* is an ordinal variable with a value ranging from zero to two, it captures whether the effect varies depending on how many minority head coaches are featured in the matchup.

Measures of actual contest quality capture within-game contest characteristics which become known to consumers as a contest unfolds. *CoverDiff* is the absolute value of the difference between the pre-game expectation set by the closing line point spread and the final scoring margin. The inclusion of this variable is to test whether the UOH holds in the context of actual contest uncertainty relative to market expectations. Values near zero indicate that the betting market expectation in terms of score differential between the competing teams matched the actual scoring margin. Larger values indicate that the betting market had difficulty predicting the actual scoring margin, which signifies a lower degree of point spread uncertainty. This variable is preferable as there are commonly collinearity issues between raw final scoring margins and the closing line point spread for games where the actual contest outcome matches pre-game expectations (Kang et al., 2018). In other words, the approach utilized here eliminates collinearity between the anticipated and actual outcome uncertainty variables.

To create an equivalent variable with respect to the actual level of total scoring, the same calculation technique that was used to measure *CoverDiff* is applied. *OUDiff* represents the absolute value of the difference between the pre-game expectation of total scoring set by the closing line over/under total and the actual total points scored by the competing teams. This variable captures consumer preference for actual total scoring in reference to the betting market expectation of total scoring. Smaller values (or values near zero) identify contests where the actual total scoring matched market expectations. Larger values indicate a greater discrepancy between the market expectation and actual game outcome in terms of total scoring.

Temporal factors may also be significant drivers of television viewership consumption (Tainsky, 2010). Accordingly, *Season*, *Month*, and *DayofWeek* are indicator variables which are equal to one when the game was played during the specified season, month of the season, and day of the week, respectively. *Season13*, *March*, and *Sunday* are the baseline for each category. A series of indicator variables representing the start time of the contest (*StartTime*) in Eastern Standard Time with one-hour differences are also included. We create thirteen indicator variables including *BeforeNoon*, *Noon*, *1PM*, *2PM*, *3PM*, *4PM*, *5PM*, *6PM*, *7PM*, *8PM*, *9PM*, *10PM*, and *11PM*. Games that started in between an hour is classified based on the hour hand. For example, a game starting at

7:30 PM is included in the *7PM* indicator. *BeforeNoon* is treated as the baseline in all estimations.[14]

To control for potential substitution effects where viewership is impacted by the number of direct substitutes available to customers, we calculate *Substitutes*, which is equal to the number of nationally televised contests that overlap the two-hour time window of a given contest. For example, for a contest that starts at 8:00 PM, all other televised matchups that overlap the 8:00-10:00 PM time window are considered as substitutes. Given that college basketball contests are generally scheduled in two-hour television time blocks with different standard starting times by television network, it is expected that viewership will decrease as the number of substitutes increases.

The modeling also includes a series of indicator variables representing the cable and over-the-air network channels where each contest was broadcast (*Channel*). In college basketball, a variety of cable and network television channels hold the rights to broadcast contests nationally. However, some of these channels are on a pay-per-view basis, meaning that not all consumers purchase access to all channels. Therefore, these indicator variables control for the differences in the consumer availability of a given contest. Table 3.1 displays a brief description of each variable utilized in this study.

Results

Descriptive Statistics

Table 3.2 provides summary statistics for all variables used in the regression analysis. The mean of viewership (*Viewers*) is 441,807 with the regular season contest

[14] At the stage of preliminary analysis, I also tested other specifications such as by generating interaction terms between day of week and contest start time, but found that making these two categories separate provides more explanatory power.

between Syracuse and Duke on Saturday, February 1, 2014, the most watched game in the sample with 4.745 million viewers. The mean and the standard deviation of *Viewers* illustrate that the viewership data utilized in this study is over-dispersed as the variance is much greater than the mean. The standard deviation is roughly 1.4 times larger than the mean given the average and the standard deviation of *Viewers* is 441,807 and 625,251, respectively.

In terms of variables of interest, Black players comprise more than 70% of a team roster (*Black*), on average, while White players only constitute about 22% of a team roster (*White*). However, about 80% of the total minutes played by all players on a team roster in a given contest is contributed by Black players (*Min_Black*), while approximately 20% of total team minutes is contributed by White players (*Min_White*). Therefore, there is evidence that Black players tend to over-contribute to playing time, on average, in proportional terms. Hispanic and other races contribute less than 1% of team rosters and total team minutes in proportional terms, respectively. The average number of minority head coaches leading the two competing teams (*HCMinority*) is 0.4634, signifying that most contests feature two White head coaches, given that this variable is an ordinal variable ranging from zero to two.

With respect to variables capturing anticipated contest quality, the mean of the combined pre-game Pomeroy power rating of the two competing teams (*AvePom*) is 78.3, ranging from 2.5 to 324. Furthermore, the mean of the combined winning percentages of the competing teams in the three prior seasons (*AveWin*) is greater than 0.600, ranging from 0.270 to 0.859. These statistics indicate that television stations concentrate on nationally broadcasting high-quality games.

The average pre-game closing line point spread (*Spread*) is approximately 7.5 points, while the average closing line over/under total (*Total*) is above 137 points. Despite the presence of some outliers, the means of 8.3 and 13.37 points for both *CoverDiff* and *OUDiff*, respectively, indicate that the actual contest outcome in terms of point spread and total scoring differs from the market expectation prior to the game. The mean of *OUDiff* indicates, on average, the actual total points scored in a contest falls 13.4 points away from the over/under total set by the market. Approximately 9% of the total number of contests were conference tournament games and approximately 3% of the contests were conference tournament championship games. With respect to conference affiliation, approximately 44% of contests represent in-conference contests in power conferences (*ACC*, *B12*, *BE*, *B10*, *Pac12*, and *SEC*).

The sample contains 49% of contests from the 2013-14 season and 51% from the 2014-15 season. On average, three (2.983) nationally televised contests overlap the two-hour time window of a given contest and more than half of the contests (60.6%) were broadcast on ESPN affiliated television channels (i.e., ESPN, ESPN2, ESPNEWS, and ESPNU).

Estimation Results – Customer Discrimination Specific to Player Race

Table 3.3 outlines estimation results assessing the relationship between player race and television viewership. Models 1 and 2 show the outcomes of the regression analysis using the percentage of the number of players by race, whereas Models 3 and 4 use the actual playing minutes contributed by race as the independent variables of interest. Particularly, Models 1 and 3 serve as the baseline models since they contain the combined percentage of the number of minority players (*NonWhite*) listed on team rosters and the actual playing minutes contributed by minorities (*Min_NonWhite*) as the independent variables of interest. To further analyze the source of potential customer discrimination in detail by individual race, *NonWhite* in Model 1 is replaced by *Black*, *Hispanic*, and *Others* in Model 2, while *Min_NonWhite* in Model 3 is replaced by *Min_Black*, *Min_Hispanic*, and *Min_Others* in Model 4, respectively. The control variables with respect to anticipated and actual contest quality, temporal factors, substitutes, and consumer availability are the same in each model.

Results from Models 1 and 3 provide evidence that the degree of contribution made by minority players in terms of the sheer number of roster players and actual playing time is not a statistically significant factor in determining consumption. Both *NonWhite* and *Min_NonWhite* in Models 1 and 3 are positive but just miss statistical significance at standard levels. This is indicating there is no statistically significant customer discrimination based either on the raw racial composition of the team rosters or actual playing time contributed by minority players. Even with the alternative specifications of the independent variables of interest in Models 2 and 4, the result indicating no statistically significant customer discrimination based on the race of players are similar with the exception of *Min_Black* in Model 4, which becomes statistically significant at the ten percent level. To illustrate, *Black*, *Hispanic*, and *Others* in Model 2, and *Min_Hispanic* and *Min_Others* in Model 4 are not statistically significant even though *Black* just misses statistical significance at ten percent level. However, viewership is expected to increase by 2.53% $[(\exp(0.025) - 1) \times 100 = 2.5315]$ for a one standard deviation increase in actual minutes played by Black players in relative to *Min_White* baseline (one standard deviation equals 14.97% of all playing minutes). Together, these findings suggest that viewership levels increase at a practically relevant level as minority players occupy more roster spots or log more playing time relative to the White players baseline, in general, despite potential customer discrimination in favor of Black players in terms of actual playing minutes.

Regardless of statistical significance, the direction of the regression coefficients for Black, Hispanic, and other race players in reference to White players in Models 2 and 4 is practically intriguing. The positive coefficient of *Black* and *Min_Black* in Models 2 and 4 means that viewership is expected to increase as the teams add an extra Black player to their rosters or as Black players play additional minutes, respectively. The negative coefficient of *Hispanic*, *Others*, *Min_Hispanic*, and *Min_Others* in relative to the *White* and *Min_White* baselines for each category indicates that viewership is expected to decline as the teams have an extra Hispanic or other race player on the roster, or as those players play additional minutes. Given the modeling accounts for a variety of other systematic factors influencing consumption, including absolute and relative contest quality, it is highlighted that the positive influence of both *NonWhite* and *Min_NonWhite* in Models 1 and 3 is primarily driven by Black players (*Black* and *Min_Black*), respectively. In other words, the results appear to indicate a potential consumption bias in favor of Black athletes competing in the actual contest, which is practically interesting given that Black players make up the bulk of rosters. These results directly oppose evidence from Kanazawa and Funk (2001) who found professional basketball teams with more White players generated significantly higher local television ratings.

Moreover, the results in Models 1 and 2 in comparison to those in Models 3 and 4 provide evidence that the significance level (i.e., p-value) and overall explanatory power (i.e., magnitude of regression coefficient) are both lower in the regression that accounts for racial composition using number of players by race (Models 1 and 2) rather than the actual playing time by race (Models 3 and 4). In other words, the magnitude of all regression coefficients of *NonWhite*, *Black*, *Hispanic*, and *Others* in Models 1 and 2 is smaller than that of all regression coefficients of *Min_NonWhite*, *Min_Black*, *Min_Hispanic*, and *Min_Others* in Model 2. As opposed to Kanazawa and Funk (2001), where the significance levels and overall explanatory power are both higher in the regression model that includes the number of White players rather than their minutes played, the current finding suggests that how much time players of a particular race actually play may matter more to consumers than the simple number of players by race on the team roster.

The regression results for the control variables are almost identical in all models. With respect to anticipated contest quality, customers respond to higher levels of anticipated absolute contest quality as lower average Pomeroy ratings (i.e., high-quality teams) are associated with significantly higher television viewership ($p < 0.01$). On average, viewership increases by 0.50% $[(\exp(-0.005) - 1) \times 100 = -0.4988]$ given a one-unit decrease in the combined average Pomeroy rating of the competing teams (*AvePom*), holding all else constant. In other words, a one standard deviation decrease in average Pomeroy rating is associated with an expected viewership increase of approximately 23.43% in all models. Positive and statistically significant ($p < 0.01$) coefficients of *AveWin* illustrate that viewership is higher when the contest features teams with higher multi-season winning percentages (*AveWin*), even after controlling for real-time contest quality. Viewership is expected to increase by approximately 17% across all models, given a one standard deviation increase in average winning percentage of the competing teams in the three prior seasons.

Viewership is also associated with anticipated outcome uncertainty as more viewers are willing to watch a contest when the absolute value of the pre-game closing line point spread (*Spread*) is larger ($p < 0.01$). This indicates that, on average, a one-point increase in the closing line point spread is associated with a viewership increase of 2.12%. In other words, consumers prefer to watch games expected to be more certain. This result is in opposition to the UOH in terms of anticipated outcome uncertainty, but supports existing work analyzing television viewership in college football (Salaga & Tainsky, 2015) and college basketball (Kang et al., 2018).

The modeling produces evidence that consumers prefer higher anticipated levels of scoring. The coefficient of *Total* is positive and statistically significant ($p < 0.01$). On average, a one-point increase in the closing line over/under total is associated with a viewership increase of about 0.60%. Similar to Paul and Weinbach (2007), this illustrates that viewership is sensitive to anticipated levels of scoring and fans prefer to watch games featuring offense relative to defense. This result is reasonable given the relatively short playing time in college basketball (40 minutes; two halves of 20 minutes) in comparison to its professional counterpart (48 minutes; four quarters of 12 minutes). This result is in opposition to Salaga et al. (2020) who find evidence that the closing line over-under total is not systematically associated with local television viewership in the NBA.

The modelling also produces evidence that conference affiliation (*Conference*) is related to the variation in television viewership in college basketball. The majority of in-conference contest indicators are statistically significant relative to the out-of-conference contest baseline that includes at least one non-power conference team (power conference vs. non-power conference or non-power conference vs. non-power conference). As expected, coefficients of in-conference contest indicators in the power conferences (i.e., *ACC*, *B12*, *BE*, *B10*, *Pac12*, and *SEC*) are positive while the majority of the "non-power" in-conference game indicators are negative. This demonstrates that consumers prefer contests between the power conferences in comparison to the non-power conferences. Particularly, contests between teams in the Big Ten (*B10*) are expected to generate the largest premiums of approximately 84% additional viewership, relative to the baseline, across all models. Alternatively, games between teams in the Southland Conference (*Slnd*) generate the greatest viewership decline in all models, in reference to the out-of-conference contest baseline. Regular season out-of-conference games between teams in power conferences (*PwerOOCGM*) generate approximately 38% additional viewership across all models.

Contest importance also plays a significant role in viewership. As expected, both *ConfTourney* and *ConfChamp* are positive and statistically significant at the one percent level ($p < 0.01$). All else equal, the results illustrate that viewership is expected to rise by approximately 25% for conference tournament games (*ConfTourney*), on average. An even greater viewership increase of approximately 50% is expected for conference tournament championship contests (*ConfChamp*). Together, the findings imply that viewership is very sensitive to contest importance and viewership rises when access to the NCAA Division I Men's Basketball Tournament is on the line.

In terms of actual contest quality, *CoverDiff* is negative but statistically insignificant across all models. Even though it is not statistically significant, a negative coefficient of *CoverDiff* denotes that viewership level is anticipated to increase in situations when there is a greater level of actual point spread outcome uncertainty. In other words, this indicates consumers prefer to watch contest that are more competitive than anticipated, which suggests support for the prediction of the UOH in the context of actual outcome uncertainty. Similarly, *OUDiff* is positive but statistically insignificant in all models providing evidence that the actual scoring levels relative to the closing line over/under total is not systematically associated with viewership levels.

Temporal factors are a significant driver of college basketball viewership. In reference to the March baseline, a statistically significant variation in viewership by month of the season (*Month*) exists and there appears to be a gradual increase in viewership throughout the course of the season. This might be due to the perceived importance of late season contests as those games are strongly related to the postseason access. Furthermore, there appears to be no “start of season” viewership premium in college basketball as viewership is lowest for contests played in November. It may be the case that college basketball loses viewers to college football in the first two months of the season – a time when the sport of college football is heading into postseason play. Additionally, as anticipated, viewership for games broadcast on weekends exceeds that of weekday contests. Similarly, the viewership for games played during prime time exceeds viewership for contests played in other time windows. We find evidence that contests played on Saturday (*Saturday*) relative to the Sunday game baseline and contests starting at 7:00 PM (*7pm*) in reference to games starting before noon generate the largest viewership premiums, respectively.

Viewership is expected to decrease as the number of direct substitutes (*Substitutes*) increases. As anticipated, the coefficient implies approximately 2% reduction in viewership in all models for every Division I broadcast that overlaps the game of interest. All network channel indicators (*Channel*) in reference to the ESPN2 baseline are statistically significant. Specifically, games broadcast on CBS generate the highest viewership, whereas contests on FS2 generate the lowest viewership. These results are reasonable given the fact that CBS is a free over-the-air network, while FS2 is a cable channel on the basis of pay-per-view.

Estimation Results – Customer Discrimination Specific to Head Coach Race

Table 3.4 outlines the estimation results from the models assessing whether the race of competing team leaders influences television consumption above and beyond the racial composition of the competing teams. The variable of interest in this section is the number of minority head coaches (*HCMinority*) leading the competing teams. Specifically, in this section, the race variables which were previously employed as the variables of interest in the player-level analyses in Table 3.3 are included as control variables in order to account for the impact of player race on television viewership. To illustrate, Models 5 and 6 include a series of player race variables with respect to the percentage of the number of players by race, whereas Models 7 and 8 contain variables in relation to the percentage of the actual playing time by race. Models 5 and 7 serve as the baseline models as they directly compare *NonWhite* versus *White* players where the player race variables correspond to the percentage of the total number of minority players (*NonWhite*) on team rosters and that of total actual playing minutes contributed by minorities (*Min_NonWhite*). Similar to the arrangement in Table 3.3, Models 6 and 8 in

Table 3.4 contain alternative specifications for the player race variables (i.e., *Black*, *Hispanic*, and *Others* in Model 6, and *Min_Black*, *Min_Hispanic*, and *Min_Others* in Model 8) which take the place of both *NonWhite* and *Min_NonWhite*. Additionally, *HCAvePom* is included in all models since this portion of the analysis is specifically interested in the relationship between the race of the head coaches and viewership. This variable makes it possible to determine whether customer preference for minority head coaches is influenced by the average quality of the competing teams. All models share the same remaining control variables.

We find evidence that the race of head coaches leading the competing teams are a significant driver of viewership. The coefficient of the number of minority head coaches (*HCMinority*) is negative and statistically significant in all models ($p < 0.01$). This means that after controlling for all other factors including variables with respect to player race, viewership is expected to decrease by approximately 13% ranging from 13.06% $[(\exp(-0.140) - 1) \times 100 = -13.0642]$ in Models 5 to 13.67% $[(\exp(-0.147) - 1) \times 100 = -13.6706]$ in Model 8, for every additional minority head coach leading the two competing teams in a given contest. In other words, viewership drops when there is one minority head coach relative to zero minority head coaches. This suggests that consumers are sensitive to the race of head coaches and prefer to watch contests with less minority head coaches.

The direction and significance of the control variables in all models in Table 3.4 are almost identical to those in all models in Table 3.3. Interestingly, we find evidence that the inclusion of the race of head coach ordinal variable has the ability to significantly impact the player race variables. The coefficient of all player race variables in all models except for the coefficient of *Others* in Model 6 becomes greater in terms of its explanatory power (i.e., magnitude) and significance level (i.e., p-value). Moreover, *NonWhite* ($p < 0.10$), *Black* ($p < 0.10$), and *Min_NonWhite* ($p < 0.10$) in Models 5, 6, and 7 become statistically significant, and the level of statistical significance of *Min_Black* in Model 8 increases ($p < 0.05$). Positive *NonWhite* and *Min_NonWhite* coefficients, along with the positive *Black* and *Min_Black* coefficients, but negative *Hispanic* (*Min_Hispanic*) and *Others (Min_Others)* coefficients in Models 6 and 8, signifies that viewers prefer to watch minority players relative to White players, but the source of this effect comes from Black players relative to players of other races. To illustrate, viewership is expected to increase by 22.02% $[(\exp(0.199) - 1) \times 100 = 22.0182]$ for every additional Black player on the team roster (*Black*) and 23.12% $[(\exp(0.208) - 1) \times 100 = 23.1213]$ for every additional minute played by Black players (*Min_Black*) in relative to *White* and *Min_White* baseline, respectively. Together with the head coach coefficient, these results appear to indicate a potential consumption bias against Black individuals in leadership positions, but not against Black athletes competing in the actual contest.

It is interesting that these modeling results reveal evidence suggesting that the absolute contest quality between two competing teams as determined by Pomeroy's ratings is related to how consumers respond to the number of minority head coaches in a given contest. To illustrate, *HCAvePom* indicates that the effect of contest quality on the average viewership is expected to decrease by an additional 0.10% ($p < 0.01$) when the teams are led by minority head coaches. In other words, given the inverse relationship between *AvePom* and absolute contest quality, the result shows that viewership increases when minority head coaches are found in games with lower absolute contest quality. This insinuates viewership decreases when minority head coaches are leading higher quality teams. In summary, the results indicate consumers do not prefer to watch games with a larger number of minority head coaches, and they prefer when minority head coaches are found in games with lower absolute contest quality.

