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Abstract

I present a study of customer discrimination in the NBA by examining total annual attendance for all 29 teams for the five-season period from 1996 to 2001. Several previous studies have been conducted on this issue and seldom have found evidence of discrimination by measuring the racial composition of a team as the percentage of white players on the roster. However, using this measure and several alternative measures of racial composition, I find that fans do discriminate against black players, and this discrimination occurs in a variety of ways. Specifically, spectators alter their decisions to attend games based on the percentage of white players on the roster, the percentage of minutes played by white players, the percentage of points scored by white players, the percentage of starts by white players, and the percentage of white players in a nine-man rotation.

I. Introduction

Discrimination manifests itself in all facets of society, and it is an issue of great interest in the study of economics. In The Economics of Discrimination (1957, p. 5), Gary Becker illustrates the general sources of discrimination and its consequences. He states, "One individual is said to discriminate against (or in favor of) another if his behavior toward the latter is not motivated by an 'objective' consideration of fact". This discrimination is often motivated by an individual's perceived disutility from the association with certain groups of people or other individuals. Although discrimination increases the welfare of the discriminating individual, it does not come without a cost. Specifically, these individuals act as if they are willing to make a direct payment or take a reduction in income to satisfy their preferences, and sometimes they actually incur this monetary cost. An individual's "taste for discrimination" largely depends on this cost and several other factors.

Becker (1957) explains that discrimination by an individual against a particular group depends on the group's social and physical distance from the individual, its socioeconomic status, its substitutability in production, and the size of its representation in society. All of these factors can be linked to and have ambiguous effects on discrimination. For instance, it might be the case that one individual will discriminate more because of an increase in contact with the group, but another individual will not. The first individual associates the increase with an increase in the power of the group; thus, he feels threatened and develops greater prejudice. On the other hand, the latter individual gains more knowledge about the group and consequently reduces his prejudice. In any market, there are many individuals, all with personal preferences, who are potential sources of discrimination.

The three major sources of discrimination are employers, employees, and consumers. As previously mentioned, discrimination occurs when an individual lacks 'objective' preferences. As Becker notes (1957, p. 31), "In the marketplace, 'objective' behavior is based on considerations of productivity alone". Using this criteria, employer discrimination occurs when an employer does not hire an individual with a greater marginal value product than his marginal cost. Therefore, an employer discriminates when he chooses not to hire an individual who can produce more revenue by his labor than the employer has to pay for that labor. In addition, employer discrimination can result in a wage differential between two individuals or groups of equal productivity. Specifically, the preferred individual or group will receive greater compensation than the other group for work that is of the same caliber. In practicing this discrimination, employers take the risk of forfeiting profits. These reduced profits are the cost of discrimination, and an individual's "taste for discrimination" will determine how willing he is to incur this loss and how much he will discriminate.

Employee discrimination occurs when one employee prefers not to work with a certain individual or group of individuals. This type of discrimination has less obvious effects on a given market, but still has important implications. For instance, a discriminating employee is willing to give up a portion of his wage to avoid working with a certain group or individual. In addition, if there is a discriminating employee with some influence over management, his preferences may contribute to employer discrimination.

Lastly, consumer discrimination occurs when an individual chooses to purchase one product instead of another based on factors other than the quality or efficiency of the product. These other factors include the sex, race, religion, and personality of the sales personnel. Consumers with discriminating preferences purchase the products that best satisfy their preferences, which increases revenue for the products that match those preferences and decreases revenue for the products that do not. Since employers would like to maximize profits and increase sales, consumer discrimination may also indirectly contribute to employer discrimination.

Discrimination is a serious issue in all markets, but it is often overlooked in sports. According to Kahn (1991), there is a public perception that the world of sports is an example of equal opportunity for all groups and individuals. He believes that this invalid belief can be attributed to the fact that the minority representation in major team sports is greater than the minority representation in the labor force. In addition, there are many high-paid blacks in sports, but do these observations suggest the absence of discrimination? Although it may appear that blacks are receiving equal treatment because some players have large salaries, it is also a common observation that there are few blacks in managerial and executive positions. Thus, the issue of discrimination in sports remains a prevalent one which should be examined.

As is the case in other industries, discrimination can emerge in sports as a result of employer, employee, or consumer behavior. Employer discrimination occurs when the owner of a franchise has a preference for one group of players over another for any factor other than productivity. The goal of owners is to maximize utility which is a function of the amount of profits and wins generated by each player and any racial preferences of the owner. For instance, an owner may prefer white players to black players.[1] If this is the case, there are several ways in which the effects of the owner's racial bias can be observed. Specifically, owners may only hire white players which can be

[1] For simplicity and relevance to this paper, the following analysis will focus on racial discrimination against blacks.

seen in the racial composition of the rosters. However, an owner may compromise too much quality and consequently revenue when practicing such extreme discrimination. Therefore, owners may be reluctant to express their racial preference in such a manner because of the reduced profits and wins that result. A more likely scenario is that owners exhibit their preference by compensating white players more than black players of equal ability. Therefore, discrimination can be observed in salary differentials between white and black players with the same productivity.[2] In addition to discriminating against players, owners may have the same racial preferences for coaches and management with the same hiring and salary consequences.

Employee discrimination occurs in sports when an athlete prefers to play with or be coached by individuals of a certain race. For instance, whites may prefer to play with or be coached by other whites. It is difficult to determine how much influence, if any, an individual player has on the racial composition of his teammates or coach, but it is possible that a certain player is so skilled and valuable to the owner that he may have some power in the team's personnel decisions. However, this type of discrimination is unlikely and impossible to detect with the information available to the public.[3] It is more likely that employee discrimination can be examined in the market for free agents, where individuals have virtually total control of the team for which they play. Thus, players may choose to play for teams with more players or a coach of their race, possibly at a lower salary (a potential cost of discrimination). Again, this type of discrimination is not as obvious and requires more information to detect.

Finally, consumers can discriminate in the market for sports with significant consequences. Consumers discriminate by choosing to attend games or watch the televised broadcasts. If consumers make their decisions based on a 'non-objective' factor like race, they are practicing discrimination.[4] If this is the case, a team's revenue can be affected by these preferences, and owners will be sensitive to those preferences so that they produce the product which maximizes profits. Therefore, consumer discrimination can result in the same hiring and salary practices of employer discrimination.