Figure 3.1 Histogram of *Viewers* and *Ln(Viewers)*

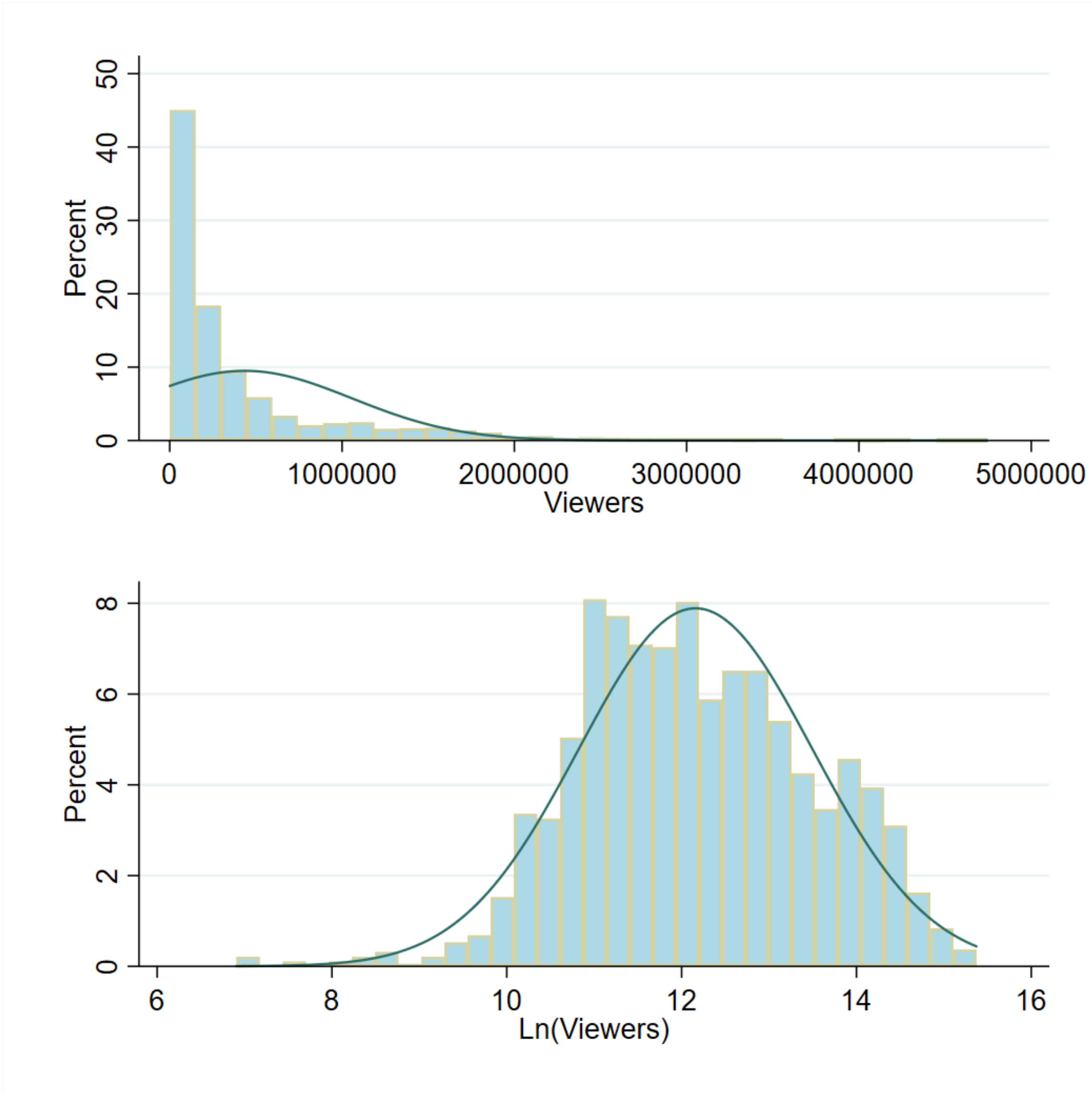

Table 3.1 Description of Variables

Variable	Description
Dependent Variable	
Ln(Viewers)	Logged total number of viewers for a contest
Race (Independent Variables of Interest)	
NonWhite	Percentage of the number of minority players on team rosters
Black	Percentage of the number of Black players on team rosters
Hispanic	Percentage of the number of Hispanic players on team rosters
White	Percentage of the number of White players on team rosters
Others	Percentage of the number of players of other races on team rosters
Min_NonWhite	Percentage of actual playing minutes contributed by minority players
Min_Black	Percentage of actual playing minutes contributed by Black players
Min_Hispanic	Percentage of actual playing minutes contributed by Hispanic players
Min_White	Percentage of actual playing minutes contributed by White players
Min_Others	Percentage of actual playing minutes contributed by players of other races
HCMinority	Number of minority head coaches leading the competing teams
Anticipated Contest Quality	
AvePom	Anticipated short-term absolute quality; average Ken Pomeroy's pre-game rating of competing teams
Ave3yrWin	Anticipated long-run absolute quality; average winning percentage of competing teams (avg. 3 prior seasons)
Spread	Anticipated outcome uncertainty (OU); absolute value of pre-game closing line point spread
Total	Anticipated scoring; pre-game closing line over/under total
Conference	1 = in-conference game in specified conference; 0 = otherwise (*Patriot* is omitted)
PowerOOCGm	1 = out-of-conference game between teams in power conferences
ConfTourney	1 = conference tournament game (*Regular* is baseline); 0 = otherwise
ConfChamp	1 = conference tournament championship game; 0 = otherwise
HCAvePom	Interaction term between minority head coach and average Ken Pomeroy's rating for competing teams
Actual Contest Quality	

ScoreSpread	Point spread market OU; absolute value of difference between final scoring margin and closing line point spread
TotalDiff	Totals market OU; absolute value of difference between total points scored and closing line over/under total
Temporal Factors	
Season	1 = game played during specified season (*Season13* is baseline); 0 = otherwise
Month	1 = game played during specified month (*March* is baseline); 0 = otherwise
DayofWeek	1 = game played during specified day (*Sunday* is baseline); 0 = otherwise
StartTime	1 = game began in specified time window (*BeforeNoon* is baseline); 0 = otherwise
Substitutes	
Substitutes	Number of nationally televised games that overlap the two-hour time window of a given contest
Consumer Availability	
Channel	1 = game played on specified network (*ESPN2* is baseline); 0 = otherwise

Table 3.2 Summary Statistics of Variables (N=1,860)

Variable	Mean	Std. Dev.	Min	Max
Viewers	441,807	625,251	1,000	4,745,000
Ln(Viewers)	12.1957	1.3078	6.9078	15.3726
NonWhite	0.7776	0.1394	0.2917	1
Black	0.7053	0.1463	0.1	1
Hispanic	0.0049	0.0155	0	0.1250
White	0.2224	0.1394	0	0.7083
Others	0.0673	0.0509	0	0.5333
Min_NonWhite	0.8034	0.1478	0.1975	1
Min_Black	0.7953	0.1497	0.1750	1
Min_Hispanic	0.0046	0.0166	0	0.1375
Min_White	0.1966	0.1478	0	0.8025
Min_Others	0.0035	0.0129	0	0.0975
HCMinority	0.4634	0.6077	0	2
AvePom	78.2987	55.3292	2.5	324
AveWin	0.6141	0.0970	0.2702	0.8594
Spread	7.5242	5.5342	0	41
Total	137.1282	10.5493	106	208
PowerOOCGM	0.1043	0.3057	0	1
ConfTourney	0.0973	0.2965	0	1
ConfChamp	0.0323	0.1767	0	1
HCAvePom	45.7575	84.2209	0	648
CoverDiff	8.2984	6.5510	0	42.5
OUDiff	13.3691	10.3983	0	67
Season13	0.4909	0.5001	0	1
Season14	0.5091	0.5001	0	1
November	0.1333	0.3400	0	1
December	0.1806	0.3848	0	1

January	0.2489	0.4325	0	1
February	0.2618	0.4397	0	1
March	0.1753	0.3803	0	1
Sunday	0.1183	0.3230	0	1
Monday	0.0823	0.2748	0	1
Tuesday	0.1452	0.3524	0	1
Wednesday	0.1140	0.3179	0	1
Thursday	0.1473	0.3545	0	1
Friday	0.0866	0.2813	0	1
Saturday	0.3065	0.4611	0	1
BeforeNoon	0.0177	0.1320	0	1
Noon	0.0780	0.2682	0	1
1PM	0.0387	0.1930	0	1
2PM	0.0844	0.2781	0	1
3PM	0.0398	0.1955	0	1
4PM	0.0640	0.2448	0	1
5PM	0.0355	0.1850	0	1
6PM	0.0591	0.2359	0	1
7PM	0.2387	0.4264	0	1
8PM	0.0618	0.2409	0	1
9PM	0.2016	0.4013	0	1
10PM	0.0274	0.1633	0	1
11PM	0.0532	0.2245	0	1
Substitutes	2.9833	2.1785	0	12
ABC	0.0011	0.0328	0	1
CBS	0.0333	0.1796	0	1
ESPN	0.1489	0.3561	0	1
ESPN2	0.2328	0.4227	0	1
ESPNEWS	0.0387	0.1930	0	1

ESPNU	0.3199	0.4666	0	1
FOX	0.0075	0.0865	0	1
FS1	0.1516	0.3587	0	1
FS2	0.0086	0.0924	0	1
NBCSN	0.0575	0.2329	0	1
ACC	0.0866	0.2813	0	1
B12	0.0801	0.2715	0	1
BE	0.0812	0.2732	0	1
B10	0.0597	0.2370	0	1
Pac12	0.0661	0.2486	0	1
SEC	0.0624	0.2419	0	1
AE	0.0022	0.0463	0	1
Amer	0.0758	0.2648	0	1
A10	0.0419	0.2005	0	1
Asun	0.0016	0.0401	0	1
Bsky	0.0011	0.0328	0	1
Bsth	0.0048	0.0694	0	1
BW	0.0070	0.0833	0	1
CAA	0.0108	0.1032	0	1
CUSA	0.0048	0.0694	0	1
Horz	0.0102	0.1006	0	1
Ivy	0.0043	0.0655	0	1
MAAC	0.0091	0.0952	0	1
MAC	0.0065	0.0801	0	1
MEAC	0.0054	0.0731	0	1
MVC	0.0118	0.1081	0	1
MWC	0.0118	0.1081	0	1
NEC	0.0032	0.0567	0	1
OVC	0.0075	0.0865	0	1

SC	0.0011	0.0328	0	1
Slnd	0.0011	0.0328	0	1
SWAC	0.0048	0.0694	0	1
SB	0.0027	0.0518	0	1
Sum	0.0011	0.0328	0	1
WCC	0.0220	0.1469	0	1
WAC	0.0011	0.0328	0	1

Table 3.3 Estimation Results – Customer Discrimination Specific to Player Race

	Model 1		Model 2		Model 3		Model 4	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
NonWhite	0.162	1.540						
Black			0.172	1.633				
Hispanic			-0.039	-0.045				
Others			-0.064	-0.257				
Min_NonWhite					0.161	1.602		
Min_Black							0.167*	1.667
Min_Hispanic							-0.448	-0.547
Min_Others							-0.764	-0.841
AvePom	-0.005***	-12.313	-0.005***	-12.236	-0.005***	-12.330	-0.005***	-12.322
AveWin	1.616***	9.619	1.623***	9.522	1.621***	9.643	1.610***	9.552
Spread	0.021***	8.452	0.021***	8.499	0.021***	8.414	0.021***	8.423
Total	0.006***	4.718	0.006***	4.889	0.006***	4.802	0.006***	4.900
PowerOOCGM	0.324***	6.575	0.324***	6.582	0.322***	6.551	0.321***	6.534
ConfTourney	0.226***	3.796	0.226***	3.780	0.227***	3.798	0.225***	3.754
ConfChamp	0.409***	5.231	0.410***	5.238	0.409***	5.224	0.411***	5.214
CoverDiff	-0.002	-1.142	-0.002	-1.068	-0.002	-1.219	-0.002	-1.220

OUDiff	0.001	1.115	0.001	1.108	0.001	1.095	0.001	1.066
Season14	0.002	0.078	0.004	0.163	0.002	0.096	0.007	0.264
November	-0.341***	-3.599	-0.341***	-3.618	-0.339***	-3.582	-0.342***	-3.617
December	-0.181**	-2.217	-0.180**	-2.218	-0.180**	-2.209	-0.181**	-2.216
January	-0.098**	-2.375	-0.099**	-2.390	-0.097**	-2.357	-0.098**	-2.374
February	-0.075*	-1.789	-0.076*	-1.807	-0.074*	-1.772	-0.074*	-1.771
Monday	-0.135**	-2.022	-0.135**	-2.014	-0.136**	-2.035	-0.131**	-1.967
Tuesday	-0.062	-1.080	-0.061	-1.052	-0.061	-1.064	-0.058	-1.006
Wednesday	-0.011	-0.180	-0.010	-0.168	-0.012	-0.193	-0.008	-0.139
Thursday	-0.214***	-3.519	-0.212***	-3.467	-0.213***	-3.502	-0.209***	-3.411
Friday	-0.016	-0.233	-0.016	-0.233	-0.015	-0.229	-0.013	-0.197
Saturday	0.168***	3.162	0.169***	3.173	0.169***	3.169	0.170***	3.197
Noon	-0.068	-0.778	-0.069	-0.794	-0.067	-0.762	-0.069	-0.799
1PM	0.016	0.165	0.013	0.134	0.016	0.171	0.015	0.157
2PM	0.018	0.192	0.019	0.207	0.019	0.209	0.019	0.212
3PM	0.065	0.684	0.067	0.698	0.067	0.708	0.067	0.711
4PM	0.069	0.730	0.072	0.755	0.072	0.754	0.073	0.779
5PM	0.077	0.694	0.074	0.670	0.077	0.698	0.074	0.674
6PM	0.199**	2.214	0.199**	2.221	0.201**	2.231	0.200**	2.242

7PM	0.226***	2.665	0.225***	2.668	0.227***	2.684	0.224***	2.679
8PM	0.142	1.494	0.142	1.499	0.143	1.505	0.142	1.505
9PM	0.159*	1.884	0.158*	1.875	0.161*	1.904	0.160*	1.917
10PM	0.200*	1.928	0.200*	1.934	0.202*	1.950	0.201*	1.955
11PM	-0.039	-0.405	-0.039	-0.401	-0.039	-0.404	-0.040	-0.422
Substitutes	-0.020***	-2.604	-0.020***	-2.613	-0.020***	-2.616	-0.020***	-2.615
ABC	0.793***	8.452	0.803***	7.967	0.795***	8.597	0.792***	8.505
CBS	0.999***	18.612	0.999***	18.544	0.995***	18.565	0.994***	18.567
ESPN	0.737***	22.244	0.736***	22.215	0.735***	22.196	0.735***	22.224
ESPNEWS	-1.109***	-14.395	-1.111***	-14.372	-1.110***	-14.409	-1.112***	-14.429
ESPNU	-0.961***	-29.634	-0.962***	-29.628	-0.961***	-29.650	-0.959***	-29.439
FOX	0.213*	1.761	0.213*	1.759	0.213*	1.770	0.210*	1.751
FS1	-1.335***	-22.067	-1.334***	-22.045	-1.336***	-22.080	-1.334***	-22.109
FS2	-3.356***	-9.824	-3.355***	-9.837	-3.352***	-9.825	-3.355***	-9.822
NBCSN	-1.232***	-14.438	-1.236***	-14.436	-1.232***	-14.411	-1.230***	-14.391
ACC	0.482***	6.049	0.487***	6.103	0.481***	6.030	0.480***	6.026
B12	0.274***	3.208	0.275***	3.210	0.269***	3.149	0.265***	3.091
BE	0.244**	2.513	0.242**	2.500	0.242**	2.493	0.235**	2.414
B10	0.607***	7.431	0.610***	7.444	0.606***	7.440	0.605***	7.409

Pac12	0.162*	1.765	0.164*	1.795	0.157*	1.722	0.157*	1.714
SEC	0.319***	3.740	0.322***	3.791	0.316***	3.701	0.318***	3.739
AE	-0.147	-1.148	-0.138	-1.067	-0.146	-1.138	-0.150	-1.163
Amer	-0.181**	-2.206	-0.184**	-2.242	-0.180**	-2.199	-0.186**	-2.262
A10	-0.343***	-3.236	-0.335***	-3.149	-0.343***	-3.234	-0.341***	-3.204
Asun	-0.565***	-3.299	-0.566***	-3.355	-0.554***	-3.187	-0.558***	-3.212
Bsky	-0.394	-1.530	-0.388	-1.551	-0.400	-1.620	-0.379	-1.621
Bsth	0.221	0.963	0.217	0.950	0.224	0.982	0.229	0.998
BW	-0.281*	-1.831	-0.282*	-1.839	-0.286*	-1.874	-0.288*	-1.909
CAA	0.036	0.183	0.047	0.241	0.041	0.212	0.046	0.234
CUSA	-0.460**	-2.262	-0.463**	-2.261	-0.463**	-2.267	-0.470**	-2.300
Horz	-0.456***	-3.547	-0.456***	-3.557	-0.452***	-3.518	-0.457***	-3.552
Ivy	0.036	0.127	0.039	0.138	0.040	0.143	0.043	0.150
MAAC	-0.649***	-5.247	-0.644***	-5.172	-0.652***	-5.282	-0.652***	-5.248
MAC	-0.314**	-2.354	-0.311**	-2.309	-0.315**	-2.371	-0.318**	-2.382
MEAC	-0.351*	-1.873	-0.346*	-1.847	-0.348*	-1.845	-0.345*	-1.820
MVC	-0.069	-0.530	-0.066	-0.507	-0.065	-0.495	-0.067	-0.507
MWC	-0.237**	-2.189	-0.234**	-2.173	-0.229**	-2.109	-0.221**	-2.048
NEC	-0.636***	-2.825	-0.635***	-2.814	-0.634***	-2.825	-0.627***	-2.962

OVC	-0.740***	-5.516	-0.723***	-5.331	-0.734***	-5.470	-0.714***	-5.215
SC	0.307*	1.933	0.304*	1.927	0.317*	1.958	0.311*	1.921
Slnd	-1.259***	-6.581	-1.256***	-6.266	-1.260***	-6.449	-1.264***	-6.422
SWAC	-0.250	-1.239	-0.243	-1.209	-0.243	-1.209	-0.242	-1.194
SB	-0.134	-0.556	-0.130	-0.533	-0.132	-0.544	-0.130	-0.537
Sum	-0.278**	-2.377	-0.273**	-2.294	-0.278**	-2.373	-0.283**	-2.401
WCC	-0.230**	-1.963	-0.224*	-1.895	-0.226*	-1.896	-0.208*	-1.727
WAC	-0.813***	-3.259	-0.805***	-3.276	-0.811***	-3.283	-0.783***	-3.427
Constant	10.861***	41.503	10.845***	41.691	10.851***	41.966	10.841***	41.982
N	1860		1860		1860		1860	
R-squared	0.8698		0.8698		0.8698		0.8699	

Note 1. Ordinary least squares with robust standard errors.
Note 2. Values listed as 0.000 are larger than zero.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3.4 Estimation Results – Customer Discrimination Specific to Head Coach Race

	Model 5		Model 6		Model 7		Model 8	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
HCMinority	-0.140***	-3.626	-0.142***	-3.650	-0.144***	-3.711	-0.147***	-3.781
NonWhite	0.186*	1.760						
Black			0.199*	1.874				
Hispanic			-0.189	-0.221				
Others			-0.042	-0.169				
Min_NonWhite					0.198*	1.939		
Min_Black							0.208**	2.034
Min_Hispanic							-0.542	-0.672
Min_Others							-0.780	-0.865
AvePom	-0.005***	-10.903	-0.005***	-10.811	-0.006***	-10.932	-0.006***	-10.937
AveWin	1.556***	9.098	1.557***	8.970	1.559***	9.115	1.543***	8.982
Spread	0.022***	8.529	0.022***	8.579	0.022***	8.475	0.022***	8.489
Total	0.006***	4.647	0.006***	4.826	0.006***	4.755	0.006***	4.864
PowerOOCGM	0.315***	6.393	0.315***	6.399	0.312***	6.350	0.311***	6.325
ConfTourney	0.224***	3.759	0.224***	3.736	0.225***	3.757	0.222***	3.707
ConfChamp	0.412***	5.284	0.413***	5.289	0.412***	5.280	0.415***	5.269

HCAvePom	0.001***	2.875	0.001***	2.874	0.001***	2.915	0.001***	2.925
CoverDiff	-0.002	-1.085	-0.002	-1.009	-0.002	-1.169	-0.002	-1.171
OUDiff	0.001	1.181	0.001	1.172	0.001	1.156	0.001	1.123
Season14	-0.001	-0.039	0.001	0.061	-0.001	-0.031	0.004	0.156
November	-0.338***	-3.595	-0.339***	-3.613	-0.336***	-3.572	-0.339***	-3.611
December	-0.188**	-2.325	-0.188**	-2.328	-0.188**	-2.320	-0.188**	-2.332
January	-0.103**	-2.515	-0.104**	-2.529	-0.103**	-2.500	-0.103**	-2.521
February	-0.080*	-1.922	-0.081*	-1.938	-0.079*	-1.908	-0.079*	-1.909
Monday	-0.137**	-2.040	-0.135**	-2.023	-0.138**	-2.057	-0.132**	-1.980
Tuesday	-0.066	-1.142	-0.064	-1.110	-0.065	-1.128	-0.062	-1.067
Wednesday	-0.012	-0.200	-0.011	-0.184	-0.013	-0.214	-0.009	-0.158
Thursday	-0.213***	-3.493	-0.210***	-3.434	-0.212***	-3.477	-0.207***	-3.380
Friday	-0.017	-0.248	-0.016	-0.241	-0.016	-0.243	-0.014	-0.206
Saturday	0.173***	3.245	0.174***	3.264	0.174***	3.260	0.176***	3.296
Noon	-0.055	-0.624	-0.056	-0.644	-0.053	-0.601	-0.055	-0.636
1PM	0.030	0.308	0.026	0.276	0.031	0.321	0.029	0.309
2PM	0.035	0.377	0.036	0.394	0.037	0.402	0.038	0.412
3PM	0.085	0.881	0.087	0.900	0.088	0.912	0.088	0.921
4PM	0.080	0.834	0.082	0.859	0.083	0.864	0.085	0.893

5PM	0.092	0.820	0.089	0.795	0.093	0.831	0.090	0.810
6PM	0.214**	2.350	0.214**	2.356	0.216**	2.377	0.215**	2.390
7PM	0.237***	2.772	0.237***	2.773	0.240***	2.799	0.237***	2.796
8PM	0.156	1.636	0.157	1.640	0.158*	1.655	0.157*	1.658
9PM	0.171**	1.992	0.170**	1.985	0.173**	2.022	0.173**	2.041
10PM	0.196*	1.887	0.197*	1.898	0.199*	1.918	0.198*	1.926
11PM	-0.027	-0.281	-0.027	-0.276	-0.026	-0.268	-0.027	-0.280
Substitutes	-0.021***	-2.709	-0.021***	-2.718	-0.021***	-2.726	-0.021***	-2.726
ABC	0.758***	9.893	0.767***	9.488	0.759***	9.988	0.754***	9.859
CBS	0.981***	18.300	0.982***	18.268	0.977***	18.250	0.976***	18.268
ESPN	0.721***	21.561	0.719***	21.534	0.718***	21.501	0.718***	21.535
ESPNEWS	-1.115***	-14.545	-1.118***	-14.525	-1.117***	-14.563	-1.119***	-14.582
ESPNU	-0.956***	-29.459	-0.956***	-29.439	-0.956***	-29.475	-0.952***	-29.245
FOX	0.177	1.477	0.176	1.466	0.175	1.478	0.171	1.447
FS1	-1.342***	-22.081	-1.341***	-22.067	-1.343***	-22.091	-1.341***	-22.125
FS2	-3.373***	-9.789	-3.371***	-9.799	-3.368***	-9.791	-3.371***	-9.792
NBCSN	-1.252***	-14.742	-1.256***	-14.751	-1.253***	-14.719	-1.251***	-14.722
ACC	0.465***	5.874	0.470***	5.943	0.463***	5.842	0.461***	5.834
B12	0.246***	2.877	0.245***	2.864	0.238***	2.789	0.233***	2.714

BE	0.258***	2.663	0.256***	2.646	0.256***	2.647	0.249**	2.565
B10	0.580***	7.130	0.581***	7.134	0.578***	7.145	0.577***	7.104
Pac12	0.168*	1.839	0.171*	1.873	0.164*	1.797	0.163*	1.791
SEC	0.353***	4.114	0.358***	4.187	0.350***	4.075	0.354***	4.140
AE	-0.111	-0.806	-0.102	-0.737	-0.107	-0.777	-0.112	-0.808
Amer	-0.184**	-2.253	-0.188**	-2.298	-0.185**	-2.257	-0.192**	-2.331
A10	-0.325***	-3.082	-0.318***	-3.002	-0.326***	-3.085	-0.324***	-3.063
Asun	-0.551***	-3.152	-0.552***	-3.209	-0.536***	-3.025	-0.541***	-3.059
Bsky	-0.371	-1.334	-0.360	-1.347	-0.376	-1.428	-0.351	-1.427
Bsth	0.231	1.032	0.230	1.026	0.234	1.050	0.240	1.066
BW	-0.284*	-1.859	-0.287*	-1.876	-0.291*	-1.909	-0.295*	-1.958
CAA	0.043	0.219	0.056	0.293	0.051	0.263	0.057	0.295
CUSA	-0.456**	-2.301	-0.460**	-2.305	-0.461**	-2.314	-0.468**	-2.355
Horz	-0.461***	-3.580	-0.463***	-3.597	-0.457***	-3.542	-0.463***	-3.582
Ivy	0.040	0.146	0.045	0.162	0.050	0.180	0.055	0.197
MAAC	-0.635***	-5.059	-0.629***	-4.984	-0.641***	-5.115	-0.641***	-5.084
MAC	-0.316**	-2.352	-0.312**	-2.293	-0.318**	-2.379	-0.322**	-2.393
MEAC	-0.564***	-3.022	-0.559***	-2.992	-0.563***	-3.007	-0.559***	-2.974
MVC	-0.089	-0.679	-0.087	-0.664	-0.083	-0.632	-0.086	-0.653

MWC	-0.258**	-2.394	-0.253**	-2.363	-0.249**	-2.304	-0.239**	-2.229
NEC	-0.621***	-2.836	-0.620***	-2.835	-0.620***	-2.846	-0.614***	-2.989
OVC	-0.729***	-5.412	-0.712***	-5.227	-0.720***	-5.342	-0.699***	-5.084
SC	0.354**	2.183	0.350**	2.169	0.365**	2.202	0.357**	2.149
Slnd	-1.279***	-6.349	-1.273***	-6.093	-1.281***	-6.208	-1.288***	-6.185
SWAC	-0.502**	-2.265	-0.495**	-2.231	-0.499**	-2.251	-0.496**	-2.223
SB	-0.135	-0.559	-0.128	-0.527	-0.133	-0.550	-0.131	-0.541
Sum	-0.269**	-2.182	-0.264**	-2.097	-0.267**	-2.147	-0.272**	-2.177
WCC	-0.238**	-2.032	-0.229*	-1.943	-0.230*	-1.928	-0.209*	-1.739
WAC	-0.871***	-3.948	-0.863***	-3.974	-0.868***	-3.998	-0.838***	-4.204
Constant	10.961***	41.710	10.947***	41.939	10.940***	42.239	10.931***	42.286
N	1860		1860		1860		1860	
R-squared	0.8707		0.8708		0.8708		0.8709	

Note 1. Ordinary least squares with robust standard errors.
Note 2. Values listed as 0.000 are larger than zero.
** p<0.10, ** p<0.05, *** p<0.01*

CHAPTER 4

Study II: ASSESSING CUSTOMER DISCRIMINATION IN NBA BASKETBALL TELEVISION VIEWERSHIP

Study II empirically examines potential customer discrimination in the context of professional basketball (NBA). Similar to the college basketball analyses in Chapter 3, this study assesses the impact of the race of players and head coaches on television viewership in the professional basketball setting. Particularly, this study utilizes contest-level data from the same time period (i.e., 2013-2014 and 2014-2015 seasons) as the data in the college basketball analyses to assess how differently (or similarly) fans react to the race of key actors (i.e., players and head coaches) of the competing teams given the different quality levels within the same sport (product) context.

Data Description

Viewership figures utilized in this study are Nielsen household television ratings (ratings point)[15] data for NBA regular season contests in 2013-14 and 2014-15 seasons. The data include all local market ratings data provided by the Nielsen Company. In other words, the data include a game rating value for the two markets where both the local and non-local teams are located. To illustrate, a contest between the Los Angeles Lakers and Golden State Warriors at the Chase Center on Saturday, November 1, 2014 generated a 3.2 rating in the Los Angeles market and a 3.6 rating in the San Francisco market.

[15] Ratings point and share point are the two most commonly used measures of viewership of a particular television program. Ratings point refers to the percentage of homes with a television in a given market tuning into a particular program while share point refers to the percentage of homes with a television actually in use tuning into a particular program.

It is noted that Toronto market ratings for Raptors games are not included since the team is located outside the United States and therefore ratings are not gathered by Nielsen. Furthermore, it is also noted that some nationally broadcast games cannot be viewed on the local market channel of the home team and/or the opponent and hence they do not produce a local rating. In total, 4,403 contest-level observations derived from 2,352 individual games are collected, and all independent variables utilized in this study are available publicly at websites such as espn.com and basketball-reference.com, except for the betting data which was purchased from sportsinsights.com.

Empirical Modelling

The empirical approach in this study follows the previous literature examining live sport consumption using television viewership data. Particularly, this study is built out from the data set used by Salaga et al. (2020) in their study of investigating the relationship between betting market outcomes and television viewership in the NBA. Consumer demand theory explains how consumers make decisions on what to consume based on their preferences and budget constraints. However, similar to the college basketball analyses, the literature using television viewership data does not consider price to be a critical factor in the consumption decision given the availability of free over-the air networks and the fact that access price for paid channels through cable and satellite is usually very similar across locations. Moreover, in reality, it is challenging to measure the exact access price for cable and satellite channels given the wide range of pricing strategies (i.e., bundling) by providers across regions (Salaga et al., 2020). Therefore, the literature almost uniformly does not take price into consideration and frequently employs market fixed effects in order to account for market heterogeneity.

In line with consumer demand theory and the exiting literature examining the determinants of television viewership, this study specifies the consumer decision to watch a contest as a function of factors related to anticipated and actual contest quality, temporal factors, substitutes, and market characteristics as follows:

$$V = f(Racial\ Characteristic, Anticipated\ Contest\ Quality, Actual\ Contest\ Quality, Temporal\ Factors, Substitutes, Market\ Characteristics),$$

where *V* represents the raw viewership of a given contest. Similar to the college basketball analyses, the current study incorporates both anticipated and actual contest characteristics since viewers can easily change their consumption while watching (Chung et al., 2016) given the substantially low opportunity cost.

This study estimates the previous equation using Ordinary Least Squares (OLS) regression with clustered standard errors by contest to account for heteroscedasticity (Cameron & Miller, 2015), given that the majority of contests in the data contain both local and non-local franchise market viewership. Particularly, this study transforms the dependent variable (*Rating*) into its natural log as television ratings are continuous but over-dispersed with a long right tail (Long, 1997). The upper and lower panel of Figure 4.1 display the histogram of the raw television ratings (*Rating*) and the log-transformed ratings (*Ln(Rating)*) along with a line representing a normal density curve, respectively. The distribution of the log-transformed ratings is closer to a normal distribution when compared to that of the raw television ratings.[16] Thus, it is reasonable to conclude logging

[16] Consistent with the college basketball analyses, this approach is acceptable as it is impossible for a game to have zero viewership.

our dependent variable avoids violating the assumption of normally distributed error terms (Long, 1997).[17]

Therefore, the general estimating equation follows:

$$
\begin{aligned}
Ln(Rating)_{gijt} \\
&= \beta_0 + \beta_1 ClosingLine_{gijt} + \beta_2 ClosingOU_{gijt} + \beta_3 CombinedWP_{gijt} \\
&+ \beta_4 LocalElo_{gijt} + \beta_5 NonLocalElo_{gijt} + \beta_6 DivisionGame_{gijt} \\
&+ \beta_7 ConfGame_{gijt} + \beta_8 NatlTV_{gijt} + \beta_9 MSAMinority_{gijt} \\
&+ \beta_{10} HCEloLo_{gijt} + \beta_{11} HCEloNLo_{gijt} + \beta_{12} CoverDiff_{gijt} \\
&+ \beta_{13} OUDiff_{gijt} + \beta_{14-46} Race_{gijt} + \beta_{47} Year_{gijt} + \beta_{48-54} Month_{gijt} \\
&+ \beta_{55-61} DayofWEek_{gijt} + \beta_{62-67} StartTime_{gijt} + \beta_{68} NFLReg_{gijt} \\
&+ \beta_{69} NFLPost_{gijt} + \beta_{70} NCAAFBReg_{gijt} + \beta_{71} NCAAFBPost_{gijt} \\
&+ \beta_{72} MLB_{gijt} + \delta_i + \delta_j + \varepsilon_{gijt}
\end{aligned}
$$

where *g* represents the individual contest between local market team *i* and non-local market team *j* in season *t*. Due to the log-transformed dependent variable, the regression coefficients are interpreted in the same way as in college basketball regression analyses using the following formula.

$$100 \times (e^{b_1} - 1) \approx Percent(\%)\ Change$$

Variable Descriptions

Dependent Variable

The dependent variable for this study is the log-transformed average local market broadcast rating for a given contest (*Rating*). By definition, average rating is interpreted

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[17] This study also confirms that heteroscedasticity is present given a statistically significant Breusch-Pagan test result ($p < 0.01$) when raw television rating is the dependent variable.

as the percentage of homes with a television in a given market tuning into a particular contest at any given point in time throughout the contest. For example, an average game rating of 3.5 indicates that 3.5% of homes equipped with a television in a specific market were tuned into the contest.

Independent Variables of Interest

The present study tests whether customers react differently based on the race of key actors at two levels (i.e., players and head coaches) given the hierarchical structure of sport organizations. Accordingly, the study incorporates two series of independent variables of interest which are tested in separate models. To assess whether customer discrimination exists at the player level, this study first collects racial information of players on team rosters. Additionally, in order to assess whether there is customer discrimination at the managerial level, this study also collects racial information of head coaches who managed the team in a given game.

In order to identify racial information of players on the team rosters and head coaches leading the sides in a given contest, a game log of all individual games was collected. Then, the race of each player and head coach was first identified using facial recognition. In other words, the profile picture of each player and head coach from the website of the respective franchise was collected in order to determine racial information. Images from Google Images and www.basketball-reference.com were used to cross-check using the same procedure. The final step was to identify the race of players and head coaches by searching their surname-based ethnic background (https://www.ancestry.com/). This procedure was put in place for further cross-checking or in the rare case that images of the players and head coaches were lacking. Through all aforementioned procedures, the race of each player and head coach was coded as Black, White, Hispanic, and all other races.[18] Players or head coaches whose racial information does not fall into Black, White, or Hispanic are labeled as "other races" due to the lack of sufficient observations to create additional categories.

This study incorporates two sets of independent variables of interest representing the racial composition of the team roster with respect to the sheer number of players on team rosters and actual playing minutes contributed by each category of player race in order to assess the existence of customer discrimination at the player level. For the analyses using the simple number of players on team rosters, I first created a series of combined variables (*White*, *Black*, *Hispanic*, and *Others*) that refer to the percentage of all players of a specific race relative to all players on the rosters regardless of teams involved in a given contest. The percentage of a certain race of players (e.g., White) is calculated using the following formula which divides the total number of White players on team rosters by the total number of players. Each of these variables has a value between zero and one since they are percentages.

$$White = \frac{Total\ number\ of\ White\ players\ on\ the\ competing\ team\ rosters}{Total\ number\ of\ players\ on\ the\ competing\ team\ rosters}$$

Then, I also constructed an additional variable (*NonWhite*) which is equal to the sum of *Black*, *Hispanic*, and *Others* in order to assess the overall impact of the number of minority players on local rating. I estimate models using various categorizations of race in order to not only determine if there is a widespread bias in favor of (or against) minority players using *NonWhite* as a variable of interest, but also to identify the source

[18] Similar to college basketball, the majority of multiracial athletes with ancestry from two or more races are coded as Black if at least one of their parents is. For example, Klay Thompson of the Golden State Warriors, who is the son of a Black father and a White mother, is coded as Black.

of potential discrimination towards (or against) a particular race of players by replacing *NonWhite* with *Black*, *Hispanic*, and *Others*.

In this study, it is necessary to also create separate independent variables of interest which represent the racial composition of the local team and non-local opponent, respectively, given that viewership in a local market is more likely to have effects tied to both local and non-local franchises. Contrary to the college basketball data in Chapter 3 where all contests were broadcast nationally, the viewership figures for this study contain television ratings of locally televised games. Accordingly, a series of variables representing all of the aforementioned variables with respect to both the local and non-local team were calculated using the following formulas. In other words, *WhiteLo*, *BlackLo*, *HispanicLo*, and *OthersLo* refer to the percentage of White, Black, Hispanic, and other race players relative to the total number of players on the local team roster, while *WhiteNLo*, *BlackNLo*, *HispanicNLo*, and *OthersNLo* are variables representing the percentage of each racial category on the non-local team roster.

$$WhiteLo = \frac{Total\ number\ of\ White\ players\ on\ the\ local\ team\ roster}{Total\ number\ of\ players\ on\ the\ local\ team\ roster}$$

$$WhiteNLo = \frac{Total\ number\ of\ White\ players\ on\ the\ non\text{-}local\ team\ roster}{Total\ number\ of\ players\ on\ the\ non\text{-}local\ team\ roster}$$

Then, I repeated the process above to measure *NonWhiteLo* and *NonWhiteNLo* based on the relationship that they are equal to the sum of *BlackLo*, *HispanicLo*, and *OthersLo*, and the sum of *BlackNLo*, *HispanicNLo*, and *OthersNLo*, respectively. The inclusion of these variables allows for the ability to determine if the influence is originating from the local or non-local market team.

For the analyses using the actual playing minutes of players, I begin by creating a series of variables based on the following formulas where the percentage of total minutes played by a certain race of players (e.g., White) equals the total game-level minutes contributed by White players divided by the total game-level minutes played by all players. *Min_White*, *Min_Black*, *Min_Hispanic*, and *Min_Others* represent the combined percentage of the actual minutes contributed by White, Black, Hispanic, and other race players relative to the total playing times of all players on the team rosters regardless of teams involved in a given contest. Similar to the combined variables representing the sheer number of players, these variables capture whether there is a pervasive prejudice in favor of (or against) a certain race of players specific to actual playing time. Since these variables are percentages, their values range from zero to one.

$$Min\_White = \frac{\textit{Total game-level minutes played by White players on the competing team rosters}}{\textit{Total game-level minutes played by all players on the competing team rosters}}$$

Given that there are 10 players on the court in a professional basketball setting regardless of the frequency of substitutions, and that each player plays 48 minutes, the denominator equals to 480 minutes unless the contest goes into overtime (12 minutes per quarter).

Then, I also constructed *Min_NonWhite*, the sum of *Min_Black*, *Min_Hispanic*, and *Min_Others* to assess the overall impact of the minority players in terms of actual playing minutes on the local television rating. Using *Min_NonWhite* as a variable of interest in the regression allows for the ability to assess a widespread bias in favor of (or against) minority players while equivalent variables in terms of individual race help to identify the source of potential discrimination towards (or against) a particular race of players.