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[2] In order to make this observation, there must be a good measure of productivity of individual players. Using statistics and team revenues, it is possible to calculate a player's marginal revenue product. According to Browning and Zupan (1999), marginal revenue product is the product of marginal product and marginal revenue. In sports, marginal product is how much a player contributes to a victory, and marginal revenue is how much revenue increases with a victory. Therefore, the product of those two values is the marginal revenue product of a player.
[3] Players and owners must be willing to publicly acknowledge that such a relationship exists for it to be known. This is not likely because it could potentially cause controversy between the players and coaches, owners and coaches, etc. Teams prefer to avoid creating issues of this nature because it may distract them from the ultimate goal of winning games and winning a championship.
[4] Although one can objectively identify a person's race, it is a 'non-objective' factor because it is not based on productivity.

When examining these types of discrimination in sports, there are several issues worth considering. For instance, how should one measure the racial composition of a team? It can be measured by the overall proportion of whites on a team, by the proportion of whites that starts on a team, by the proportion of minutes played by whites, or by the race of certain positions on a team, etc. The answer to this question and others is likely determined by an individual's willingness to incur the potential costs of discrimination.

In this paper, I will examine consumer (customer) discrimination in the National Basketball Association for the five-season period from 1996-2001. In the following section (Section II), I will provide a review of the existing literature on the subject and other relevant issues. Section III will include an explanation of the underlying theory, variables, and model specifications. In Section IV, I present and discuss the empirical results. Section V includes some additional results. Finally, Section VI includes a summary of my findings and a discussion of possible future research on this topic.

II. Literature Review

For the topic of discrimination in sports, Kahn (1991) provides the most comprehensive review of the existing literature. In his study, he discusses the forms in which discrimination can arise in sports, followed by a summary index of all the studies on discrimination in professional sports and their results. Possible forms of discrimination in sports are salary discrimination, hiring discrimination, positional segregation, customer discrimination, and gender discrimination. Specifically, salary discrimination occurs when white players are compensated more than equally qualified black players. Hiring discrimination occurs when black players face higher standards than white players in order to be hired by a team. Positional segregation occurs when white players, instead of equally or more talented black players, play key positions such as pitcher in baseball and quarterback in football. Customer discrimination occurs when fans prefer to watch white players play more than black players, and lastly, gender discrimination occurs when there is unequal treatment of men and women in any sport in which they both participate.[5] This paper will focus on customer discrimination and its consequences. Several papers have studied this issue and have obtained a variety of results.

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[5] Tennis is one of the few sports in which this type of discrimination can occur. Specifically, the prize money for women's champions is normally lower than for men's champions, eventhough there is evidence indicating that the women produce as much or more revenue than the men.

McCormick and Tollison (2001) examine the salary differential between white and black players in the National Basketball Association (NBA). In a previous study, Kahn and Sherer (1988) found that black players earn less than otherwise comparable white players. McCormick and Tollison do not attribute this salary differential to customer discrimination, but rather, they discover that black players actually play more minutes than white players of equal ability. In fact, they argue that price discrimination resulting from relative supplies and supply elasticities, not racial discrimination, is the source of this inequality.

McCormick and Tollison estimate a number of NBA home attendance functions and obtain some interesting results. Using dummy variables for each season from 1981 to 1987, they find that attendance grows over time. Attendance is positively linked to stadium capacity; however, median ticket price, income per capita for Standard Metropolitan Statistical Area (SMSA), and the number of All-Star players on a team have no statistically significant effects. The presence of another NBA team in an SMSA reduces attendance and the presence of a Major League Baseball (MLB) team is negatively linked to attendance, but there is no relationship to the presence of either a National Football League (NFL) or a National Hockey League (NHL) team. Attendance is positively related to the population of the SMSA, but the percent of blacks in the SMSA is only marginally significant with a negative effect. Consistent with theory, an increase in regular season wins has a positive effect on attendance.

McCormick and Tollison further analyze the effects of regular season wins by interacting them with population, but the interaction is insignificant. Most relevant to the examination of customer discrimination, they find that the racial composition of a team, measured by either the ratio of white players to black players or the ratio of total minutes played by whites to total minutes played by blacks, has no statistically significant effect on attendance. In addition, the race of the head coach is also insignificant. Given these results, McCormick and Tollison obtained no evidence of racial preference by the fans. However, in order to bolster the validity of their results and to eliminate the possibility of endogeniety issues, they jointly estimated attendance and ticket prices. In support of their initial results, the racial composition of a team had no effect on both attendance and ticket prices.

In their first attendance equation, McCormick and Tollison used the percent of blacks in the SMSA as a control variable; however, this does not explore regional or local differences in racial preferences. Specifically, the racial composition of a local population may effect the racial composition of the local team. Therefore, they divide the SMSA data into three separate groups based on the black percentage of the population (BPP): predominately black ($BPP \geq 18.2$), mixed ($5.7 \leq BPP \leq 18.2$), and predominately white ($BPP \leq 5.7$). The results of this investigation show that mixed areas do not have any racial preference, but both blacks and whites prefer to watch players of their own race (this effect is greater in black SMSA's).

McCormick and Tollison's results suggest that customer discrimination is not the source of the salary differential between whites and blacks. Instead, they offer an alternative theory of market segmentation price discrimination. They argue that because of racial discrimination in society and lower socio-economic standards, black children are not afforded the same opportunities as white children. This lack of opportunity forces these black children to do what comes at the least cost. Basketball can be played as long as there is a court, a ball, and players; so it is easy for black children to play it frequently and excel with little financial burden. Overall, once they grow up, blacks may not have the same non-basketball opportunities as whites causing them to be less responsive to wage changes in that profession. Thus, blacks have a less elastic supply in the basketball labor market, and are willing to accept lower salaries.