To further analyze the source of potential customer discrimination, the percentage of the actual minutes contributed by White, Black, Hispanic, and other race players relative to the total playing times of all players on the local team roster (*Min_WhiteLo*, *Min_BlackLo*, *Min_HispanicLo*, and *Min_OthersLo*), and equivalent variables for the non-local team roster (*Min_WhiteNLo*, *Min_BlackNLo*, *Min_HispanicNLo*, and *Min_OthersNLo*) were calculated based on the following formulas. The denominator of these formulas equals to 240 minutes (12 minutes per quarter).

$$Min\_WhiteLo = \frac{\text{Total game-level minutes played by White players on the local team roster}}{\text{Total game-level minutes played by all players on the local team roster}}$$

$$Min\_WhiteNLo = \frac{\text{Total game-level minutes played by White players on the non-local team roster}}{\text{Total game-level minutes played by all players on the non-local team roster}}$$

The second part of the analysis investigates the existence of potential customer discrimination at the managerial level by examining the racial information of head coaches, given that they are assumed to have a significant role in representing their teams as they are comparable to chief executive officers in other industries (Nesseler et al., 2020). To assess this question, I begin by creating a variable which represents the number of minority head coaches (i.e., non-White) in a given contest. *HCMinority* is a variable denoting the number of minority head coaches of the two competing teams in a given contest. It is an ordinal variable with a minimum of zero and a maximum of two, given that there are two opposing teams with one head coach leading each team. Similar to the player-level analyses, this variable is included to see if head coach race is a statistically significant and practically important consumption driver by assessing the overall number of minority head coaches on local television ratings regardless of the teams involved in a given contest.

Then I create two additional variables where *HCMinorityLo* and *HCMinorityNLo* are measured in order to further examine if the overall effect of minority head coaches differ based on whether the head coach is leading the local market team or non-local market team. These variables are indicator variables equal to unity if the race of head coach for the local and non-local teams is non-White, respectively. Given the perceived significance of the position in affecting success, particularly in team sports (Salaga & Juravich, 2020), fans may be sensitive to not only the race of local head coach but also that of non-local head coach.

Control Variables

Anticipated contest quality variables include game characteristics that consumers can recognize prior to the start of the contest. *ClosingLine* refers to the absolute value of the pre-game closing line point spread, which serves as a proxy for anticipated contest uncertainty and the assumed relative quality difference between competing teams. Smaller values of this variable indicate a contest expected to be less certain by the betting market and vice versa for larger values. Accordingly, the relationship between this variable and television ratings is expected to be negative based on the UOH (Rottenberg, 1956). Similarly, *ClosingOU* refers to the pre-game closing line over/under total which accounts for consumer preference in terms of the anticipated level of total scoring (Paul & Weinbach, 2007, 2015). Ratings are expected to rise as the expectation of total scoring increases based on empirical results in other sports (e.g., Buraimo & Simmons, 2009; Forrest et al., 2005; Grimshaw & Burwell, 2014; Tainsky, 2010; Tainsky & McEvoy, 2012).

This study incorporates two variables to capture anticipated contest quality. *CombinedWP* measures the combined winning percentage of the local and non-local teams prior to the start of the contest. The inclusion of this variable represents absolute contest quality and assesses the possibility that consumer preference could be strong for contests with higher anticipated absolute quality, as previous studies have illustrated this relationship (e.g., Paul & Weinbach, 2007; Tainsky, 2010; Tainsky & McEvoy, 2012).

In addition to conventional winning percentage, the Elo rating system, which has been commonly used in recent studies (e.g., Mills et al., 2016; Sung & Mills, 2018), is used here to account for consumer preference for the quality of the individual competing teams. *LocalElo* and *NonLocalElo* refer to the pre-game Elo ratings of the local market team and its opponent, respectively. These variables are included because local market consumers may have quality preferences for the local market team as well as its opponent that are not captured in the absolute contest quality variable above. The Elo rating system was originally invented to measure performance quality differences of chess players, but has been gradually adopted by other sports such as football, baseball, basketball, soccer, and table tennis. The ratings for this study were collected from the fivethirtyeight.com database. The Elo system for NBA teams is a zero-sum and dynamic (i.e., game-by-game) system where the winning team takes points from the losing team after every game. Moreover, the difference of ratings between teams becomes a critical factor as teams earn more points for upsets or for winning by larger scoring margins. Every franchise begins with the rating of 1300 in its inaugural season and the rating carries over a portion of a team's rating from the previous season. Thus, the Elo system is preferable to individual team winning percentages as it captures individual team quality (Salaga et al., 2020) as well as changes in team quality. According to fivethirtyeight.com, the long-term average Elo rating in the NBA is 1500 where more than ninety percent of all teams fall between 1300 and 1700 (Silver & Fischer-Baum, 2015). Including both *CominedWP* and *LocalElo* (and *NonLocalElo*) in a single model is acceptable with respect to concerns of potential collinearity as the correlation between *CominedWP* and *LocalElo* (and *NonLocalElo*) is 0.5447 and 0.5560, respectively.

DivisionGame and *ConfGame* are indicator variables that are equal to unity if a given contest is an intra-division and intra-conference matchup, respectively. Currently, the NBA is made up of thirty teams and they are split into two conferences (Eastern and Western), with three divisions in each conference based largely on geographical proximity. Eastern Conference teams are split into the Atlantic, Central, and Southeast divisions whereas Western Conference teams are split into the Northwest, Pacific, and Southwest divisions, with five teams in each division. These variables are included based on the assumption that local fans may prefer games against teams from the same division or conference, while others may prefer games featuring teams from other divisions or conferences due to the variation in matchup frequency per season.

NatlTV is an indicator variable equal to one when NBA TV or one of the league's network television partners simultaneously aired the game on a national level. In general, games that are broadcast nationally are typically heavily advertised, which may raise consumer interest in the local market. However, this might negatively affect the consumption level of the local market channel since some fans may prefer to watch the game through the national network. *MSAMinority* refers to the percentage of minority (i.e., non-White) population in the local metropolitan statistical area (MSA) airing the given contest. This variable is included to control for the possibility that minority population percentage is related to viewership, given that there is variation in the racial makeup of the fan base in each local market and due to the possibility that fans may prefer to watch athletes of their own race, ethnicity, or nationality. I began by gathering raw population statistics by race from the U.S. Census Bureau database for MSAs where NBA franchises are located. After that, the percentage of minorities was calculated according to the formula that it equals the total number of minority population divided by total population in each MSA where the franchise is situated.

For the second portion of the analysis which examines potential customer discrimination at the managerial level, I also include variables which jointly account for the race of head coaches and Elo ratings. *HCEloLo* and *HCEloNLo* are interaction terms which refer to the product of *HCMinorityLo* (and *HCMinorityNLo*) and *LocalElo* (and *NonLocalElo*) for the local and non-local teams, respectively. The inclusion of these interactions assesses whether team quality is related to how consumers respond to head coach race. This allows to test whether consumers respond differently to non-White head coaches depending on the quality of the team they manage. Thus, these variables capture whether the effect differs when a minority coach is coaching a high-quality team, as both *HCMinorLo* and *HCMinorNLo* take on a value of zero if the race of head coach is White and one otherwise.

Measures of actual contest quality include in-game characteristics that consumers discover as the contest progresses. Similar to the college basketball analyses, this study incorporates *CoverDiff* which represents the absolute value of the difference between the closing line point spread and the final scoring margin. This variable enables the opportunity to evaluate if the UOH holds in the context of actual contest uncertainty as it accounts for consumer preference for actual contest uncertainty in the point spread outcome. In other words, it measures how closely anticipated contest uncertainty corresponds with actual contest uncertainty. Accordingly, smaller values (or values closer to zero) indicate that score differential between the competing teams predicted by the betting market matched the actual scoring margin, which signifies a higher level of point spread uncertainty. Larger values indicate that the betting market failed to predict the actual scoring margin well and signifies a lower level of point spread uncertainty. The inclusion of this variable is acceptable given the correlation between *ClosingLine* and *CoverDiff* is – 0.0442, which signifies there are not collinearity issues between the two variables.

OUDiff measures the absolute value of the difference between the closing line over/under total and the actual total points scored by the competing teams. Thus, it captures consumer preference for outcome uncertainty in terms of total scoring. Similar to *CoverDiff,* smaller values (or values near zero) signify contests where the actual outcome matched market expectation in terms of total scoring. The correlation of 0.0602 between *ClosingOU* and *OUDiff* indicates there is no concern regarding collinearity between the closing line over/under total and the actual level of total scoring.

Temporal factors represent characteristics that may have an impact on viewership due to the timing of the contest. *Year*, *Month,* and *DayofWeek* are included as series of indicator variables to represent the specified year, month of the season, and day of the week, respectively. The *2013-2014 season, October*, and *Sunday* are treated as the baseline for each category. Past research also indicates the specific time that the contest begins also plays a significant role in determining the level of viewership (Borland & MacDonald, 2003; Salaga et al., 2020). Thus, *StartTime* is a series of indicator variables denoting the start time window of the contest in Eastern Standard Time. Six start time windows are as follows: *Before6PM* designates a contest starting before 6:00 PM, *6PM* serves an indicator variable for a game starting between 6:00 PM and 6:59 PM, and equivalent indicators are created for games beginning during the *7PM*, *8PM*, *9PM*, and *10PM* windows.[19]

I create a series of dummy variables representing popular sports programming that is broadcast concurrently to the NBA observation of interest. The inclusion is to account for the potential reduction in viewership as the number of relevant substitutes increases (Mongeon & Winfree, 2012). To control for the availability of popular sports programming, this study includes *NFLReg*, *NFLPost*, *NCAAFBReg*, *NCAAFBPost*, and *MLB* indicator variables, which refer to contests where a given NBA observation was broadcast concurrent to NFL regular season, NFL postseason, NCAA Football Bowl Subdivision regular season, NCAA Football Bowl Subdivision postseason, and MLB game, respectively.[20]

This study also includes market fixed effects (δ_i and δ_j) for markets where both the local and non-local franchises are located in order to account for heterogeneity between markets. Heteroscedasticity is present in the sample given the wide variation in NBA game ratings across local markets. Thus, the inclusion of market fixed effects seeks

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[19] Alternative measures were also tested at the preliminary analysis stage by creating interaction terms that jointly account for day of week and contest start time. However, the results are almost identical to what is presented here.

[20] Typically, the NBA regular season lasts from mid-October through mid-April. The league's calendar thus coincides with that of MLB through the end of October, NFL through the first week of February, and NCAA Football through January.

to capture any unobserved heterogeneity across markets. Table 4.1 shows the designated market number for NBA franchises. This study employs fixed effects to prevent collinearity problems as the sample only contains two seasons of data (Salaga et al., 2020). Table 4.2 displays a brief description of each variable utilized in this study.

Results

Descriptive Statistics

Table 4.3 provides descriptive statistics for all variables included in the regressions. The mean rating in the sample (*Rating*) is 2.645 with the contest between the Houston Rockets and San Antonio Spurs on Friday, April 10, 2015 generating the highest rating of 16.9 in San Antonio market. The mean rating illustrates that on average, 2.645% of homes with a television in a local market were tuned into a contest where the local franchise is featured.

Black players represent the highest percentage of players by race on a team roster with respect to both the number of players (*Black*) and the actual playing minutes (*Min_Black*). To illustrate, Black players account for approximately 75% of the team rosters and about 78% of the actual playing minutes for the two competing teams, on average. This is evidence to support the claim that Black players tend to over-contribute to playing minutes in proportional terms, on average. Hispanic and other races contribute relatively less than Black and White players on team rosters and total playing minutes as the mean values are less than 5% for Hispanic (*Hispanic* and *Min_Hispanic*) and less than 1% for other races (*Others* and *Min_Others*). The average number of minority head coaches leading the two competing teams (*HCMinority*) is less than one (0.7097), signifying that the majority of contests features two White head coaches given that it is an ordinal variable ranging from zero to two.

The mean of the absolute value of the pre-game closing line point spread (*ClosingLine*) is approximately 6.35 points, while the average of the pre-game closing line over/under total (*ClosingOU*) is approximately 200 points. Given these results with the means of 9.14 and 13.5 points for both *CoverDiff* and *OUDiff*, respectively, informs us that the actual contest result with respect to point spread and total scoring varies from the expectations set by the betting market prior to the game.

The mean of both *LocalElo* and *NonLocalElo* is almost identical at 1500, ranging approximately from 1175 to 1780. Given that Elo rating in the NBA is a zero-sum system, these statistics confirm the fact that the long-term average Elo rating in the NBA is 1500. Approximately 20% of the total observations in the sample were intra-division matchups (*DivisionGame*) while approximately 63% of the contests were intra-conference games (*ConfGame*). Fifteen percent of the total observations were concurrently broadcast through national channels (*NatlTV*). The contests in 2013-2014 and 2014-2015 season are equally represented in the sample. More than a half of the total observations (66%) started between 7:00 PM and 8:59 PM eastern time.

Estimation Results – Customer Discrimination Specific to Player Race (White vs. Non-White)

Table 4.4 presents the estimation results assessing whether the racial composition of players on team rosters has an impact on television ratings for NBA contests. Models 1 and 3 are the baseline models as they include the combined percentage of the number of minority players (*NonWhite*) on team rosters and that of actual playing minutes contributed by minority players (*Min_NonWhite*) as the variables of interest. In Models 2 and 4, these variables are split into variables representing the local market team (*NonWhiteLo* and *Min_NonWhiteLo*) and non-local team (*NonWhiteNLo* and *Min_NonWhiteNLo*) players, respectively. These separate specifications first test whether fans have any racial bias against minority players in general as those players comprise more spots on team rosters and play more minutes relative to White players. Then they assess whether the impact of minority players on viewership primarily comes from the local market team or the opponent team. The rest of the control variables specific to anticipated and actual contest quality, temporal factors, substitutes, and market characteristics are identical in all models.

The results indicate the racial information of athletes is a practically relevant and statistically significant driver of consumption. The coefficient of *NonWhite* and *Min_NonWhite* is positive and statistically significant ($p < 0.10$ and $p < 0.05$), respectively. These are interpreted such that a one standard deviation increase in the percentage of *NonWhite* and *Min_NonWhite* is associated with a 2.02% [$(\exp(0.020) - 1) \times 100 = 2.0201$] and 2.43% [$(\exp(0.024) - 1) \times 100 = 2.4290$] increase in the average game rating, respectively. One standard deviation represents slightly more than 2 total players and 35 total minutes, respectively, given two 15-man rosters and 480 minutes per game. Moreover, the significance level (i.e., p-value) and overall explanatory power (i.e., magnitude of regression coefficient) of *NonWhite* are lower than those of *Min_NonWhite*. This indicates that viewership appears to be influenced more by how much time players of a certain race actually play on the court rather than by the sheer number of players on the squad. Together, these imply that NBA fans prefer to watch minority players occupying more spots on team rosters and playing more minutes relative to White players. Kanazawa and Funk (2001) found evidence that teams with more White players had noticeably higher local television ratings. Their regression results also indicated the number of White players rather than their minutes played had greater levels of significance and overall explanatory power. However, the results in this study directly contradict their findings and appear to suggest a potential consumption bias in favor of minority athletes competing in the actual contest in professional basketball.

Furthermore, it is interesting that the aforementioned impact of minority players on local television ratings primarily came from the local team roster. To illustrate, in Model 2, the coefficient of *NonWhiteLo* is positive and significant ($p < 0.01$) while that of *NonWhiteNLo* is negative and significant ($p < 0.01$). Similarly, *Min_NonWhiteLo* is positive and significant while *Min_NonWhiteNLo* is negative and significant in Model 4. This suggests that local market viewership increases along with the local team fielding more minority players on team rosters with respect to the sheer number and actual playing time. However, the local rating declines when non-White players on the non-local team roster occupy more roster spots and play more game minutes relative to White baselines.

All models yield nearly identical regression results with respect to control variables. In terms of factors associated with anticipated contest quality, *ClosingLine* is negative and statistically significant across all models. It is interpreted that on average, a one-point decrease in the closing line point spread is associated with a viewership increase of 0.49% in Model 1 and 0.39% in all other models. This suggests that consumers prefer to watch games which are expected to be more uncertain (competitive).

In other words, smaller point spreads – which suggest a smaller relative quality difference between the teams in a match – are associated with larger viewership, on average. This provides a support for the prediction of the UOH in the context of anticipated outcome uncertainty and is consistent with earlier studies investigating television viewership in professional sports (e.g., Forrest et al., 2005; Paul & Weinbach, 2015).

Given that *ClosingOU* is positive, but not statistically significant across all models produces evidence that the anticipated level of scoring set by the closing line over/under total is not systematically associated with local market viewership. This result opposes not only the result found in Chapter 3 in the context of college basketball, but also the previous results of Paul and Weinbach (2007) and Kang et al. (2018) who found evidence that viewership is sensitive to anticipated levels of scoring in professional football and college basketball, respectively. One possibility is that the disparities may be caused by the type of television viewership data utilized, as the data utilized in this study is local whereas the data used in all aforementioned studies is national.

The regression coefficient of *CombinedWP* is positive, but statistically insignificant across all models which indicates viewership is not systematically associated with the combined simple winning percentages of the competing teams. In other words, this study finds evidence that fans may not respond to higher levels of absolute contest quality measured by simple winning percentages. However, both *LocalElo* and *NonLocalElo* are positively associated with the average rating ($p < 0.01$). To illustrate, local market viewership is expected to increase when a higher quality local team competes against a higher quality opponent. Along with the result of *ClosingLine*, it seems to be reasonable to infer that local market consumers prefer games expected to be more uncertain (competitive) and that both the local and opposing team are of high quality.

Game type is a significant predictor of live sport consumption. Specifically, both *DivisionGame* and *ConfGame* are positive and statistically significant. These results imply that after controlling for other contest characteristics, contests featuring teams in the same division and conference are expected to increase viewership by 3.36% and 3.67%, respectively, based on the results of Model 1. Under the NBA league schedule, each franchise has to play the same number of out-of-division and out-of-conference matches per season. The playoff and postseason qualifying criteria are dependent on the final ranking of teams in individual conferences, which may make matchups between teams from the same division or conference more significant. Thus, it seems to be reasonable that local fans would pay more attention to intra-division and intra-conference games.

The results of this study also provide evidence that the concurrent airing of a particular contest on a national channel affects local market viewership. A negative and significant coefficient of *NatlTV* ($p < 0.05$) across all models indicates a viewership drop of 5.07% (Model 1) on the local market channel, when the game is concurrently broadcast on a national television channel. *MSAMinority* is negative and statistically insignificant in all models. This indicates that average rating is not systematically associated with the percentage of minority population in the local MSA, which produces evidence suggesting racial demographics in a MSA are not systematically related to viewership.

In terms of actual contest quality, *CoverDiff* is negative and statistically significant ($p < 0.01$) in all models. Specifically, the regression coefficient provides evidence that all else equal, the average rating is expected to rise by 0.50% (Model 1) as the absolute value of the difference between the closing line point spread and the final scoring margin decreases. In other words, viewership is expected to increase by 3.25% given a one standard deviation change in the final scoring margin relative to the pre-game market expectation in Model 1. Given that values closer to zero indicate the actual contest becomes more competitive than anticipated, this result suggests consumers are sensitive to outcome uncertainty in terms of the point spread, providing a support for the prediction of the UOH in the context of betting market outcome uncertainty. This is aligned with exiting work analyzing television viewership in college football (Salaga & Tainsky, 2015) and college basketball (Kang et al., 2018). *OUDiff* is positive and statistically significant ($p < 0.001$) across all models, illustrating viewership is greater in games where there is a larger difference between expected points set by the closing line over/under total and actual points scored.

In terms of temporal factors, this study also finds evidence that timing of the contest affects local market viewership. Positive and statistically significant coefficients of *Year* ($p < 0.01$) across all models illustrates that average local market rating for contests in 2014-2015 season relative to that in previous season is expected to increase by 4.60%, holding all else constant. Local market viewership appears to have “start of season” premium as the average rating is expected to be largest in the season-opening month (i.e., October) given that all regression coefficients for *Month* are negative and significant ($p < 0.01$). Interestingly, there appears to be a sharp drop of viewership for

NBA contests in last two months (*March* and *April*) of the regular season as the average rating is expected to decrease by 37.12% and 41.55%, respectively, in reference to the October baseline. Additionally, evidence suggests that viewership varies by day of the week and by the start time of the contest as ratings are expected to be lowest for games on Saturday relative to the Sunday game baseline and for contests broadcast prior to 6:00 PM (baseline of the category).

The modelling provides evidence that specific types of direct substitute programming has an impact on NBA local market television viewership. Particularly, local market ratings for NBA games suffer from a severe drop in viewership level when both NFL regular season and postseason contests (*NFLReg* and *NFLPost*) are concurrently broadcast against an NBA game. To illustrate, there exists a statistically significant viewership drop of 16.72% and 26.14%, respectively, when NFL regular season and postseason contests are televised alongside NBA programming, holding all else equal. Together with the result of *Month*, one possible explanation is that a time when NFL is heading into postseason play may play a substantial role in the reduction in NBA local market ratings. However, NCAA Football Bowl Subdivision (*NCAAFBReg* and *NCAAFBPost*) and MLB games (*MLB*) have no systematic association with NBA local market viewership.

Estimation Results – Customer Discrimination Specific to Individual Player Race

From the baseline models displayed in Table 4.4, this study finds evidence of the existence of potential customer discrimination in favor of minority players at the player level. Specifically, *NonWhite* and *Min_NonWhite* are positive and statistically significant ($p < 0.10$ and $p < 0.05$), suggesting that contests with two competing teams fielding more minority players are preferable to watch by local NBA fans. Additionally, Models 2 and 4 in Table 4.4 uncover evidence that the impact of minority players on local ratings is primarily attributable to minority players on the local team roster rather than those on the opposing team roster.

Due to the results noted above, I estimate an additional set of regressions using alternative specifications of the independent variables of interest in order to more thoroughly investigate the source of potential customer discrimination in favor of minority players by specific race, and Table 4.5 provides estimation results. To illustrate, *Black*, *Hispanic*, and *Others* are used in lieu of *NonWhite* in Model 5 while *Min_Black*, *Min_Hispanic*, and *Min_Others* are used in place of *Min_NonWhite* in Model 7. Then, Models 6 and 8 separate all the aforementioned variables into local and non-local team variables in order to examine customer discrimination based on player race specific to the local and non-local teams. All models contain the same control variables as previous models and the results specific to these variables are almost identical as those in Table 4.4. Thus, this section focuses exclusively on the interpretation of the independent variables of interest.

In reference to the White player baseline, the coefficients of *Black* and *Hispanic* are positive and statistically significant ($p < 0.05$ and $p < 0.01$), respectively. This indicates that after controlling for all other factors, the average local rating is expected to increase by 2.43% $[(\exp(0.024) - 1) \times 100 = 2.4290]$ and 3.98% $[(\exp(0.039) - 1) \times 100 = 3.9770]$ given a one standard deviation increase in the percentage of Black and Hispanic players on the two competing teams relative to White players, respectively. Likewise, *Min_Black* and *Min_Hispanic* in Model 7 are also positive and statistically significant ($p < 0.05$), showing that a one standard deviation increase in the percentage of Black and Hispanic players in terms of their actual playing minutes is associated with a 2.94% $[(\exp(0.029) - 1) \times 100 = 2.9425]$ and 3.15% $[(\exp(0.031) - 1) \times 100 = 3.1486]$ increase in the average local rating, respectively, holding all else equal. One standard deviation of *Min_Black* and *Min_Hispanic* refers to 42 minutes and slightly more than 21 minutes, respectively, given the 480 minutes of total playing time per game. The findings reveal that local NBA fans are particularly sensitive to the race of players since they have a significant interest in watching Black players which appears to be an even larger interest in watching Hispanic players in terms of sheer number of players and actual playing time when compared to the White baseline of each category.

Models 6 and 8 of Table 4.5 reveal that a negative effect of minority players from the non-local opposing team on the average local NBA ratings in Table 4.4 might be attributable to Black players. To illustrate, both the number of Black and Hispanic players on the local team roster (*BlackLo* and *HispanicLo*) and actual playing minutes (*Min_BlackLo* and *Min_HispanicLo*) are positive and statistically significant ($p < 0.01$). To put it differently, the average local viewership is expected to increase by 6.93% $[(\exp(0.067) - 1) \times 100 = 6.9295]$ and 4.92% $[(\exp(0.048) - 1) \times 100 = 4.9171]$ as the number of both Black and Hispanic players on the local team roster increase by one standard deviation, respectively. Similarly, an average local rating increase of 6.82% $[(\exp(0.066) - 1) \times 100 = 6.8227]$ and 3.56% $[(\exp(0.035) - 1) \times 100 = 3.5620]$ is expected as the actual playing minutes contributed by Black and Hispanic players on the local team increase by one standard deviation, respectively. However, both *BlackNLo* and *Min_BlackNLo* are negative and significant, signifying that the average local NBA rating is expected to decline by 3.05% [$(\exp(-0.031) - 1) \times 100 = -3.0524$] and 2.37% [$(\exp(-0.024) - 1) \times 100 = -2.3714$] for a one standard deviation increase in the sheer number of Black player and playing time contributed by Black player on the non-local team, respectively. Together, the findings suggest evidence that NBA local fans prefer to watch more Black and Hispanic players on the local team roster whereas they prefer to watch less Black players on the non-local team with respect to both the sheer number and actual playing minutes.

Estimation Results – Customer Discrimination Specific to Head Coach Race

Table 4.6 provides estimation results from the models assessing whether the race of team leaders (head coaches) has an impact on local market NBA television consumption. Accordingly, in Models 9 and 11, the variable of interest is *HCMinority*, which is an ordinal variable with a minimum of zero and a maximum of two, denoting the number of minority head coaches leading the two competing teams in a respective contest. Similar to the player-level analysis, in Models 10 and 12, this variable is divided to represent both the local and non-local team head coaches (*HCMinorLo* and *HCMinorNLo*), respectively.

Specifically, for this analysis, I include the various player race variables utilized in the previous models to control for the impact of player race on local viewership levels. In other words, all player race variables that are previously used in the player-level analysis for local and opposing teams with respect to the sheer number of players and actual playing minutes are included as control variables. Models 9 and 10 include the percentage of Black, Hispanic, and other race players for both local and non-local teams in reference to the White player baseline, while Models 11 and 12 contain the same variables, but with respect to actual playing minutes contributed by players of each race category. Additionally, all models also include *HCEloLo* and *HCEloNLo* as the race of head coaches is of particular interest in this analysis and these variables allow for the ability to assess whether customer racial preference specific to head coaches depends on the quality of the local and non-local teams.

Results in Table 4.6 provide evidence that the race of the head coaches directing the competing teams are a significant determinant of viewership after controlling for all other factors including variables specific to player race. Specifically, *HCMinority* in Models 9 and 11 is negative and statistically significant ($p < 0.01$). This indicates that for every minority head coach leading the two competing teams in a given contest, viewership is expected to decrease as the average local ratings drop by 67.99% $[(\exp(-1.139) - 1) \times 100 = -67.9861]$ and 67.40% $[(\exp(-1.121) - 1) \times 100 = -67.4046]$, respectively. Similar to the college basketball analyses in Chapter 3, this result provides evidence that NBA local fans are keenly aware of the racial background of head coaches and favor watching contests with fewer minority head coaches.

To assess where this negative impact of the race of head coaches on the average NBA local television rating primarily originates from, Models 10 and 12 include the racial information of the head coach leading the local and non-local teams, respectively. Both *HCMinorityLo* and *HCMinorityNLo* are negative and statistically significant ($p < 0.01$), signifying that while minority head coaches for both the local and non-local teams negatively influence the average local NBA rating for a given contest, a non-local minority head coach has a greater negative impact than a minority local-market head coach. To illustrate, the presence of minority head coach in local and non-local team is associated with 61.94% $[(\exp(-0.966) - 1) \times 100 = -61.9397]$ and 73.15% $[(\exp(-1.315) - 1) \times 100 = -73.1525]$ decrease in Model 10, and a 60.66% $[(\exp(-0.966) - 1) \times 100 = -60.6628]$ and 73.04% $[(\exp(-1.311) - 1) \times 100 = -73.0450]$ decrease in Model 12.

In these models, the variables controlling for player race have nearly the same magnitude and direction as those in Table 4.5. In other words, in these estimations, the results from previous estimations hold with respect to the impact of player race on average local viewership level. This finding along with the negative impact of the minority head coaches on local viewership level suggests that local NBA fans may have an opposing bias towards minority leaders given the hierarchical structure of sport organizations, as they seem to have a potential consumption bias against minorities in leadership positions, but not against minorities who compete as athletes in the contest itself.

Interestingly, this study finds evidence that the effect of individual team quality measured by Elo ratings on local television ratings is different based on the race of head coaches. To illustrate, both *HCEloLo* and *HCEloNLo* are positive and statistically significant ($p < 0.01$), indicating that the effect of individual team quality on the average local viewership is expected to increase by an additional 0.10% when both local and non-local teams are managed by minority head coaches, respectively. In other words, the results indicate that viewership increases when a minority head coach, relative to a White head coach, is leading a high-quality team, and the effect is consistent for both the local market and non-local market team given the similarity in the magnitude of the regression coefficients. This result opposes the result found in the college basketball analysis in Chapter 3.

Figure 4.1 Histogram of *Rating* and *Ln(Rating)*

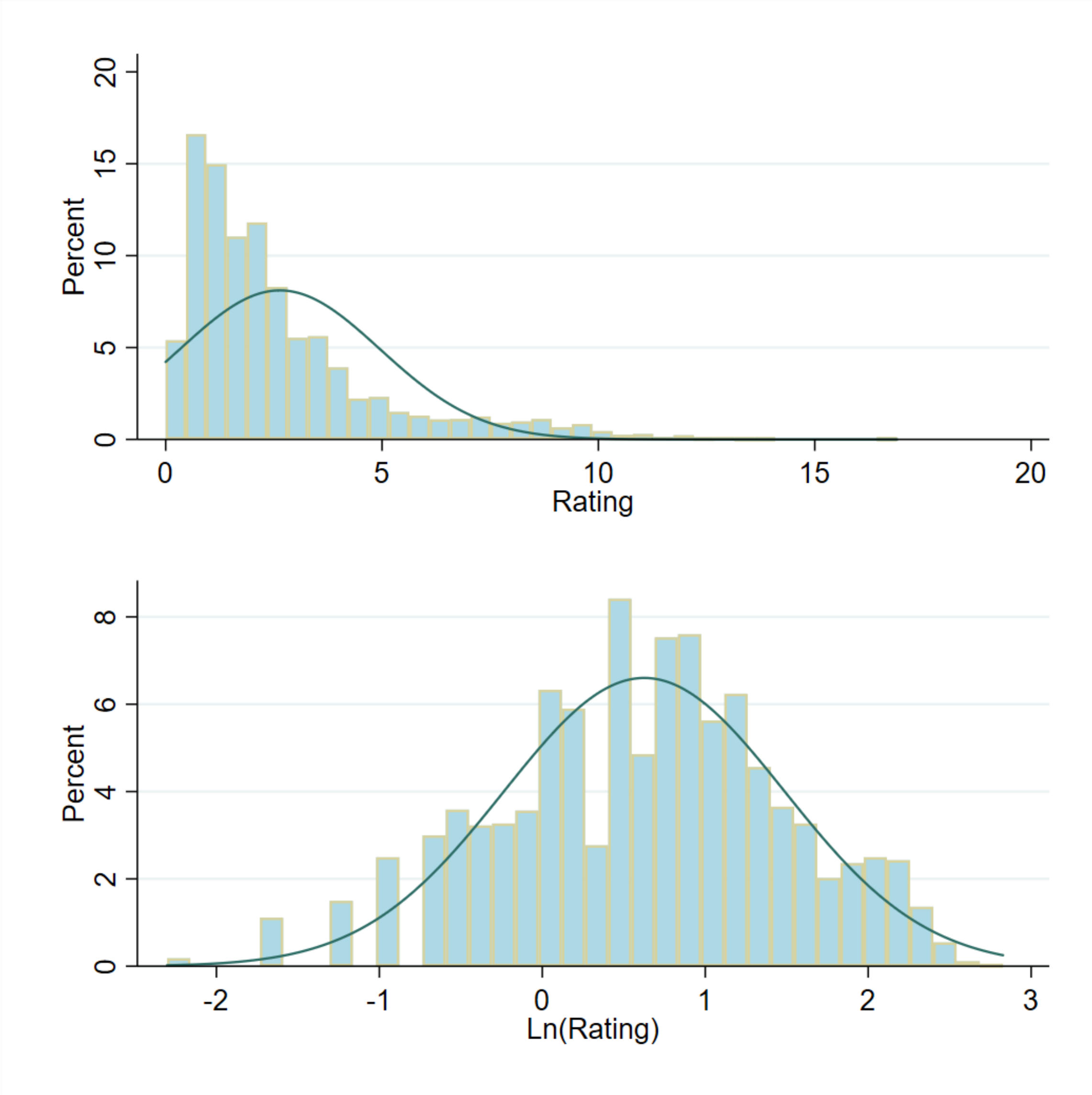

Table 4.1 Team Fixed Effects

Number	Team
1	Atlanta
2	Boston
3	Brooklyn
4	Charlotte
5	Chicago
6	Cleveland
7	Dallas
8	Denver
9	Detroit
10	Golden State
11	Houston
12	Indiana
13	L.A. Clippers
14	L.A. Lakers
15	Memphis
16	Miami
17	Milwaukee
18	Minnesota
19	New Orleans
20	New York
21	Oklahoma City
22	Orlando
23	Philadelphia
24	Phoenix
25	Portland
26	Sacramento
27	San Antonio
28	Toronto
29	Utah
30	Washington

Table 4.2 Description of Variables

Variable	Description
Dependent Variable	
Ln(Rating)	Logged local market television rating for a contest
Race (Independent Variables of Interest)	
NonWhite	Percentage of the number of minority players on team rosters
NonWhiteLo *NonWhiteNLo*	Percentage of the number of minority players on local and non-local team rosters
Black	Percentage of the number of Black players on team rosters
BlackLo *BlackNLo*	Percentage of the number of Black players on local and non-local team rosters
Hispanic	Percentage of the number of Hispanic players on team rosters
HispanicLo *HispanicNLo*	Percentage of the number of Hispanic players on local and non-local team rosters
White	Percentage of the number of White players on team rosters
WhiteLo *WhiteNLo*	Percentage of the number of White players on local and non-local team rosters
Others	Percentage of the number of players of other races on team rosters
OthersLo *OthersNLo*	Percentage of the number of players of other races on local and non-local team rosters
Min_NonWhite	Percentage of actual playing minutes contributed by minority players
Min_NonWhiteLo *Min_NonWhiteNLo*	Percentage of actual playing minutes contributed by minority players on local and non-local team rosters
Min_Black	Percentage of actual playing minutes contributed by Black players
Min_BlackLo *Min_BlackNLo*	Percentage of actual playing minutes contributed by Black players on local and non-local team rosters
Min_Hispanic	Percentage of actual playing minutes contributed by Hispanic players
Min_HispanicLo *Min_HispanicNLo*	Percentage of actual playing minutes contributed by Hispanic players on local and non-local team rosters
Min_White	Percentage of actual playing minutes contributed by White players
Min_WhiteLo *Min_WhiteNLo*	Percentage of actual playing minutes contributed by White players on local and non-local team rosters
Min_Others	Percentage of actual playing minutes contributed by players of other races
Min_OthersLo *Min_OthersNLo*	Percentage of actual playing minutes contributed by players of other races on local and non-local team rosters

HCMinority	Number of minority head coaches leading the competing teams
HCMinorityLo *HCMinorityNLo*	Number of minority head coach leading local and non-local teams
Anticipated Contest Quality	
ClosingLine	Anticipated outcome uncertainty (OU); absolute value of pre-game closing line point spread
ClosingOU	Anticipated scoring; pre-game closing line over/under total
CombinedWP	Anticipated absolute quality; average winning percentage of competing teams
LocalElo	Anticipated individual team quality for local team
NonLocalElo	Anticipated individual team quality for non-local team
DivisionGame	1 = intra-division game; 0 = otherwise
ConfGame	1 = intra-conference game; 0 = otherwise
NatlTV	1 = game concurrently broadcast nationally; 0 = otherwise
HCEloLo	Interaction term between minority head coach and Elo rating for local team
HCEloNLo	Interaction term between minority head coach and Elo rating for non-local team
Actual Contest Quality	
CoverDiff	Point spread market OU; absolute value of difference between final scoring margin and closing line point spread
OUDiff	Totals market OU; absolute value of difference between total points scored and closing line over/under total
Temporal Factors	
Year	1 = contest in 2014-15 season; 0 = otherwise
Month	1 = game played during specified month (*October* is baseline); 0 = otherwise
DayofWeek	1 = game played during specified day (*Sunday* is baseline); 0 = otherwise
StartTime	1 = game began in specified time window (*Before6PM* is baseline); 0 = otherwise
Substitutes	
NFLReg *NFLPost* *NCAAFBReg* *NCAAFBPost* *MLB*	1 = game concurrently broadcast to NFL regular season game, NFL post season game, NCAA Football Subdivision regular season game, NCAA Football Subdivision post season game, and MLB game; 0 = otherwise
Market Characteristics	

MSAMinority	Percentage of minority population in local MSA
Market Fixed Effects	

Table 4.3 Summary Statistics of Variables (N=4,403)

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Rating	2.6448	2.3098	0.1	16.9
Ln(Rating)	0.6260	0.8614	-2.3026	2.8273
NonWhite	0.7989	0.0723	0.5760	1
White	0.2009	0.0723	0	0.4230
Black	0.7536	0.0797	0.5000	0.9620
Hispanic	0.0379	0.0338	0	0.1600
Others	0.0075	0.0159	0	0.0800
NonWhiteLo	0.7992	0.1034	0.5000	1
WhiteLo	0.2007	0.1034	0	0.5000
BlackLo	0.7535	0.1137	0.4550	1
HispanicLo	0.0383	0.0485	0	0.1820
OthersLo	0.0075	0.0230	0	0.0910
NonWhiteNLo	0.7984	0.1051	0.5000	1
WhiteNLo	0.2016	0.1051	0	0.5000
BlackNLo	0.7534	0.1155	0.4550	1
HispanicNLo	0.0375	0.0483	0	0.1820
OthersNLo	0.0075	0.0230	0	0.0910
Min_NonWhite	0.8267	0.0734	0.5550	1
Min_White	0.1734	0.0734	0	0.4450
Min_Black	0.7751	0.0875	0.4080	0.9890
Min_Hispanic	0.0445	0.0450	0	0.2240
Min_Others	0.0070	0.0184	0	0.1270
Min_NonWhiteLo	0.8259	0.1044	0.3780	1
Min_WhiteLo	0.1742	0.1044	0	0.6220
Min_BlackLo	0.7732	0.1242	0.3230	1
Min_HispanicLo	0.0453	0.0641	0	0.2730
Min_OthersLo	0.0073	0.0271	0	0.1840

Min_NonWhiteNLo	0.8275	0.1049	0.3740	1
Min_WhiteNLo	0.1726	0.1049	0	0.6260
Min_BlackNLo	0.7770	0.1247	0.2930	1
Min_HispanicNLo	0.0437	0.0636	0	0.2940
Min_OthersNLo	0.0067	0.0256	0	0.1830
HCMinority	0.7097	0.6698	0	2
HCMinorLo	0.3586	0.4796	0	1
HCMinorNLo	0.3511	0.4774	0	1
ClosingLine	6.3474	3.7475	0	21.5
ClosingOU	200.3755	9.0216	175.5	229.5
CombinedWP	0.9824	0.2929	0	2
LocalElo	1502.9490	114.0392	1174.7010	1779.6460
NonLocalElo	1500.0070	114.0771	1175.4470	1787.6010
DivisionGame	0.1967	0.3975	0	1
ConfGame	0.6341	0.4817	0	1
NatlTV	0.1451	0.3523	0	1
MSAMinority	0.4706	0.1426	0.2490	0.7050
HCEloLo	527.0179	707.9638	0	1716.7340
HCEloNLo	515.9792	704.5422	0	1712.0120
CoverDiff	9.1384	7.3039	0	47
OUDiff	13.4916	10.8115	0	75
Year	0.4999	0.5001	0	1
October	0.0159	0.1251	0	1
November	0.1885	0.3912	0	1
December	0.1862	0.3893	0	1
January	0.1860	0.3892	0	1
February	0.1356	0.3424	0	1
March	0.1940	0.3954	0	1
April	0.0938	0.2916	0	1