Schollaert and Smith (1987) also find that team racial composition has no effect on attendance in the NBA. In their examination of attendance, they focus on three categories of explanatory variables in addition to team racial composition: team characteristics, facility characteristics, and market characteristics. Team characteristics include won-lost record, number of star performers, relative record in division, prior season's won-lost record, and ticket prices. Facility characteristics include facility size and location, and market characteristics include metropolitan population, household income, percent black in metropolitan area, and the number of competing franchises. Their study specifically examines the effect of racial composition on home attendance in the NBA from 1969 to 1982 for all teams in the league over that period.[6] Further, they use four different methods of measuring attendance: total attendance (adjusted for games never played), average attendance divided by arena capacity, the number of unsold seats per season, and per capita attendance in the region. These different techniques of measuring attendance provide a more thorough model for examining the effects of team racial composition, which they measure by the percent of blacks on a team. This measurement was calculated at the beginning of each season for the sample periods. Using a modified generalized least squares method, Schollaert and Smith obtain some interesting results.

For the equation using total attendance, the current season's won-lost record and the prior season's won-lost record appear to be the most influential factors. For the larger sample, the relative finishing position has a

[6] There were only 12 teams in the league from 1969-1976, so a subset of the sample from 1977-1982 was also examined when there were 21 teams in the league. In addition, this sample allows them to analyze the variation of attendance over time as well as between teams.

positive effect, but it is negative in the smaller sample. The number of All-Star players and the facility size are positively related to attendance, but the location of the facility is not significant. Contrary to theory, ticket prices are positively related to attendance. The metropolitan area population and median income are strongly linked to attendance, but the percentage of black population and the number of competing franchises have negative effects on attendance. Most importantly, the percent of black players does not have a significant effect on attendance.

When attendance is measured by the percent of seats sold (average attendance/arena capacity), the results are virtually the same except that there is a small negative correlation between the percent of black players and attendance in the sample from 1977-1982. Using the number of unsold seats as the measure of attendance, the results are the same with opposite signs since it is a measure of excess supply. There is no significance attributed to the percent of black players on a team. Lastly, the model using per capita attendance shows no link between team racial composition and attendance, but produces some different results for the other explanatory variables. The effects of winning are highly reduced, if significant at all, and the market characteristics have a greater effect on attendance. Specifically, the number of competing franchises is more influential in the determination of attendance. This result may occur because larger regions may have more professional sports teams or because the geographical extent of the region may inhibit many fans from attending the games. Therefore, it is possible that the number of competing franchises may be a proxy variable for city size. To examine this, Schollaert and Smith include dummy variables for various city sizes. Their results suggest that the metropolitan area population is negatively related to per capita attendance, even though it is positively related to total attendance.

Although they find no evidence linking team racial composition to attendance, Schollaert and Smith further examine the issue by interacting the team racial composition variable with other factors. Specifically, they interact team racial composition with team performance record (winning or losing season), team location (North or South), racial composition of the market, and large increases in the fraction of black players on a team (twenty percent interannual black increase dummy variables). None of these interaction variables is significant except for the large interannual increment in the percent of blacks on a team. In fact, the coefficient on this variable is positive and significant indicating that the increased presence of blacks on a team increases attendance. Schollaert and Smith attribute this phenomenon to large personnel changes that increase the quality of the team and consequently, the won-lost record.

Overall, Schollaert and Smith find no link between team racial composition and attendance. They believe that there are a few possible explanations for this. First, it is possible that the NBA is so largely black that it only attracts fans that do not have any racial bias. Secondly, it is unlikely that any racial preference against blacks exists; otherwise, some owners would only hire white players to maximize gate revenues and profits. Finally, it may be the case that people do not have any racial preferences when choosing to attend an NBA game.

Brown, Spiro, and Keenan (1991) provide additional insight to the study of customer discrimination in the NBA by exploring the salary differential between white and black players, regional biases of fans, attendance, and hiring standards. Assuming that a player's salary is directly linked to his performance, the authors estimate a compensation function using data from the 1984-1985 season. The explanatory variables include a dummy variable for race (one if black and zero if otherwise), points per minute played, rebounds per minute played, average minutes played per game, percent of career as an All-Star, a dummy variable of one for first-round draft picks (zero otherwise), and the number of years played in the NBA.[7] The results indicate that salary is positively related to a number of performance variables, but negatively related to the race variable. Therefore, Brown, Spiro, and Keenan find that black players, on average, are compensated less than white players of equal ability. Given this evidence, the authors examine customer preferences as a potential cause of this salary differential. First, they hypothesize that fan preferences for white players are greatest in the most predominantly white areas, and they find this to be true. Although this result implies that, to some extent, there is customer discrimination in the NBA, Brown, Spiro, and Keenan extend their analysis to attendance.

White players may receive larger salaries than equally qualified black players and white fans may prefer to have white players on their local teams, but this does not necessarily imply that customer discrimination affects who plays on an NBA team. Specifically, the authors measure team racial composition as the percentage of total minutes played by a team's black players.[8] If there is customer discrimination, attendance should be negatively related to this variable.[9] The analysis uses home attendance data from the 1983-1984 season and includes winning percentage, average ticket price, the number of superstar players (players who have been All-Stars for at least 50% of their careers), metropolitan population, metropolitan per capita income, the number of other major league professional

[7] Salary data are from the 1984-1985 season, but points and rebounds per minute played are calculated over the duration of each player's career.

[8] The study only includes the 12 players per team who have played the most minutes.

[9] Brown, Spiro, and Keenan assume that coach's want to win games, and therefore, they do not make playing time decisions based on any factor besides productivity.

sports teams in the metropolitan area, and the number of years a team has been in its city as variables in addition to the team racial composition variable. As suggested by theory, winning percentage, metropolitan population, and the number of superstar players have positive and significant effects on attendance, and the number of competing major league professional sports teams and the number of years in a city have negative effects on attendance.[10] Average ticket prices are negatively related to attendance and metropolitan per capita income is positively related to attendance, but both are only marginally significant. Most importantly, the results indicate no significant relationship between team racial composition and attendance. This result is interesting because it suggests the possibility that fans' preferences may be satisfied by the mere presence of white players on a team (bench players) instead of their actual participation as starters or significant contributors.[11] If this is true, it may be the result of a trade-off between racial preferences and winning. Fans may prefer to have white players on their team, but not at the cost of winning, and consequently accept more talented black players as starters.

Burdekin and Idson (1991) also examine the relationship between attendance and the racial composition of NBA teams. Particularly, they focus on the effect of the racial composition of a team's market area (SMSA) relative to the racial composition of the team as well as the effect, if any, of measuring team racial composition for starters instead of the entire roster. Their analysis examines average attendance for each NBA team from the 1980-1981 season through the 1985-1986 season. In their first estimation, they use winning percentage, SMSA population size, the percentage of the population in blue-collar occupations, the median ticket price, white and black income, the numbers unemployed, the number of players on the first or second All-NBA teams, a dummy variable equal to one for playoff teams, the total number of competing franchises in the SMSA, and the ratio of percentage white on the team to percentage white in the population of the SMSA as the independent variables.[12] In a separate equation, they perform the same regression with one exception. They disaggregate the ratio of percentage white on the team to that in the population into two groups, the ratio of percentage white starters to percentage white in the population and the

[10] The authors indicate that Noll (1974) argued that teams in their first year in a city draw more fans than teams that have been in a city for several years. However, an alternative theory is that teams that have been in a city for a longer period of time have established tradition and a consistent fan-base, thus having a positive effect on attendance.

[11] In addition to these findings, Brown, Spiro, and Keenan examine the minimum entry standards for white and black players, but find no evidence indicating that they are higher for black players than for white players of equal ability. However, it is possible that white players are selected to enter the NBA over equally talented black players. Unfortunately, there is no way to prove this since there are no productivity measurements for players not in the NBA.

equivalent measure for bench players. This distinction allows Burdekin and Idson to determine if fans have racial preferences for the entire team or a certain portion of the team. It is possible that fans with racial biases may be satisfied with the mere presence of a white player on a team which would indicate a greater significance for the racial composition of bench players, but on the other hand, fans may have racial preferences for the most visible players, the starters.

Burdekin and Idson estimate attendance using a maximum likelihood Tobit procedure which caps off the dependent variable at its maximum (i.e. arena capacity for attendance). They find that the logarithm of the ratio of the percentage white on the team to that in the population, winning percentage, and the logarithm of the SMSA population are positively related to attendance.[13] For the first equation, in which starters and bench players are grouped together, none of the other variables is significant. The variables accounting for superstars and playoff teams may be insignificant because they are already captured by the effect of winning percentage. Ticket price, income, and unemployment are also insignificant, but Burdekin and Idson argue that this result is consistent with other literature on the subject. In the second equation, they find that the ratio of percentage white starters to percentage of white in population is significant and positive, while the ratio of percentage white bench to percentage white in population is insignificant.[14] This suggests that the racial composition of starters is more influential in the determination of attendance than the racial composition of bench players. As stated before, this phenomenon may be due to the increased visibility and participation of starters. Overall, Burdekin and Idson find that attendance increases for NBA teams whose racial composition closely resembles the racial composition of its market (SMSA).

McCormick and Tollison (2001), Schollaert and Smith (1987), and Brown, Spiro, and Keenan (1991) fail to find evidence of customer discrimination, but Kahn and Sherer (1988) do. In an investigation of 1985-1986 salaries, they find that black players receive less compensation than equally skilled white players.[15] As a result, they explore attendance results for the same period to address the hypothesis that customer discrimination is the cause of this salary differential. Using data from the 1980-1981 season through the 1985-1986 season, Kahn and Sherer examine

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[12]It is important that they define the racial composition variable as the percent white on a team to the percent white in the SMSA because non-whites in the NBA is predominantly black, but non-whites in SMSA's is not exclusive to blacks.
[13] Burdekin and Idson use logarithmic form to account for the truncation of attendance at any given arena's capacity.
[14] Starters are defined as the five players who accumulated the most minutes of playing time over the duration of the season.
[15] Kahn and Sherer use an elaborate set of variables, accounting for performance and other factors, to estimate salaries.

home attendance.[16] In their equations, they include a variable equal to each season (i.e. 1985-1986 season equals 86), winning percentage, number of players on the first or second All-NBA teams, arena capacity, number of other major league sports franchises in the area, minimum ticket price, and the percentage of white players on the team as explanatory variables. They find that attendance increases with larger arenas, higher winning percentages, small percentages of blacks in an SMSA, and high incomes. Ticket prices, again, are not significant. The authors suggest that this occurs because ticket price is an endogenous variable. Most importantly, Kahn and Sherer observe that the percentage of white players on a team is positively related to attendance providing evidence of customer discrimination. Using a rough approximation of average ticket price in the NBA, they show that an additional white player in place of a black player of equal ability generates more than enough revenue to explain the salary differential. In order to bolster the validity of their results, Kahn and Sherer create several interaction variables with attendance. Of the several interaction variables, only the percentage of white players on a team interacted with arena size has a significant effect, and it is a negative one. In total, Kahn and Sherer find that there is a significant salary differential between white and black players of equal ability, and there is evidence suggesting that the source of this differential is fan preferences for white players.

There have been other attempts to examine the existence of customer discrimination. These studies use television ratings, the demand for memorabilia, and data from fan All-Star voting to determine if fans have racial preferences. Kanazawa and Funk (2001) use Nielsen ratings for locally televised NBA games and advertising revenues for those games to examine this phenomenon. Their analysis reveals that the size of the television audience increases with greater participation by white players. Furthermore, they explain that white players create more advertising revenues, given that commercial advertisers are willing to pay more when the television audience is larger. Specifically, a larger television audience increases the influence of commercials; therefore, advertisers will pay more for commercial slots during those games in which white players are more abundant. Commercial advertisers pay the television networks to air their commercials, but the networks pay the league and the teams for the rights to broadcast their games. As a result, any increase in the demand for commercials during a particular team's game will bring added revenue to that franchise. Since white players can attract larger audiences, they are producing additional revenue that black players of equal ability cannot; their marginal revenue product is greater. Marginal revenue product is the amount by which revenue increases with the addition of another unit of labor. In

[16] Kahn and Sherer estimate annual home attendance and the natural logarithm of annual home attendance. They

basketball, this is how much revenue increases from a player's productivity both on and off the court. This difference in marginal revenue product may contribute to the salary differential between white and black players found in other studies of the NBA.