Sunday	0.1161	0.3203	0	1
Monday	0.1379	0.3448	0	1
Tuesday	0.1124	0.3159	0	1
Wednesday	0.2262	0.4184	0	1
Thursday	0.0311	0.1736	0	1
Friday	0.2162	0.4117	0	1
Saturday	0.1601	0.3668	0	1
Before6PM	0.0120	0.1091	0	1
6PM	0.0400	0.1959	0	1
7PM	0.3797	0.4854	0	1
8PM	0.2803	0.4492	0	1
9PM	0.1172	0.3217	0	1
10PM	0.1460	0.3532	0	1
NFLReg	0.0995	0.2993	0	1
NFLPost	0.0273	0.1628	0	1
NCAAFBReg	0.1640	0.3703	0	1
NCAAFBPost	0.0793	0.2702	0	1
MLB	0.0425	0.2017	0	1

Table 4.4 Estimation Results – Customer Discrimination Specific to Player Race (White vs. Non-White)

	Model 1		Model 2		Model 3		Model 4	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
NonWhite	0.274*	1.773						
NonWhiteLo			0.571***	5.153				
NonWhiteNLo			-0.281***	-2.679				
Min_NonWhite					0.329**	2.180		
Min_NonWhiteLo							0.508***	4.730
Min_NonWhiteNLo							-0.179*	-1.716
ClosingLine	-0.005**	-2.036	-0.004*	-1.805	-0.004**	-1.961	-0.004*	-1.682
ClosingOU	0.002	1.208	0.002	1.357	0.002	1.224	0.002	1.311
CombinedWP	0.071	1.445	0.072	1.465	0.074	1.515	0.073	1.485
LocalElo	0.002***	12.635	0.002***	12.506	0.002***	12.626	0.002***	12.530
NonLocalElo	0.002***	14.012	0.002***	14.120	0.002***	14.007	0.002***	13.980
DivisionGame	0.033*	1.878	0.031*	1.758	0.033*	1.835	0.031*	1.726
ConfGame	0.036**	2.413	0.037**	2.438	0.037**	2.457	0.038**	2.539
NatlTV	-0.052**	-2.508	-0.053**	-2.513	-0.053**	-2.517	-0.053**	-2.532
MSAMinority	-0.183	-1.484	-0.156	-1.268	-0.184	-1.489	-0.180	-1.462
CoverDiff	-0.005***	-5.147	-0.005***	-5.044	-0.005***	-5.107	-0.004***	-4.949

OUDiff	0.002***	3.177	0.002***	3.121	0.002***	3.174	0.002***	3.220
Year	0.045***	3.398	0.045***	3.405	0.045***	3.414	0.044***	3.345
November	-0.269***	-2.700	-0.278***	-2.766	-0.272***	-2.741	-0.276***	-2.774
December	-0.332***	-3.334	-0.338***	-3.365	-0.337***	-3.397	-0.338***	-3.403
January	-0.300***	-2.970	-0.303***	-2.983	-0.304***	-3.022	-0.306***	-3.044
February	-0.364***	-3.596	-0.371***	-3.639	-0.367***	-3.652	-0.374***	-3.712
March	-0.464***	-4.572	-0.467***	-4.574	-0.466***	-4.621	-0.472***	-4.671
April	-0.537***	-5.458	-0.546***	-5.511	-0.538***	-5.507	-0.547***	-5.581
Monday	0.010	0.262	0.011	0.284	0.010	0.265	0.015	0.395
Tuesday	0.005	0.121	0.011	0.283	0.006	0.142	0.012	0.295
Wednesday	-0.073*	-1.899	-0.072*	-1.870	-0.072*	-1.878	-0.071*	-1.844
Thursday	-0.140**	-2.575	-0.144***	-2.620	-0.142***	-2.610	-0.140**	-2.550
Friday	-0.122***	-3.093	-0.118***	-2.994	-0.122***	-3.104	-0.119***	-3.012
Saturday	-0.174***	-4.375	-0.170***	-4.232	-0.175***	-4.400	-0.170***	-4.242
6PM	0.309***	5.200	0.306***	5.152	0.307***	5.188	0.303***	5.106
7PM	0.376***	7.327	0.376***	7.316	0.374***	7.292	0.372***	7.211
8PM	0.419***	7.438	0.415***	7.359	0.418***	7.426	0.410***	7.276
9PM	0.431***	6.696	0.432***	6.747	0.429***	6.688	0.424***	6.644
10PM	0.420***	5.833	0.413***	5.819	0.418***	5.819	0.409***	5.768

NFLReg	-0.183***	-5.380	-0.180***	-5.196	-0.182***	-5.355	-0.187***	-5.470
NFLPost	-0.303***	-6.115	-0.300***	-5.969	-0.301***	-6.095	-0.304***	-6.078
NCAAFBReg	0.033	0.936	0.034	0.977	0.034	0.970	0.033	0.956
NCAAFBPost	0.018	0.672	0.018	0.670	0.019	0.716	0.013	0.477
MLB	-0.052	-0.909	-0.045	-0.788	-0.052	-0.910	-0.046	-0.812
LocalMarket1	-0.091*	-1.667	-0.062	-1.127	-0.094*	-1.732	-0.065	-1.185
LocalMarket2	0.377***	7.494	0.404***	8.089	0.375***	7.470	0.393***	7.826
LocalMarket3	-0.390***	-6.474	-0.349***	-5.693	-0.389***	-6.503	-0.355***	-5.799
LocalMarket4	-0.249***	-4.347	-0.235***	-4.146	-0.247***	-4.317	-0.228***	-3.944
LocalMarket5	0.505***	7.869	0.568***	8.590	0.501***	7.877	0.544***	8.363
LocalMarket6	0.633***	11.617	0.684***	12.280	0.632***	11.679	0.668***	12.002
LocalMarket7	0.082	1.339	0.101*	1.647	0.084	1.384	0.121**	1.962
LocalMarket8	-0.172**	-2.285	-0.146*	-1.947	-0.171**	-2.277	-0.149**	-1.981
LocalMarket9	0.218***	4.253	0.249***	4.885	0.214***	4.202	0.232***	4.535
LocalMarket10	0.148*	1.746	0.187**	2.219	0.146*	1.728	0.179**	2.115
LocalMarket11	-0.161**	-2.392	-0.122*	-1.812	-0.163**	-2.428	-0.124*	-1.848
LocalMarket12	0.347***	6.092	0.353***	6.187	0.342***	5.994	0.339***	5.932
LocalMarket13	-0.361***	-4.316	-0.336***	-4.068	-0.365***	-4.392	-0.343***	-4.141
LocalMarket14	0.266***	3.318	0.282***	3.567	0.265***	3.328	0.281***	3.552

LocalMarket15	0.261***	3.975	0.327***	4.853	0.256***	3.938	0.299***	4.530
LocalMarket16	0.713***	11.909	0.738***	12.251	0.711***	11.922	0.729***	12.076
LocalMarket17	-0.010	-0.151	0.042	0.625	-0.010	-0.156	0.024	0.358
LocalMarket18	0.084	1.269	0.134**	2.020	0.081	1.238	0.124*	1.856
LocalMarket19	0.099	1.553	0.168***	2.584	0.089	1.421	0.133**	2.082
LocalMarket20	0.299***	5.256	0.343***	6.050	0.297***	5.229	0.326***	5.716
LocalMarket21	0.642***	9.545	0.664***	9.814	0.637***	9.481	0.653***	9.583
LocalMarket22	0.016	0.302	0.028	0.536	0.018	0.345	0.039	0.735
LocalMarket23	-	-	-	-	-	-	-	-
LocalMarket24	0.079	1.072	0.125*	1.719	0.076	1.043	0.121*	1.657
LocalMarket25	0.379***	4.667	0.422***	5.227	0.374***	4.621	0.403***	4.993
LocalMarket26	0.229***	3.158	0.257***	3.563	0.225***	3.107	0.243***	3.375
LocalMarket27	0.530***	7.572	0.584***	8.209	0.526***	7.574	0.563***	8.012
LocalMarket28	-0.136	-1.592	-0.109	-1.261	-0.142*	-1.655	-0.122	-1.416
LocalMarket29	0.442***	6.267	0.485***	6.825	0.447***	6.348	0.492***	6.887
LocalMarket30	-0.219***	-4.109	-0.210***	-3.957	-0.218***	-4.086	-0.199***	-3.714
NLocalMarket1	-0.131*	-1.726	-0.132*	-1.720	-0.128*	-1.684	-0.137*	-1.791
NLocalMarket2	0.233***	2.970	0.249***	3.131	0.235***	3.013	0.240***	3.051
NLocalMarket3	-0.482***	-5.973	-0.495***	-6.105	-0.479***	-5.951	-0.494***	-6.122

NLocalMarket4	-0.268***	-3.420	-0.242***	-3.053	-0.264***	-3.370	-0.257***	-3.263
NLocalMarket5	0.464***	5.753	0.439***	5.406	0.467***	5.797	0.446***	5.497
NLocalMarket6	0.707***	8.805	0.693***	8.563	0.707***	8.820	0.694***	8.605
NLocalMarket7	0.011	0.152	0.018	0.245	0.020	0.268	0.011	0.148
NLocalMarket8	-0.166**	-2.086	-0.154*	-1.912	-0.165**	-2.075	-0.161**	-2.019
NLocalMarket9	0.125	1.574	0.130	1.629	0.124	1.563	0.127	1.599
NLocalMarket10	0.096	1.254	0.077	1.000	0.097	1.273	0.085	1.114
NLocalMarket11	-0.278***	-3.461	-0.289***	-3.528	-0.275***	-3.444	-0.288***	-3.551
NLocalMarket12	0.327***	4.203	0.353***	4.487	0.325***	4.200	0.347***	4.448
NLocalMarket13	-0.457***	-5.589	-0.463***	-5.601	-0.455***	-5.590	-0.459***	-5.599
NLocalMarket14	0.307***	3.845	0.315***	3.931	0.307***	3.863	0.313***	3.906
NLocalMarket15	0.207***	2.627	0.188**	2.371	0.205***	2.620	0.195**	2.471
NLocalMarket16	0.677***	8.642	0.678***	8.585	0.677***	8.659	0.677***	8.623
NLocalMarket17	-0.039	-0.473	-0.051	-0.606	-0.040	-0.478	-0.056	-0.661
NLocalMarket18	0.002	0.023	-0.009	-0.105	0.005	0.066	-0.016	-0.196
NLocalMarket19	0.084	1.067	0.057	0.712	0.082	1.044	0.066	0.836
NLocalMarket20	0.226***	2.903	0.217***	2.770	0.229***	2.947	0.217***	2.772
NLocalMarket21	0.586***	7.374	0.598***	7.473	0.589***	7.431	0.596***	7.449
NLocalMarket22	-0.094	-1.148	-0.073	-0.875	-0.091	-1.111	-0.086	-1.044

NLocalMarket23	-0.077	-0.931	-0.053	-0.625	-0.077	-0.934	-0.070	-0.841
NLocalMarket24	0.096	1.284	0.078	1.031	0.097	1.300	0.083	1.103
NLocalMarket25	0.281***	3.711	0.281***	3.673	0.278***	3.682	0.282***	3.702
NLocalMarket26	0.262***	3.384	0.276***	3.513	0.261***	3.385	0.268***	3.450
NLocalMarket27	0.555***	6.925	0.528***	6.490	0.558***	6.979	0.542***	6.713
NLocalMarket28	-	-	-	-	-	-	-	-
NLocalMarket29	0.443***	5.589	0.438***	5.479	0.452***	5.690	0.432***	5.397
NLocalMarket30	-0.338***	-3.995	-0.322***	-3.796	-0.332***	-3.938	-0.331***	-3.914
Constant	-5.474***	-12.687	-5.592***	-12.784	-5.528***	-12.765	-5.561***	-12.677
N	4403		4403		4403		4403	
R-squared	0.4229		0.4277		0.4232		0.4263	

Note 1. Ordinary least squares with robust standard errors.
Note 2. Values listed as 0.000 are larger than zero.
** p<0.10, ** p<0.05, *** p<0.01*

Table 4.5 Estimation Results – Customer Discrimination Specific to Individual Player Race

	Model 5		Model 6		Model 7		Model 8	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Black	0.305**	1.962						
Hispanic	1.164***	3.190						
Others	0.209	0.273						
BlackLo			0.588***	5.268				
HispanicLo			0.984***	3.784				
OthersLo			0.472	0.919				
BlackNLo			-0.267**	-2.501				
HispanicNLo			0.172	0.663				
OthersNLo			-0.255	-0.506				
Min_Black					0.336**	2.226		
Min_Hispanic					0.682**	2.365		
Min_Others					0.058	0.089		
Min_BlackLo							0.529***	4.919
Min_HispanicLo							0.542***	2.621
Min_OthersLo							-0.384	-0.910
Min_BlackNLo							-0.189*	-1.803

Min_HispanicNLo							0.136	0.666
Min_OthersNLo							0.591	1.334
ClosingLine	-0.005**	-2.020	-0.004*	-1.772	-0.004*	-1.925	-0.003	-1.533
ClosingOU	0.001	1.067	0.002	1.213	0.001	1.153	0.002	1.202
CombinedWP	0.071	1.455	0.072	1.472	0.074	1.508	0.073	1.470
LocalElo	0.002***	12.531	0.002***	12.400	0.002***	12.583	0.002***	12.395
NonLocalElo	0.002***	13.774	0.002***	13.874	0.002***	13.909	0.002***	14.060
DivisionGame	0.034*	1.919	0.032*	1.801	0.032*	1.822	0.032*	1.806
ConfGame	0.035**	2.334	0.035**	2.356	0.036**	2.440	0.037**	2.485
NatlTV	-0.049**	-2.378	-0.051**	-2.386	-0.051**	-2.429	-0.052**	-2.497
MSAMinority	-0.181	-1.462	-0.155	-1.253	-0.183	-1.479	-0.190	-1.534
CoverDiff	-0.005***	-5.053	-0.004***	-4.943	-0.004***	-5.036	-0.004***	-4.938
OUDiff	0.002***	3.073	0.002***	3.020	0.002***	3.111	0.002***	3.114
Year	0.045***	3.428	0.045***	3.434	0.045***	3.428	0.044***	3.364
November	-0.273***	-2.756	-0.282***	-2.821	-0.272***	-2.755	-0.281***	-2.823
December	-0.332***	-3.347	-0.338***	-3.380	-0.335***	-3.394	-0.342***	-3.449
January	-0.297***	-2.960	-0.301***	-2.974	-0.301***	-3.000	-0.308***	-3.065
February	-0.363***	-3.601	-0.370***	-3.644	-0.366***	-3.648	-0.378***	-3.748
March	-0.461***	-4.567	-0.465***	-4.571	-0.463***	-4.605	-0.473***	-4.688

April	-0.535***	-5.469	-0.544***	-5.521	-0.535***	-5.492	-0.546***	-5.578
Monday	0.010	0.261	0.010	0.276	0.010	0.265	0.014	0.368
Tuesday	0.004	0.111	0.011	0.265	0.005	0.125	0.007	0.186
Wednesday	-0.074*	-1.926	-0.074*	-1.904	-0.073*	-1.903	-0.076**	-1.978
Thursday	-0.141***	-2.606	-0.145***	-2.653	-0.142***	-2.613	-0.140**	-2.555
Friday	-0.121***	-3.096	-0.118***	-3.004	-0.122***	-3.120	-0.122***	-3.114
Saturday	-0.173***	-4.360	-0.169***	-4.222	-0.175***	-4.407	-0.172***	-4.299
6PM	0.313***	5.226	0.308***	5.152	0.306***	5.154	0.293***	4.933
7PM	0.377***	7.322	0.377***	7.298	0.373***	7.256	0.365***	7.061
8PM	0.421***	7.451	0.416***	7.362	0.418***	7.419	0.406***	7.185
9PM	0.432***	6.698	0.433***	6.734	0.429***	6.687	0.417***	6.522
10PM	0.423***	5.850	0.415***	5.829	0.419***	5.832	0.406***	5.694
NFLReg	-0.182***	-5.384	-0.179***	-5.207	-0.181***	-5.352	-0.189***	-5.557
NFLPost	-0.303***	-6.133	-0.301***	-6.006	-0.301***	-6.105	-0.307***	-6.165
NCAAFBReg	0.033	0.962	0.035	0.998	0.034	0.990	0.033	0.952
NCAAFBPost	0.021	0.786	0.022	0.794	0.021	0.763	0.018	0.660
MLB	-0.053	-0.945	-0.047	-0.827	-0.053	-0.939	-0.052	-0.920
LocalMarket1	-0.097*	-1.768	-0.066	-1.201	-0.096*	-1.766	-0.054	-0.976
LocalMarket2	0.374***	7.457	0.402***	8.061	0.375***	7.475	0.396***	7.908

LocalMarket3	-0.397***	-6.583	-0.355***	-5.757	-0.392***	-6.539	-0.344***	-5.569
LocalMarket4	-0.246***	-4.247	-0.232***	-3.991	-0.244***	-4.222	-0.212***	-3.614
LocalMarket5	0.501***	7.807	0.565***	8.551	0.498***	7.800	0.550***	8.410
LocalMarket6	0.625***	11.476	0.677***	12.119	0.628***	11.567	0.674***	12.025
LocalMarket7	0.068	1.117	0.090	1.448	0.079	1.297	0.129**	2.074
LocalMarket8	-0.169**	-2.269	-0.144*	-1.931	-0.171**	-2.281	-0.147*	-1.957
LocalMarket9	0.217***	4.241	0.249***	4.879	0.218***	4.275	0.241***	4.705
LocalMarket10	0.156*	1.838	0.195**	2.313	0.149*	1.769	0.186**	2.199
LocalMarket11	-0.173**	-2.555	-0.131*	-1.911	-0.164**	-2.429	-0.089	-1.293
LocalMarket12	0.335***	5.828	0.343***	5.923	0.338***	5.896	0.346***	6.012
LocalMarket13	-0.352***	-4.196	-0.326***	-3.950	-0.362***	-4.357	-0.333***	-4.048
LocalMarket14	0.261***	3.228	0.280***	3.495	0.265***	3.309	0.308***	3.845
LocalMarket15	0.255***	3.885	0.322***	4.775	0.249***	3.807	0.304***	4.545
LocalMarket16	0.715***	12.026	0.740***	12.347	0.714***	11.998	0.731***	12.135
LocalMarket17	-0.009	-0.141	0.043	0.634	-0.010	-0.154	0.020	0.304
LocalMarket18	0.072	1.095	0.123*	1.871	0.074	1.126	0.124*	1.855
LocalMarket19	0.101	1.605	0.171***	2.645	0.090	1.442	0.140**	2.205
LocalMarket20	0.285***	5.065	0.331***	5.841	0.291***	5.111	0.327***	5.678
LocalMarket21	0.654***	9.489	0.677***	9.605	0.647***	9.444	0.693***	9.846

LocalMarket22	0.016	0.314	0.029	0.554	0.020	0.375	0.045	0.852
LocalMarket23	-	-	-	-	-	-	-	-
LocalMarket24	0.087	1.183	0.133*	1.832	0.078	1.079	0.129*	1.763
LocalMarket25	0.365***	4.490	0.410***	5.059	0.366***	4.513	0.403***	4.967
LocalMarket26	0.230***	3.158	0.257***	3.570	0.225***	3.105	0.245***	3.408
LocalMarket27	0.524***	7.499	0.580***	8.141	0.523***	7.537	0.573***	8.115
LocalMarket28	-0.148*	-1.736	-0.120	-1.392	-0.149*	-1.744	-0.121	-1.402
LocalMarket29	0.446***	6.331	0.489***	6.895	0.448***	6.370	0.497***	6.974
LocalMarket30	-0.225***	-4.215	-0.216***	-4.057	-0.222***	-4.134	-0.199***	-3.676
NLocalMarket1	-0.137*	-1.792	-0.138*	-1.783	-0.132*	-1.732	-0.143*	-1.863
NLocalMarket2	0.236***	2.988	0.252***	3.150	0.237***	3.032	0.246***	3.116
NLocalMarket3	-0.489***	-6.024	-0.502***	-6.143	-0.483***	-5.987	-0.496***	-6.107
NLocalMarket4	-0.261***	-3.317	-0.236***	-2.956	-0.259***	-3.313	-0.258***	-3.260
NLocalMarket5	0.465***	5.738	0.440***	5.388	0.464***	5.750	0.438***	5.387
NLocalMarket6	0.705***	8.694	0.691***	8.455	0.704***	8.745	0.692***	8.519
NLocalMarket7	-0.001	-0.014	0.006	0.081	0.014	0.191	0.000	0.000
NLocalMarket8	-0.160**	-1.996	-0.148*	-1.820	-0.163**	-2.050	-0.155*	-1.943
NLocalMarket9	0.126	1.570	0.130	1.622	0.127	1.597	0.137*	1.719
NLocalMarket10	0.111	1.436	0.093	1.189	0.104	1.356	0.094	1.217

NLocalMarket11	-0.285***	-3.529	-0.298***	-3.578	-0.276***	-3.438	-0.321***	-3.853
NLocalMarket12	0.317***	4.054	0.342***	4.310	0.322***	4.144	0.334***	4.243
NLocalMarket13	-0.446***	-5.425	-0.451***	-5.423	-0.451***	-5.532	-0.452***	-5.498
NLocalMarket14	0.305***	3.806	0.313***	3.856	0.309***	3.864	0.294***	3.637
NLocalMarket15	0.203**	2.560	0.184**	2.304	0.199**	2.524	0.183**	2.295
NLocalMarket16	0.684***	8.674	0.686***	8.606	0.681***	8.689	0.688***	8.727
NLocalMarket17	-0.034	-0.402	-0.045	-0.534	-0.038	-0.462	-0.049	-0.583
NLocalMarket18	-0.009	-0.107	-0.020	-0.238	-0.000	-0.006	-0.031	-0.373
NLocalMarket19	0.093	1.172	0.066	0.821	0.085	1.078	0.076	0.956
NLocalMarket20	0.213***	2.711	0.204***	2.579	0.222***	2.848	0.213***	2.697
NLocalMarket21	0.601***	7.553	0.611***	7.552	0.601***	7.568	0.576***	7.062
NLocalMarket22	-0.090	-1.090	-0.068	-0.816	-0.090	-1.091	-0.078	-0.947
NLocalMarket23	-0.076	-0.914	-0.051	-0.603	-0.078	-0.941	-0.065	-0.772
NLocalMarket24	0.108	1.437	0.090	1.188	0.102	1.364	0.092	1.223
NLocalMarket25	0.273***	3.581	0.273***	3.531	0.273***	3.601	0.270***	3.518
NLocalMarket26	0.268***	3.436	0.282***	3.563	0.263***	3.405	0.276***	3.544
NLocalMarket27	0.556***	6.904	0.529***	6.468	0.558***	6.974	0.538***	6.629
NLocalMarket28	-	-	-	-	-	-	-	-
NLocalMarket29	0.450***	5.649	0.446***	5.530	0.455***	5.714	0.440***	5.476

NLocalMarket30	-0.339***	-3.988	-0.322***	-3.773	-0.335***	-3.968	-0.333***	-3.909
Constant	-5.421***	-12.572	-5.538***	-12.660	-5.495***	-12.695	-5.535***	-12.602
N	4403		4403		4403		4403	
R-squared	0.4239		0.4286		0.4235		0.4279	

Note 1. Ordinary least squares with robust standard errors.
Note 2. Values listed as 0.000 are larger than zero.
** p<0.10, ** p<0.05, *** p<0.01*

Table 4.6 Estimation Results – Customer Discrimination Specific to Head Coach Race

	Model 9		Model 10		Model 11		Model 12	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
HCMinority	-1.139***	-5.222			-1.121***	-5.173		
HCMinorLo			-0.966***	-3.178			-0.933***	-3.069
HCMinorNLo			-1.315***	-4.361			-1.311***	-4.389
BlackLo	0.577***	5.172	0.578***	5.179				
HispanicLo	0.980***	3.770	0.980***	3.771				
OthersLo	0.629	1.223	0.623	1.213				
BlackNLo	-0.278***	-2.604	-0.278***	-2.608				
HispanicNLo	0.175	0.674	0.173	0.671				
OthersNLo	-0.137	-0.271	-0.135	-0.267				
Min_BlackLo					0.518***	4.831	0.519***	4.840
Min_HispanicLo					0.534***	2.592	0.535***	2.595
Min_OthersLo					-0.276	-0.653	-0.275	-0.651
Min_BlackNLo					-0.193*	-1.855	-0.194*	-1.861
Min_HispanicNLo					0.138	0.679	0.138	0.677
Min_OthersNLo					0.677	1.525	0.675	1.522
ClosingLine	-0.003	-1.415	-0.003	-1.420	-0.003	-1.176	-0.003	-1.181

ClosingOU	0.001	0.871	0.001	0.892	0.001	0.868	0.001	0.891
CombinedWP	0.080	1.628	0.079	1.613	0.080	1.640	0.080	1.624
LocalElo	0.001***	8.943	0.001***	8.864	0.001***	9.016	0.001***	8.960
NonLocalElo	0.002***	10.985	0.002***	10.122	0.002***	11.218	0.002***	10.320
DivisionGame	0.032*	1.809	0.032*	1.814	0.031*	1.805	0.032*	1.809
ConfGame	0.035**	2.354	0.035**	2.361	0.037**	2.478	0.037**	2.485
NatlTV	-0.053**	-2.505	-0.053**	-2.511	-0.055***	-2.617	-0.055***	-2.625
MSAMinority	-0.156	-1.257	-0.156	-1.256	-0.190	-1.535	-0.190	-1.534
HCEloLo	0.001***	4.568	0.001***	2.743	0.001***	4.546	0.001***	2.653
HCEloNLo	0.001***	4.752	0.001***	4.049	0.001***	4.703	0.001***	4.077
CoverDiff	-0.004***	-4.989	-0.004***	-4.993	-0.004***	-4.990	-0.004***	-4.994
OUDiff	0.002***	3.185	0.002***	3.190	0.002***	3.273	0.002***	3.279
Year	0.034**	2.285	0.034**	2.297	0.033**	2.270	0.034**	2.284
November	-0.270***	-2.760	-0.271***	-2.759	-0.269***	-2.759	-0.269***	-2.759
December	-0.321***	-3.280	-0.321***	-3.283	-0.325***	-3.344	-0.326***	-3.347
January	-0.281***	-2.843	-0.282***	-2.849	-0.288***	-2.931	-0.289***	-2.938
February	-0.345***	-3.478	-0.346***	-3.481	-0.353***	-3.581	-0.354***	-3.583
March	-0.447***	-4.499	-0.448***	-4.502	-0.455***	-4.613	-0.456***	-4.617
April	-0.532***	-5.533	-0.533***	-5.534	-0.534***	-5.586	-0.535***	-5.589

Monday	0.009	0.249	0.008	0.219	0.013	0.339	0.011	0.307
Tuesday	0.002	0.050	0.001	0.036	-0.001	-0.033	-0.002	-0.047
Wednesday	-0.078**	-2.046	-0.079**	-2.074	-0.081**	-2.119	-0.082**	-2.149
Thursday	-0.141***	-2.605	-0.141***	-2.613	-0.136**	-2.508	-0.136**	-2.517
Friday	-0.124***	-3.185	-0.124***	-3.203	-0.127***	-3.293	-0.128***	-3.312
Saturday	-0.172***	-4.350	-0.172***	-4.363	-0.174***	-4.428	-0.174***	-4.443
6PM	0.301***	5.167	0.300***	5.145	0.286***	4.949	0.285***	4.926
7PM	0.368***	7.302	0.368***	7.307	0.357***	7.061	0.357***	7.066
8PM	0.408***	7.324	0.407***	7.298	0.398***	7.143	0.397***	7.116
9PM	0.423***	6.584	0.423***	6.567	0.408***	6.380	0.407***	6.362
10PM	0.403***	5.655	0.402***	5.640	0.393***	5.533	0.393***	5.518
NFLReg	-0.186***	-5.492	-0.186***	-5.506	-0.195***	-5.840	-0.196***	-5.856
NFLPost	-0.309***	-6.299	-0.309***	-6.310	-0.315***	-6.455	-0.315***	-6.470
NCAAFBReg	0.029	0.874	0.029	0.866	0.028	0.824	0.027	0.816
NCAAFBPost	0.021	0.790	0.020	0.752	0.018	0.663	0.016	0.620
MLB	-0.038	-0.680	-0.040	-0.709	-0.043	-0.771	-0.045	-0.801
LocalMarket1	0.010	0.183	0.001	0.011	0.020	0.357	0.010	0.171
LocalMarket2	0.441***	8.853	0.436***	8.779	0.434***	8.669	0.429***	8.589
LocalMarket3	-0.194***	-2.781	-0.197***	-2.840	-0.190***	-2.726	-0.193***	-2.789

LocalMarket4	-0.194***	-3.378	-0.200***	-3.488	-0.174***	-2.982	-0.180***	-3.097
LocalMarket5	0.641***	9.587	0.632***	9.466	0.625***	9.409	0.616***	9.282
LocalMarket6	0.817***	14.249	0.807***	13.840	0.809***	14.020	0.798***	13.630
LocalMarket7	0.182***	2.851	0.171***	2.670	0.218***	3.396	0.207***	3.203
LocalMarket8	0.025	0.306	0.021	0.262	0.014	0.169	0.010	0.123
LocalMarket9	0.331***	6.284	0.325***	6.165	0.320***	6.068	0.313***	5.945
LocalMarket10	0.330***	3.765	0.325***	3.716	0.314***	3.588	0.309***	3.537
LocalMarket11	-0.032	-0.458	-0.044	-0.616	0.007	0.106	-0.005	-0.071
LocalMarket12	0.423***	7.274	0.414***	7.077	0.426***	7.332	0.415***	7.117
LocalMarket13	-0.222**	-2.393	-0.213**	-2.267	-0.238***	-2.578	-0.228**	-2.436
LocalMarket14	0.414***	5.035	0.406***	4.907	0.438***	5.310	0.429***	5.175
LocalMarket15	0.417***	6.047	0.407***	5.885	0.396***	5.791	0.385***	5.625
LocalMarket16	0.874***	12.281	0.879***	12.322	0.857***	11.967	0.862***	12.004
LocalMarket17	0.174***	2.617	0.164**	2.459	0.148**	2.231	0.137**	2.063
LocalMarket18	0.174***	2.628	0.169**	2.555	0.174***	2.586	0.168**	2.508
LocalMarket19	0.337***	4.679	0.334***	4.642	0.299***	4.193	0.296***	4.152
LocalMarket20	0.516***	8.076	0.507***	7.947	0.503***	7.775	0.494***	7.663
LocalMarket21	0.780***	10.871	0.768***	10.627	0.794***	11.035	0.781***	10.760
LocalMarket22	0.248***	4.096	0.233***	3.693	0.255***	4.195	0.239***	3.778

LocalMarket23	-	-	-	-	-	-	-	-
LocalMarket24	0.205***	2.793	0.195***	2.635	0.198***	2.693	0.187**	2.528
LocalMarket25	0.512***	6.260	0.500***	6.075	0.502***	6.131	0.489***	5.942
LocalMarket26	0.330***	4.626	0.324***	4.543	0.316***	4.441	0.310***	4.354
LocalMarket27	0.704***	9.578	0.690***	9.273	0.695***	9.501	0.680***	9.189
LocalMarket28	0.012	0.126	0.014	0.154	0.003	0.029	0.006	0.060
LocalMarket29	0.603***	8.385	0.597***	8.263	0.607***	8.401	0.600***	8.278
LocalMarket30	-0.144***	-2.668	-0.152***	-2.823	-0.129**	-2.348	-0.138**	-2.515
NLocalMarket1	-0.156*	-1.822	-0.144*	-1.649	-0.161*	-1.896	-0.148*	-1.709
NLocalMarket2	0.196**	2.208	0.204**	2.290	0.191**	2.173	0.199**	2.263
NLocalMarket3	-0.462***	-5.604	-0.457***	-5.518	-0.456***	-5.572	-0.450***	-5.481
NLocalMarket4	-0.292***	-3.312	-0.283***	-3.185	-0.312***	-3.568	-0.302***	-3.428
NLocalMarket5	0.422***	4.754	0.435***	4.817	0.421***	4.748	0.435***	4.825
NLocalMarket6	0.719***	8.430	0.732***	8.449	0.720***	8.486	0.735***	8.528
NLocalMarket7	0.003	0.036	0.017	0.195	-0.004	-0.043	0.011	0.133
NLocalMarket8	-0.108	-1.317	-0.103	-1.247	-0.117	-1.448	-0.111	-1.370
NLocalMarket9	0.107	1.244	0.115	1.328	0.114	1.331	0.123	1.423
NLocalMarket10	0.103	1.295	0.110	1.370	0.104	1.316	0.111	1.400
NLocalMarket11	-0.291***	-3.185	-0.276***	-2.973	-0.315***	-3.430	-0.299***	-3.199

NLocalMarket12	0.322***	3.686	0.335***	3.784	0.315***	3.630	0.329***	3.746
NLocalMarket13	-0.473***	-5.569	-0.481***	-5.641	-0.474***	-5.647	-0.483***	-5.725
NLocalMarket14	0.332***	3.884	0.342***	3.953	0.313***	3.682	0.325***	3.766
NLocalMarket15	0.179**	2.041	0.194**	2.165	0.178**	2.031	0.194**	2.170
NLocalMarket16	0.681***	8.463	0.680***	8.428	0.683***	8.566	0.681***	8.526
NLocalMarket17	-0.023	-0.256	-0.009	-0.100	-0.027	-0.306	-0.012	-0.135
NLocalMarket18	-0.061	-0.670	-0.051	-0.564	-0.071	-0.786	-0.061	-0.670
NLocalMarket19	0.108	1.332	0.115	1.398	0.118	1.459	0.125	1.531
NLocalMarket20	0.275***	3.354	0.288***	3.457	0.282***	3.454	0.296***	3.572
NLocalMarket21	0.622***	6.958	0.638***	7.017	0.588***	6.506	0.605***	6.587
NLocalMarket22	0.027	0.309	0.045	0.500	0.015	0.168	0.034	0.383
NLocalMarket23	-0.144	-1.550	-0.142	-1.520	-0.157*	-1.701	-0.154*	-1.668
NLocalMarket24	0.072	0.856	0.084	0.986	0.074	0.888	0.087	1.032
NLocalMarket25	0.275***	3.209	0.289***	3.323	0.271***	3.193	0.287***	3.325
NLocalMarket26	0.247***	2.901	0.256***	2.983	0.243***	2.880	0.252***	2.973
NLocalMarket27	0.550***	6.105	0.568***	6.153	0.559***	6.236	0.578***	6.300
NLocalMarket28	-	-	-	-	-	-	-	-
NLocalMarket29	0.446***	5.233	0.456***	5.311	0.440***	5.186	0.451***	5.277
NLocalMarket30	-0.348***	-3.789	-0.337***	-3.604	-0.359***	-3.913	-0.346***	-3.717

Constant	-4.483***	-9.803	-4.495***	-9.838	-4.507***	-9.835	-4.521***	-9.867
N	4403		4403		4403		4403	
R-squared	0.4318		0.4318		0.4309		0.4309	

Note 1. Ordinary least squares with robust standard errors.
Note 2. Values listed as 0.000 are larger than zero.
** p<0.10, ** p<0.05, *** p<0.01*

CHAPTER 5

DISCUSSION AND CONCLUSION

This dissertation uses television viewership figures to empirically assess the potential existence of customer discrimination in the context of collegiate and professional basketball. Particularly, this dissertation examines customer discrimination in two dimensions, given the hierarchical nature of sport team organizations. To illustrate, this dissertation assesses the impact of the race of key actors (i.e., players and head coaches) on television viewership in both settings. At the player-level analysis, this study builds on Kanazawa and Funk (2001) by utilizing two series of variables for player race with respect to both the sheer number of roster players by race (RQ1) and actual playing minutes by race (RQ2). At the managerial-level analysis, this study investigates how the race of head coaches influences television viewership (RQ3) given that they are assumed to be comparable to chief executive officers (e.g., Foreman & Soebbing, 2015; Ndofor et al., 2009) since they hold a prominent and significant leadership role in team sports (Nesseler et al., 2020). Additionally, based on the hypothesis that audience composition may vary between different quality levels of competition within the same sport (product) context, this study examines customer discrimination in both college (Chapter 3) and professional (Chapter 4) basketball over the same time period to determine whether basketball fans display distinctive (or comparable) patterns of discriminatory preferences.

In this chapter, the select findings from the regression analyses in collegiate and professional basketball regarding customer discrimination based on the race of key personnel (i.e., players and head coaches) that are pertinent to the research questions will be reviewed.

Theoretical contributions to the existing literature, practical implications, and limitations of this dissertation will follow, with the concluding remarks and directions for future research in the final section.

Discussion of Findings

Customer Discrimination Specific to Player Race (RQ1 and RQ2)

Chapters 3 and 4 empirically test for the presence of customer discrimination using television viewership data. In order to assess if the racial makeup of players on the team rosters and the actual playing minutes contributed by race are systematically associated with viewership level, this dissertation integrates game-level participation data with national (NCAAB) and local market (NBA) television viewership data. Thus, explanation of these findings is detailed in the sections that follow, with a particular emphasis on customer discrimination.

After controlling for a number of factors related to contest quality and characteristics, the results indicate evidence of customer preference in favor of minority players both in collegiate and professional basketball. In terms of the sheer number of roster players by race (RQ1) and the actual playing time by race (RQ2), *NonWhite* and *Min_NonWhite* are positive and statistically significant in professional basketball in Chapter 4, while they are positive but just miss statistical significance in college basketball in Chapter 3, respectively. Viewership is expected to rise as minority players fill more roster spots or play more minutes relative to White players. All of this implies that the degree of contribution made by minority players in terms of the sheer number of roster players and actual playing minutes is a practically relevant driver in both national (collegiate basketball) and local market (professional basketball) live television sport product consumption. Particularly in professional basketball, the aforementioned impact of minority players on local television ratings primarily originated from the local team roster.

Moreover, I estimate several additional specifications which result in relatively consistent magnitudes for the independent variables of interest. The findings suggest evidence that a positive effect of *NonWhite* and *Min_NonWhite* is potentially due to Black players in relation to White players in collegiate basketball. The positive coefficients of *Black* and *Min_Black*, though *Black* closely misses statistical significance, along with the negative coefficients of *Hispanic* (and *Min_Hispanic*) and *Others* (and *Min_Others*) indicate that Black players are the primary cause of the positive effect of minority players on viewership. This provides evidence of potential reverse customer discrimination against White players as fans prefer to watch Black player occupying more spots on team rosters and playing more minutes relative to White players.

The use of local television ratings data in professional basketball reveals a similar consumption pattern for both Black and Hispanic players in terms of the number of roster players (*Black* and *Hispanic*) and the actual playing time by race (*Min_Black* and *Min_Hispanic*) as the coefficients are all positive and statistically significant. This indicates that local NBA fans prefer to watch more Black and Hispanic players on the team rosters in relation to White players, which also provides an evidence of potential reverse customer discrimination against White players. This effect is more evident in the professional basketball context since the signs of the coefficients for all race variables in combined form (*Black*, *Hispanic*, *Others*, *Min_Black*, *Min_Hispanic*, and *Min_Others*) relative to the White player baselines are positive, regardless of its statistical significance. Further investigation finds evidence that the local team, not the non-local team, is mostly accountable for the positive impact of Black and Hispanic players on local television ratings. This suggests that NBA local fans prefer to watch more Black and Hispanic players on the local team roster whereas they prefer to watch less Black players on the non-local team with respect to both the sheer number of players and actual playing minutes.

This dissertation finds evidence that Black players are positively associated with both national and local market viewership in terms of the sheer number of roster players and actual playing minutes in both the collegiate and professional basketball settings. One possible explanation is that the positive effects of Black players act as a proxy for other characteristics of contests that the modeling fails to sufficiently account for. These may include games with a higher level of offensive or defensive efficiency, tempo, three-point shooting, passing, or other specific styles of play that might be influencing the results. It might also be the case that Black players are simply just better players at the individual level, or the tasks they are assigned (i.e., racial tasking) are more in demand by consumers. Therefore, future studies can potentially explore this idea further since such characteristics are quantifiable through publicly assessible sources (e.g., KenPom.com or basketball-reference.com).