In their analysis, Kanazawa and Funk use data on television viewing of local non-cable broadcasts of NBA games during the second half of the 1996-1997 basketball season from the Nielsen Media Research company. The Nielsen rating is defined as the percentage of the total number of households with televisions in a given ratings area that are tuned in to a particular show. In their estimation of Nielsen Ratings, they include variables for local and opposing team winning percentages, the time and day of the game, the rating of the prior television program, the sizes of the total and white viewing audiences, the number of other professional sports teams in the SMSA, the number of All-Star players on the team, and the racial composition of the team. Specifically, they measure the racial composition by both the percentage of white players on a team and the percentage of minutes played by white players. They separate these variables for both the local and opposing teams since the results of F-tests allow them to reject the hypothesis that the local and opposing players had the same effect on the rating. They find that the presence of white players on the local team had greater and more significant effect on the ratings than the presence of white players on the opposing team.

The results of their analysis indicate that both measures of racial composition had positive and significant coefficients indicating that viewers had a greater preference for white players. However, the significance and explanatory power of the equation using the percentage of white players was greater than the equation using the percentage of minutes played by white players. This implies that the presence of white players on a team was more important to viewers than the actual participation of those players in the games. Given these results, Kanazawa and Funk conclude that there is customer discrimination in the NBA and that this discrimination may be linked to the salary differential between white and black players, since advertisers will pay more for a more highly viewed broadcast.

Stone and Warren, Jr. (1999) make a significant contribution to the study of customer discrimination in the NBA by examining the trading-card market. Using data from the 1976-1977 season, they examine basketball card prices to identify sources of discrimination. In their card-price equation, they use dummy variables for race, post-

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use generalized least squares (GLS), in addition to ordinary least squares (OLS), to account for serial correlation.

career coaching experience, rookie status, and positions.[17] In addition, they use a player-performance rating index and the number of years of professional experience prior to the sample season as explanatory variables.[18] Their results indicate that individuals in the trading-card market have no racial preferences. To further examine discrimination, however, they interact the race dummy with all the other variables and find some interesting results. First, they observe that the positive effect of career length on card-price is greater for black players than for white players. This suggests that fans are less discriminatory towards black players with whom they have become more comfortable or that these black players exhibit other qualities that increase their fan approval. Furthermore, the results imply that cards for black players, who became coaches, have lower prices than card prices for white players who became coaches. Stone and Warren, Jr. explain that this may occur because card collectors discriminate against the black players who gain a position of authority as a coach or because those players receive less media exposure as the coaches of lower-quality or small-market teams. Finally, they test the null hypothesis that all the race variables are equal to zero, and these results, consistent with most of their other findings, indicate that there is no racial preference in the trading-card market for NBA cards.

From the papers above, it is evident that there is no definitive evidence of customer discrimination in the NBA. This uncertainty may be the result of the various methods of analysis that can be employed to conduct a study of this nature. Schofield (1983) provides an excellent overview of the different approaches that can be taken in the studies of 'performance and attendance at professional team sports'.[19] Schofield explains that most studies use ordinary least squares to estimate an attendance function, but there are several adjustments that can be made to the model. The first distinction he discusses revolves around the nature of the data. Specifically, the data set can be cross-sectional (across teams) or time-series (over time). Of the existing literature on attendance, both types of data have been studied individually and as a combination. Secondly, Schofield describes how past data are used to determine the forecasting value of the estimated equations. By using this technique, an author can bolster the credibility of his results. Different functional forms can have significant implications in the analysis of attendance. Frequently, authors have employed the log-linear form in which the logarithm of attendance is estimated. Schofield points out that this form allows for the use of interaction variables and easy calculations of elasticities to determine

[17] These variables equal one if the player is white, if the player was an NBA head coach in the 1993-1994 season, if the player was a rookie, and for whatever position the player played, respectively. For the other position variables, the dummy variable equals zero.
[18] Tendex, the player-performance rating index, is essentially a measure of a player's points per minute.
[19] This paper only reviews his discussion of attendance.

the relative significance of explanatory variables. In the estimation of attendance, the problem of serial correlation between winning percentage and the error term can exist. As a result, an ordinary least squares regression produces biased and inconsistent estimates. Schofield describes how one author corrects this problem with the use of two-stage least squares. Lastly, each model of attendance includes different independent variables which create a variety of results.

Schofield explains that there are several variables that are expected to influence attendance. These variables are ticket price, price and availability of substitutes or complements, average income, population size, and consumer preferences. However, there are numerous variables which can be included in a model of attendance. Schofield defines four categories into which these different variables can fall. First, there are economic variables including price, substitutes, complements, and income. Then, there are demographic variables such as population size and ethnic mix. Furthermore, quality of competition, team records (home and opposition), player characteristics, and special game days are variables of quality and attractiveness. Schofield describes residual preference variables like weather, stadium quality, time of week or season, and number of years a team has been in a city. Lastly, variables that account for the presence of star players and racial composition have been significant in estimating attendance.[20] From this diverse selection of variables and methods of analysis, it is not surprising that there is no universal belief on the existence of customer discrimination in the NBA.

In theory, ticket prices should significantly influence attendance, but the results do not always indicate this. Specifically, as ticket price decreases, attendance should rise. Most papers find this negative relationship, but the result is not always statistically significant, contradicting a priori expectations. Marburger (1997) and Boyd and Boyd (1998) examine ticket pricing and its relationship to attendance in detail.

Marburger (1997) finds that in order to maximize profits, ticket price should be in the inelastic section of demand. The linchpin assumption to his argument is that the price setter receives a portion of the revenue generated by concession sales.[21] Since it is necessary to purchase a ticket to attend a sporting event, a reduction in ticket prices increases attendance. This increased attendance immediately increases the market for concessions. Marburger assumes that concessions prices do not affect ticket sales, but ticket prices determine the size of the concessions market. With increased concessions sales, the team's profits increase. Therefore, it is optimal for firms to set prices

[20] Hausman (2001) gives a thorough analysis of star players' effects on television ratings and subsequent revenue for their teams. His study focuses on Michael Jordan's effect throughout the league.