The evidence of reverse customer discrimination against White players directly opposes the empirical results from Kahn and Sherer (1988) and Kanazawa and Funk (2001) in professional basketball that are most closely related to the contribution of this dissertation. Both studies found evidence of consumer preference for White players using game-day attendance and local television ratings, respectively. They speculated that customer discrimination in favor of White players stems from scarcity. However, it appears to be unsuitable to explain the findings of the current study in this manner given the participation of White players declined significantly throughout the decade (see figures in Chapter 1). Alternatively, this study finds opposing results which signifies customer preference for Black players (and Hispanic players in professional basketball). The result aligns with recent studies on salary discrimination in football (e.g., Gius & Johnson, 2000; Groothuis & Hill, 2013), and customer discrimination using All-Star voting data in baseball (e.g., Depken II & Ford, 2006) as well as television ratings in professional football (Aldrich et al., 2005). For instance, Aldrich et al. (2005) found evidence that Monday Night Football contests in 1998 featuring at least one Black quarterback generated more than two million additional viewers per game. However, it is important to note that they only looked at a single key position (i.e., quarterbacks) while the current study assesses the racial composition of complete team rosters by taking into consideration all athletes who are representing the product.

The findings of the two studies presented in this dissertation directly contradicts evidence from Kanazawa and Funk (2001), who discovered that professional basketball teams with more White players produced significantly higher local television ratings. There are some possible explanations for this result. The discrepancy of findings between the study in Chapter 3 and Kanazawa and Funk (2001) may be due to the variation in competition level between collegiate and professional basketball. Or, it also could be due to the difference in fan base as Kanazawa and Funk (2001) used local television viewership data which are likely to represent highly informed home fans of the local-market club, whereas the study in Chapter 3 utilizes national television viewership which represents a more diverse range of customers.

However, the opposing findings in Chapter 4 relative to Kanazawa and Funk (2001) given the same local television ratings data along with the same specification of variables of interest may be due to a substantial time difference between the referenced study (games played in the second half of the 1996-97 season) and the current study (games played in 2013-14 and 2014-15 seasons). In other words, the change in results could be driven by a positive change in the racial attitudes of live sport consumers. This implies that public sentiment towards diversity may be shifting in the 2010s as opposed to 1990s. The current results provide evidence suggesting customer discrimination against minority players (particularly against Black athletes) appears to be diminishing over time. Further analyses and discussion about this possibility are needed to compare results in order to improve our knowledge of whether racial attitudes and corresponding actual behavior have changed over time (Berri, 2017).

Customer Discrimination Specific to Head Coach Race (RQ3)

This dissertation also assesses customer discrimination at the managerial level with respect to the race of head coaches in both collegiate (Chapter 3) and professional (Chapter 4) basketball settings, respectively. The results indicate evidence of potential customer discrimination against minority head coaches leading the competing teams as the coefficient of *HCMinority* is negative and statistically significant after controlling for all other factors including variables with respect to player race. Viewership is expected to decrease when there is at least one minority head coach. Furthermore, a negative effect of minority head coaches comes from both local and non-local team minority head coaches in professional basketball (Chapter 4) as both *HCMinorityLo* and *HCMinorityNLo* are negative and statistically significant. However, a non-local minority head coach has a greater negative impact than a minority local-market head coach. Together, this suggests evidence that the race of head coaches is also a significant driver of live sport product consumption as fans appear to be keenly aware of their racial background.

Together with the player race outcomes, the findings suggest a potential bias in consumption against minorities in leadership positions, but not against minorities who are participating as athletes in the actual competition. In other words, the findings provide evidence that fan perceptions of minorities vary depending on the role in the team hierarchy, as seen by the fact that minority head coaches and players are viewed differently. This indirectly indicates that fans may assess the characteristics (traits) of key actors including race differently depending on their position in the organization. This is novel to the literature on the race of head coaches in sports using television viewership figures since no study has directly examined team leadership and how individual traits such as race may affect consumer behavior in viewership.

One possible explanation is that minority head coaches are not favored because fans may still believe they are underqualified for this position despite their ability. The implicit leadership theory (ILT) asserts that individuals tend to construct their prototype of what a leader is or should be based on their implicit ideas (i.e., stereotypes), and they then use this prototype to evaluate leaders (Lord et al., 1984). Race is one of the primary characteristics of implicit ideas, and failure or poor performance moderated by leader race sometimes promotes this stereotyping process (Carton & Rosette, 2011). Evidence of this interactive effect was discovered by Avery et al. (2015), however, it gradually weakened over time due to pressures to refrain from overt displays of racism. Even if the findings indicate the opposite, the interaction terms in this dissertation – *HCAvePom* in collegiate basketball and *HCEloLo* and *HCEloNLo* in professional basketball – partially accounts for this effect.

Meanwhile, the same findings (customer discrimination against minority head coaches) in both collegiate and professional basketball are somewhat unexpected given the disparity in television audiences between the two (national versus local). During the 2013-14 and 2014-15 seasons, minorities made up roughly half of the head coaches in the NBA but only about a third of the head coaches in NCAA Division I Men's Basketball (Figure 1.3). Thus, the figures are surprising given that prior experience is a key advantage in management and leadership positions in team sports (Dawson & Dobson, 2002), particularly in basketball (Goodall et al., 2011). Hiring practices sometimes result from demand-side pressure (Kuppuswamy & Younkin, 2020). In other words, the owner's decision to hire minority head coaches may be influenced by consumer preferences. Less minority head coaches in collegiate basketball suggests hiring decisions in collegiate basketball may follow consumer preferences, but this appears to be less prevalent in professional basketball, although fans still have racial bias against minority head coaches in both settings. This may serve as an excellent illustration of why eliminating customer discrimination is particularly crucial because it is difficult to isolate customer-related discrimination from other forms of discrimination, as discriminatory customer preferences may provide a reason for employers to justify their discriminatory hiring practices (Kuppuswamy & Younkin, 2020), which would explain why such practices remain (Nardinelli & Simon, 1990).

Uncertainty of Outcome Hypothesis

Chapters 3 and 4 include the identical measures of outcome uncertainty but the regression results vary. In order to capture perceived (or anticipated) contest-level outcome uncertainty (Paul et al., 2011) and actual (within-in game) contest uncertainty relative to market expectations, both studies measure the absolute value of the pre-game closing line point spread (*Spread* in Chapter 3 and *ClosingLine* in Chapter 4) and the absolute value of the difference between the pre-game expectation set by the closing line point spread and the final scoring margin (*CoverDiff* in both Chapters), respectively. If the UOH holds, viewership level is expected to rise as fans prefer, hypothetically, to watch highly contested contests between two quality teams (i.e., degree of closeness).

Basketball fans who watch collegiate and professional contests on television have very different preferences when it comes to anticipated outcome uncertainty. To illustrate, a positive and statistically significant *Spread* coefficient suggests college basketball fans prefer to watch games with outcomes that are anticipated to be more certain (i.e., outcome certainty), which is in opposition to the UOH. This is consistent with previous studies in college football and basketball (e.g., Brown & Salaga, 2018; Kang et al., 2018; Salaga & Tainsky, 2015). However, in professional basketball, *ClosingLine* is negative and statistically significant signifying that fans prefer to watch games expected to be uncertain (i.e., outcome uncertainty), a result supporting for the prediction of the UOH. This aligns with earlier studies investigating television viewership in professional sports (e.g., Buraimo & Simmons, 2009; Forrest et al., 2005; Grimshaw & Burwell, 2014; Tainsky, 2010; Tainsky & McEvoy, 2012).

One possible explanation is that fan preferences for outcome uncertainty differ depending on the absolute quality level of the competition since the literature provides evidence that UOH holds in professional sports, but not in collegiate sports. This seems to be reasonable given the significant variation in competition quality throughout the spectrum of collegiate programs as a result of the heightened variation in program revenues and subsequent team quality in college athletics (Kang et al., 2018). Additionally, the difference in team numbers between college and professional basketball contributes to the divergence in contest quality, given the fact that there are 30 teams in the NBA as opposed to more than 300 Division I schools in college basketball. As a result, the respective college basketball programs may have different season schedule in terms of the number of games they play each year and the relative quality of their opponents. However, each franchise is required to play the same amount of games each season in the NBA.

The second possibility is that the disparity may be caused by the type of television audience and game types being analyzed. Specifically, the college basketball analyses in Chapter 3 use national television viewership data for both regular and postseason conference tournament contests, while local television viewership data for regular season games only is used for the professional basketball analyses in Chapter 4. However, the results are relatively surprising given the fact that national viewership is more likely to reflect a wide spectrum of customers while local television viewership is more likely to contain highly informed fans supportive of the local team. It seems to be realistic that local fans would be more concerned with seeing their team succeed, but the regression results in terms of anticipated outcome uncertainty is opposite. It is feasible that consumer preference for anticipated outcome uncertainty fluctuates as the season advances since Kang et al. (2018) find evidence that preference for anticipated outcome certainty is reduced during postseason play.[21] In other words, consumer preference for specific contest types change over the course of a season, along with perceived contest importance.

In terms of within-game outcome uncertainty, both studies arrive to the same conclusion, despite the fact that the coefficient of *CoverDiff* is not statistically significant in collegiate basketball. A negative impact on viewership indicates fans prefer to watch contests expected to be more competitive than expected between the two competing teams given that lower values of *CoverDiff* suggest the actual scoring margin is closer to the betting market expectation. Thus, both studies provide support for the prediction of the UOH in the context of actual outcome uncertainty, a finding consistent with existing studies on television viewership in collegiate sports (e.g., Kang et al., 2018; Salaga & Tainsky, 2015). It is also evident that fan preference for actual outcome uncertainty is uniform across audiences (national versus local) and levels of competition (collegiate versus professional) in basketball.

Contributions and Implications

The findings of the two studies in this dissertation contribute to the existing body of work on labor economics and sport management in several ways, particularly with respect to customer discrimination. First, this dissertation contributes to the literature on customer discrimination by utilizing television viewership figures to assess fan preference for the race of players. This dissertation expands the previous work conducted by Kanazawa and Funk (2001) by measuring

[21] Unlike other sports, college basketball still offers virtually all teams the chance to compete in the postseason in their respective conference tournament.

the variables of interest in the same manner (i.e., the sheer number of roster players and the actual playing time by player race), but with the use of more recent viewership data to determine whether fan preferences for the race of players have changed over time at the player-level analyses. The findings provide evidence of a shift in actual consumer behavior toward minority players in live sport product consumption in basketball. This dissertation provides evidence of partial reverse customer discrimination against White players both in collegiate and professional basketball settings, which is in opposition to the finding of Kanazawa and Funk (2001), as minority players, particularly Black players, have a positive impact on television viewership level relative to White player in terms of the sheer number of roster players and actual playing time. Therefore, this dissertation adds to the existing customer discrimination literature since this is the first study to assess potential customer discrimination in basketball at the player level since Kanazawa and Funk (2001), to the best of my knowledge.

Second, this dissertation also contributes to the literature by utilizing television viewership figures to evaluate fan preference for the race of head coaches given the hierarchical structure of sport team organizations. To my knowledge, this is the first study to use television viewership to investigate potential customer discrimination specific to the race of coaching position. Specifically, this study assesses fan preference for the race at the managerial level by quantifying the impact of the number of minority head coaches on viewership levels in both collegiate and professional basketball. In both settings, a potential consumption bias against minority head coaches is uncovered. The regressions provide evidence of the conflicting racial behaviors (or preference) basketball fans have toward players and head coaches, illustrating that race is still a practically relevant and statistically significant driver of live sport product consumption. This is a unique result as I am not aware of any existing research which estimates potential customer discrimination both at the player and managerial levels. Thus, a relevant question for the future studies is to determine whether fans of any other sports possess similar viewing preferences for minority players and head coaches.

Third, this dissertation also adds to the customer discrimination literature by comparing the preferences of fans specific to the race of players and head coaches between two different quality levels of basketball competition, and also comparing those between national and local audiences. Using data from the NBA, Mongeon and Winfree (2012) analyzed whether fans at the stadium vary fundamentally from those who watch game on television, and discovered disparities in the demand determinants between television audiences and gate attendance. Similarly, this dissertation indirectly compares fan preferences between collegiate and professional basketball. Under the same specification of variables of interest, this dissertation examines potential customer discrimination in college and professional basketball during the same 2013-14 and 2014-15 seasons using national television viewership and local television ratings, respectively. Regardless of viewership type, fans of both sports exhibit a similar pattern with respect to discriminating preferences. This suggests that fan preferences for the race of key actors do not systematically change depending on the audience composition between two different quality levels of competition in basketball. This is an interesting result given the robustness of control variables which are comparatively equivalent in the two studies and completely different proportion of Black viewers between collegiate and professional basketball (Paulsen, 2014). Therefore, given the disparity in competition quality between collegiate and professional levels, this dissertation contributes to the literature by providing the groundwork for subsequent studies that compare the audiences of other sports.

Fourth, this dissertation provides practical implications for basketball in the U.S. in terms of how it should operate. The NBA has recently become more ethnically diverse as a result of the infusion of players of different countries from across the world, according to self-promotion by the league. In coaching positions, the league also has become more ethnically diverse as more than half of the head coaches are minorities (including 14 Black coaches) at the start of the 2022-23 season (Zillgitt, 2022). This is a meaningful and important benchmark given that the league lacks a formalized, league-wide guideline for the promotion of hiring minority coaches or front office personnel such as the Rooney Rule in the NFL. This change may be attributable to league-wide efforts since the NBA and the National Basketball Coaches Association (NBCA) together launched the Coaches Equity Initiative (CEI). However, the findings of this dissertation indicate that basketball fans continue to exhibit a racial bias against minority head coaches, despite the league-driven top-down efforts. Moreover, the NCAA also provides their universities and programs with a wide range of diversity and inclusion initiatives, but only approximately 26% of Division I Men's Basketball head coaches are minorities, according to data from The Institute for Diversity and Ethics in Sport in 2021. Therefore, this dissertation raises the subsequent questions of how basketball in the U.S. should function to lessen customer discrimination.

Limitations and Direction for Future Studies

As with all studies, this dissertation has limitations. First, the dataset used in this study is from the mid-2010s, which may prevent its conclusions from being definitive. This dissertation examines the possibility of customer discrimination in collegiate and professional basketball using data on national and local market television viewership from the 2013-14 and 2014-15 seasons. The most recent publicly accessible data was used in this dissertation because it is extremely difficult to acquire. Due to data limitations, this dissertation may not be able to provide an accurate assessment of customer discrimination in recent years. Furthermore, the racial bias of spectators toward minority players and head coaches over the course of two consecutive seasons of television viewership, which is an inevitable byproduct of analysis in this setting, is robust, but may not be able to be widely generalized. However, this study is meaningful in that the findings, particularly in professional basketball in Chapter 4, compared to those from Kanazawa and Funk (2001), show that actual consumer behavior toward minorities appears to have changed in 2010s and that customer discrimination against minority players (especially against Black players) appears to be decreasing over time. This is consistent with earlier studies on customer discrimination using All-Stars voting data (e.g., Depken II & Ford, 2006; Hanssen & Andersen, 1999). According to Berri (2017), however, results from different studies should not be directly compared because each study employs different methodology and new data. Hence, given that there is a relatively small but growing line of study which assesses potential customer discrimination in sports using television viewership, further research should replicate this dissertation using more recent television viewership figures in order to better understand whether consumer actions regarding race have changed over time.

Second, this dissertation may have a higher percentage of Black players in the sample because players who have mixed ancestry of two or more races are categorized as Black if at least one of their parents fits that category, a concept actualized based on the one-drop rule (e.g., Iverson et al., 2022). Since this study employs facial recognition to determine each player's race through their profile picture, identifying whether a player is Black or Hispanic is a challenging task. However, facial recognition might sometimes be considered problematic since race and ethnicity are dynamic social constructs that are difficult to measure (Gomez-Gonzalez et al., 2020). More Black players in the sample than there are in reality might lead to biased estimates in the regression analysis. Moreover, both Black and White spectators may find it more interesting to watch a multiracial player, for example, one who has a mixed Black and White ancestry. However, the mean of *Black* in Table 4.3 indicates that around 75% of the players of this dissertation are Black in the NBA, for example, and in actuality, it was about 77% during the 2013-14 and 2014-15 seasons based on the calculations of another source (Lapchick, 2021). Therefore, the difference between the sample and reality in the NBA appears to be negligible. Furthermore, this classification approach is aligned with existing work analyzing racial discrimination (e.g., Cunningham & Sagas, 2005; Tainsky et al., 2015).

Third, it would be interesting to evaluate potential customer discrimination based on the country of origin (nationality) of players rather than based on their racial information. This may raise the question of whether we need to reconsider the way we measure the degree of diversity, and whether it refers to multi-racial or multi-country diversity. For example, the NBA has arguably become more ethnically diverse, partially attributable to the influx of international players from European and South American countries (e.g., Hill & Groothuis, 2017; Yang & Lin, 2012), but the racial composition of professional basketball teams has changed dramatically from about two-thirds to approximately three-quarters Black players today. Thus, it might not be suitable to categorize players based on their race; instead, it might be preferable to assess their nationality. Alternatively, future work could simultaneously address potential consumption bias based on race and nationality so the two can be compared.

Fourth, the audience types for collegiate and professional basketball differ in this dissertation, making it difficult to draw firm conclusions from comparisons between the two distinct quality levels of competition. As Kanazawa and Funk (2001) proposed, it would be more informative to see if national and local audiences for collegiate basketball or professional basketball have comparable (or different) preferences for the race of key actors (e.g., players and head coaches). Given that nationally broadcast games, especially those with playoff implications at the end of the season, generally increase consumer interest considerably, it is not obvious if national NBA fans (or local college basketball fans), for instance, have the same racial preference in favor of Black players. On the other hand, the findings of this dissertation on fan preference for watching Black players would be strengthened if we discovered a comparable trend across two different audience categories in professional basketball (or in collegiate basketball).

Conclusion

Since Becker (1971) first outlined the potential sources of discrimination in the labor market, discrimination has received significant scholarly attention across a wide range of disciplines. In particular, sports labor markets have drawn significant interest in comparison to other industries because they provide an excellent testing ground for discrimination due to the abundance of publicly available data pertaining to the performance, employment status, and personal characteristics of athletes and coaches over long periods of observation. Numerous studies have investigated discrimination in sports (Kahn, 1991), and customer discrimination is of particular interest in this dissertation because there has been a dearth of knowledge regarding actual consumer behavior in response to the racial composition of a firm or the key individuals representing it.

Sports fans are said to engage in customer discrimination when they show a significant consumption preference for certain characteristics of athletes including race (Kahn, 1992), leading them to favor the products or services offered or sold by individuals from their own group (Aldrich et al., 2005). This line of research largely examines how fans react to characteristics such as race in order to identify potential sources of discrimination within the behaviors of sport consumers. This dissertation, therefore, seeks to assess potential customer discrimination by examining the consumption of the live sport product using national and local market television viewership data in collegiate and professional basketball, respectively. By using two series of variables to quantify player race – the sheer number of roster players by race and actual playing minutes by race – and the variable representing the number of minority head coaches leading the competing teams, this dissertation specifically examines viewing preference of fans based on the race of key individuals.

The findings of this dissertation uncover evidence that race of key individuals is still a practically relevant and statistically significant driver of live sport product consumption. In terms of the sheer number of roster players and the actual playing time contributed by those players at the player level in both collegiate and professional basketball, minority players have a positive impact on television viewership, indicating that viewers, regardless of viewership type (national versus local market viewership), prefer to watch minority players occupying more roster spots and playing more minutes on the court. Additionally, Black players are the main cause of the positive effect of minority players on viewership in both collegiate and professional basketball, a result, in part, suggesting a reverse discrimination against White players. At the managerial level, the findings demonstrate consumption bias against minority head coaches in both collegiate and professional basketball, signifying that fans are conscious of their racial background. Together, the findings suggest a potential bias in consumption that may be present against minorities in leadership positions, but not when they are competing as athletes in the actual competition.

Lastly, this dissertation adds to the body of discrimination literature by assessing customer discrimination based on the race of both players and head coaches using television viewership data, given the hierarchical structure of sport team organizations. Moreover, this dissertation contributes to the literature as it compares discriminating consumption patterns of live sport product in two different competition levels of basketball (collegiate versus professional basketball). Since Kanazawa and Funk (2001), this dissertation is the first to analyze customer discrimination at the player level in the basketball context, and the first study to use television viewership figures to assess customer discrimination specific to the race of the head coaching position. Despite some potential limitations that may have an impact on the results, the findings of this dissertation lay the groundwork for future research in other sports contexts.

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