[21] Marburger describes concessions as any nonobligatory consumption goods which complements ticket-buying.

in the inelastic portion of demand, where individuals are less responsive to changes in ticket price, to increase attendance and maximize profits. Marburger concludes his paper with an estimation of attendance (logarithm of home attendance) for Major League Baseball (MLB) teams using the logarithm of the team's average real ticket price (in 1991 dollars), the winning percentages of current and previous seasons, relative ticket prices (box to reserve seats and reserve to general admission seats), population of city, a dummy variable for the presence of other major league teams in the SMSA, and a dummy variable for the age of the ballpark.[22] Consistent with his expectations, the coefficient on the logarithm of the team's average real ticket price equals (-0.568) which lies within the inelastic portion of demand and implies a negative relationship between ticket price and attendance.

Boyd and Boyd (1998) also examine inelastic ticket pricing, but attribute it to a home field advantage. Specifically, they argue that a decrease in ticket price causes an increase in attendance. This increase in attendance, in turn, increases home field advantage which increases the probability of victory. Assuming fans prefer to see their teams win, this increased probability of winning will further increase attendance, and so the process continues. This process creates a multiplier effect which continues until attendance reaches its maximum (facility capacity). As a result, Boyd and Boyd suggest that teams should consider home field advantage when setting ticket prices since it increases winning percentage which has been shown to increase revenue. Similar to Marburger, they estimate seasonal home attendance for all MLB teams for the 1984 season. Consistent with their expectations, ticket prices fall into the inelastic portion of demand.

In addition to basketball, there have been several studies on customer discrimination in baseball. Medoff (1986) estimates official paid attendance for the 1980 MLB season using these variables: average ticket price, the number of other professional (NHL, NFL, and NBA) teams in SMSA, 1980 per capita income in SMSA, 1980 population of SMSA, a dummy variable for age of stadium, a dummy variable equal to one for National League (NL) teams, divisional standing in 1980, and the percentage of black players (non-pitchers). The variable for racial composition is negatively related to attendance, but is not significant. Therefore, Medoff finds that fans do not discriminate against black non-pitchers. In a separate estimation, the results for attendance are virtually the same when the percentage of black starting pitchers becomes the racial composition variable, indicating that fans do not discriminate against black pitchers either. Medoff discusses the ambiguity behind these results. Although the results suggest that there is no decrease in attendance due to the increased presence of black players, it is possible

[22] The sample consisted several time intervals over a 20 year period from 1969-1989.

that this occurs because a decrease in white attendance is negated by an increase in black attendance. Unfortunately, it is difficult to prove this unless there is a racial breakdown of attendance. However, Medoff argues that the positive effect of increased black attendance will most likely be overcome by the negative effect of decreased white attendance. He believes that the increased presence of black fans will cause more discriminatory white fans to stop attending and augment the decrease in white attendance. As a result, he uses the percentage of blacks residing in each team's SMSA to determine if the racial make-up of a market area affects attendance. Again, the coefficient is insignificant implying that attendance is not affected by the racial composition of an area. Overall, Medoff finds no evidence of racial preferences.

Contrary to Medoff, Hanssen (1998) finds evidence of customer discrimination in Major League Baseball (MLB). Using data from the MLB for the period of 1950-1984, he examines the relationship between performance and discrimination.[23] Hanssen estimates winning percentage to determine the impact of black starters.[24] He finds that teams with more black starters won more frequently, but this trend decreased over time and with an increase in black starters around the league. In addition, he did not find any difference between the NL and AL (American League). Assuming that owners like to win because winning attracts fans, increases profits, gets attention, and is more fun; Hanssen illustrates a trade-off between winning and racial preferences. Discriminatory owners pay the price in losses. Consistent with this assumption, worse teams started black players more quickly. Seeing that black players have a significant effect on winning, Hanssen turns his attention to attendance and customer discrimination.

Using the same data set, Hanssen estimates attendance using the following explanatory variables: population, per capita income, the "newness" of the stadium, the number of star players on the roster, involvement in a pennant race, the amount of "entertainment" competition, recent first place finishes, games behind first place at the season's end, the percentage of the population that is black, and dummy variables for movement to a new city, stadium capacity, the number of competing baseball franchises in the SMSA, and for teams that played 162 games (equal to one). To test for discrimination, he includes the number of black players on the roster as the racial composition variable. The results of this equation indicate that attendance fell in both the NL and AL, but more so in the AL, with the addition of more black players to a roster. To further examine the trade-off between discriminatory preferences (of fans and owners), Hanssen breaks the racial composition variable into two separate variables, the number of black starters and the number of black substitutes. Hanssen observes that black substitutes

[23] The data includes 16 MLB teams excluding post-1960 expansion teams and pitchers.

have a smaller positive impact on winning than black starters, but the same negative impact on attendance as black starters. Given this result, he suggests that black starters would be more abundant than black substitutes, and this was the case. The winning benefits of playing black starters exceed the reduced attendance costs, but the opposite is true for black substitutes.[25]

Although customers have not always been the source, there have been a number of studies on discrimination in professional sports and particularly the NBA. Kahn and Sherer's results, indicating a large salary differential between white and black players of equal ability, encouraged several authors to examine this issue further. Scott, Long, and Somppf (1985) argue that NBA players, in general, have received salaries that do not fairly compensate them for the amount of revenue they produce for their employers. However, they find that as restrictions on salary negotiations are reduced (i.e. free agency), salaries approach players' marginal revenue products. In addition, they find no evidence of racial discrimination in the salaries of NBA players during a period from 1970-1981. This is not the only literature that does not find racial preferences in the NBA. Gius and Johnson (1998) use a log-linear wage regression to show that no salary discrimination existed in the NBA.[26] In fact, they find that a player's performance (measured by various statistics), experience, free agency, and draft status of a player are the most important factors in wage determination in the NBA.[27]

In addition, Hamilton (1997) finds no evidence of racial discrimination in NBA salaries for the 1994-1995 season. Interestingly though, he observes that quantile regressions exhibit significant racial differences in white and black players' salaries. Specifically, whites earn less than blacks at the lower end of the spectrum, but they earn more at the higher end. Hamilton explains that this is consistent with discrimination theory. As black players become more visible because of their performance, their salaries increase, but not as much as those of equally talented white players. This is a clear indication of customer discrimination in which fans' racial preferences are greater for players that are highly visible and active as opposed to those who sit on the bench or play sparingly. Finally, Jenkins (1996) also finds no evidence of salary discrimination in the NBA using an alternative method.

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[24] He defines black as African Americans and black Latins.
[25] In addition to this paper, Hanssen and Andersen (1999) examine customer discrimination in baseball over time using fan voting for the All-Star game. The results of their study show that blacks received fewer votes in the 70's, but over time, this trend has diminished and possibly reversed. Thus, Hanssen and Andersen identify the presence of customer discrimination in MLB, but it is important to note that they also find that racial preferences have changed over time.
[26] They use performance data from the 1995-1996 season and salary data from the following season.
[27] Although each author uniquely calculates player performance, Berri (1999) employs a very detailed analysis of how a player's value is determined.

Instead of using annual salaries of all players in a given season, he only uses free-agent salaries from 1983-1994. Overall, these more recent papers have not found evidence supporting the salary differential, driven by racial preferences, discussed by Kahn and Sherer. This may be an indication that over time, these discriminatory practices have reduced in the NBA.

As presented by Kahn and Sherer and numerous other authors, there exists a salary differential between white and black players in the NBA. Although this is not disputed, the source of this differential is. Specifically, is this discrepancy justified by player skill and productivity, or is it the result of racial discrimination? There are a number of papers that examine this issue, but the results are ambiguous. For instance, Brown, Spiro, and Keenan obtain results indicating that white players receive greater compensation than black players of equal ability, but Gius and Johnson do not. However, for those who do find evidence of salary discrimination, there is further debate on the source of this discrimination. Why do white players get paid more? In particular, a number of studies have been done examining the effects of team racial composition on attendance: customer discrimination. Kahn and Sherer suggest that attendance increases as the percentage of whites on a team's roster increases, but others, like McCormick and Tollison and Schollaert and Smith, find results indicating otherwise. In this paper, I will reexamine the topic of customer discrimination in the NBA using an estimation of total annual attendance for every NBA team from the 1996-1997 season through the 2000-2001 season.

III. Theory, Variables, and Model Specifications

There are a number of factors that may have significant effects on team annual attendance. First and foremost, the quality of any product is important to a potential consumer, and so the quality of basketball is important to any potential spectator. Specifically, NBA fans should prefer to see a winning team; therefore, teams with higher winning percentages should have a higher attendance. In addition to winning percentage, the quality of a team may also be captured by a superstar factor. That is, teams with more superstars may play a more skilled and attractive game that leads to victories, and in turn attracts more fans.[28] Although the product being sold is the basketball on the court, tickets must be purchased for fans to attend. Consistent with the law of demand, there

[28] The problem of multicollinearity may exist between a team's winning percentage and the number of superstars on a team. Specifically, winning percentage may be a function of the number of superstars in that a team with more superstars will have a higher winning percentage. If this relationship exists, one of these variables may capture the effect of the other causing ordinary least squares (OLS) to produce odd results such as unexpected coefficient signs or insignificant t-statistics.

should be an inverse relationship between attendance and ticket prices; as ticket prices increase, attendance at NBA games should decrease.[29] However, there is a maximum level of attendance for all teams. This maximum level is determined by the size (number of seats available) of the facility in which the team plays. In particular, a team's total annual attendance is, in theory, maximized at the level of the facility capacity times 41, the number of NBA home regular season games. Therefore, assuming capacity is a constraint on attendance, total annual attendance will increase as a result of an increase in arena capacity. However, if a team is not selling out its home games, an additional seat in its arena will not cause attendance to increase. In addition to these team and facility factors, there are market characteristics that should have an effect on attendance.

The population, income, and the existence of substitutes in a team's SMSA may significantly influence attendance. As population and income increase in an SMSA, so should the level of total annual attendance. If there are more people in a team's market, there is a greater likelihood that there will be people interested in attending a game. Further, as income increases in an SMSA, people will have more disposable income with which they can purchase tickets. In addition, the number of available substitutes in an SMSA may have an effect on attendance. Specifically, the existence of another NBA team in a team's SMSA may decrease attendance. This may also occur due to the presence of other professional teams in the other major leagues: the National Football League (NFL), Major League Baseball (MLB), and the National Hockey League (NHL). If a team is in a market with several competing franchises or is not having a very good season in terms of winning, attendance will not necessarily decrease. Certain teams that have been in a city (SMSA) for a long period of time may have developed a rich tradition which causes fans to attend games despite other factors. Therefore, the longer a team has been in a city may cause attendance to increase. On the other hand, attendance may be high for a new team entering the league, but as the novelty wears off, attendance will decrease.

The final factor that may affect attendance is the potential existence of racial preferences of fans. Although the effects are less clear, it is possible that the percentage of whites and the percentage of blacks in an SMSA affect attendance. Previous literature has shown that attendance appears to increase as the percentage of whites

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[29] There may be an endogeneity issue between attendance and ticket prices. An increase in ticket price should cause a decrease in attendance, which in turn, should cause a decrease in ticket price. Since these variables are jointly determined and exhibit feedback effects, they are best solved using simultaneous equations. The two-stage least squares method of estimation may be used to correct for this simultaneity. Boyd and Boyd (1998) use this method to estimate attendance. Further, the existence of multicollinearity is possible between the number of superstars and ticket price. Fans may be willing to pay a premium to watch superstars like Michael Jordan, Kobe Bryant, Allen Iverson, etc.

increases.[30] However, if there is any customer discrimination, the effects of these two variables may depend on the racial composition of the team. If there is customer discrimination against black players, there should be a negative relationship between the percentage of black players on a team and attendance. As the percentage increases, attendance should decrease. The same relationship holds true if there is discrimination against white players; as the percentage of white players on a team increases, attendance should decrease. In addition, fans may be preferential to their own race, which implies that attendance will be higher in an SMSA in which the racial composition is similar to the racial composition of the team in that SMSA. For instance, a predominantly white SMSA will have higher attendance if the market's team is predominantly white as well.[31] However, if there is no customer discrimination, the racial composition of a team should have no effect on attendance. In the majority of previous literature, the racial composition of a team has been measured by the percentage, ratio, or fraction of white or black players on a team.[32] However, there are alternative measures of team racial composition, and the goal of this paper is to examine several of these alternative measures to determine if there is customer discrimination in the NBA.

In addition to the percentage of white players on the roster (*WPCTPLYRS*), I will use *WPCTMIN* (the percentage of total minutes in a season played by white players), *WPCTPTS* (the percentage of total points in a season scored by white players), *WPCTSTARTS* (the percentage of total starts in a season started by white players), *WPCTROTATION* (the percentage of white players in the top nine roster spots determined by points per game)[33], and *ROC* (equal to one for any team that had a black head coach at any point in the season and zero otherwise) as alternative measures of racial composition.[34] If there is customer discrimination using *WPCTPLYRS* to measure racial composition, it implies that fans prefer to see white players on a given team's roster.[35] However, it does not account for different levels of player participation, importance, or the race of the head coach, hence my decision to

[30] This result may be attributed to higher income levels for whites.
[31] This issue can be examined using interaction variables to determine if the effects of team racial composition, on attendance, vary with the racial composition of the market.
[32] There are some papers, as discussed in the literature review, which use other measures of racial composition.
[33] The decision to use a nine-man rotation was not entirely arbitrary. It is very common to hear of an eight-man rotation in the NBA, but it is not the rule. According to the current head coach of the Boston Celtics, Jim O'Brien, "The rotation is negotiable. An eight-man rotation is not the product of the number eight. It's a product of the amount of players that you feel good about being able to contribute to a winning effort. If you have 11 men that can all contribute at what you think is a high level, then you have an 11-man rotation. There's no magic number on eight" (http://www.bostonherald.com/sport/celtics/cnots03172002.htm).
[34] The race of each player was determined by the collective knowledge of myself and Professor David W. Findlay (Professor of Economics, Colby College). To identify the race of any unknown player, I examined individual photographs provided by the Sporting News Official NBA Registers for each of the seasons included in this study. A player is defined as black if he is black and white if otherwise.
[35] For this analysis, I assume that any customer discrimination is against blacks.

use these alternative measures of racial composition.[36] Specifically, each of these variables illustrates the visibility, productivity, and importance of white players during a season.

WPCTMIN captures the actual amount of time that white players are on the court. If customer discrimination exists using this measure, it implies that fans prefer to see white players on the court regardless of their place in the lineup (they can be starters or role players). Although *WPCTMIN* is a good measure of participation, *WPCTPTS* more accurately gauges player productivity and importance. In order for a player to score, he must have the ball; and when he does have it, he is the focal point of the game at that moment. Thus, if individuals with racial preferences focus on points scored, they will prefer to watch white players have the ball, score, and be more visible. *WPCTSTARTS* and *WPCTROTATION* measure how much each race is represented among the starters and the players who are in the nine-man rotation, respectively. The starters and the players in the rotation are the most influential to a team's success and are the most visible since they are the players who score the most on average. The existence of discrimination using either of these measures of racial composition implies that fans prefer to see white players in the game, scoring the points, and presumably gaining all the notoriety. All of these variables independently pose interesting questions about fan preferences, but when comparing them to *WPCTPLYRS*, there is more to be explored. Specifically, if discrimination is found using *WPCTPLYRS* but not using any of the other measures of racial composition, it is possible that there is a trade-off between a team's success and a fan's racial preferences; a fan will discriminate until winning is compromised by those discriminatory preferences. He may be more accepting of black players who contribute more to winning by scoring points or playing a key role on the team, and thus will only discriminate against those who are on the bench and not contributing to the team's success. On the other hand, if discrimination is found using the alternative measures and not found using the percentage of white players on the roster, customers are satisfied when white players are more significant and visible, not just because they are on the bench. As a result of these potential implications, it is highly valuable to examine the effects of these alternative variables.

[36] Hanssen (1998) also served as motivation for the use of these alternative measures of racial composition. In his paper on MLB, Hanssen finds that fans discriminated against black bench players more than black starters since they did not contribute as much to the success of the team.

IV. Empirical Results

Given theoretical analysis and three models of attendance presented in previous studies, I will attempt to replicate these papers using my data set and then specify a model of my own for the five-season period from 1996 to 2001. It is my hope that this examination of attendance will provide a comprehensive analysis of customer discrimination.

The first model on which I will focus is presented by Kahn and Sherer (1988). Using ordinary least squares, they find that the number of superstar players, the number of substitutes in the SMSA, and ticket price have positive, but insignificant coefficients and thus have no effect on attendance.[37] They find that the coefficient on the percentage of blacks in the SMSA is significant, but is negative. Conversely, the coefficients on the variable measuring the change in attendance from one season to the next, winning percentage, arena capacity, population of the SMSA, income of the SMSA, and most importantly the percentage of white players on the roster are positive and significant. Their results suggest that customer discrimination existed from the 1980-1981 season to the 1985-1986 season.

For this replication, I assume that total annual attendance (*ATT*) is a function of winning percentage (*WIN*), the number of All-Star players on the roster (*STAR*), arena capacity (*CAP*), the percentage of blacks in the SMSA (*PCTB*), the population of the SMSA (*POP*), the per capita income of the SMSA (*INC*), the number of all other professional teams (i.e. NBA, NFL, MLB, and NHL) in the SMSA (*ALLCOMP*), average ticket price (*TPR*), and the racial composition of the team for any given season (*SEASON*).[38] This is represented by equation (1.1) in which the standard measure of team racial composition, *WPCTPLYRS* (the percentage of white players on the roster), is used:

$$(1.1) \qquad ATT = \beta_0 + \beta_1 SEASON + \beta_2 WIN + \beta_3 STAR + \beta_4 CAP + \beta_5 PCTB + \beta_6 POP + \beta_7 INC + \beta_8 ALLCOMP + \beta_9 TPR + \beta_{10} WPCTPLYRS + \varepsilon_1$$

where ε is a random error term.[39]

[37] They also estimate their equation using generalized least squares to correct for serial correlation.
[38] The inclusion of the *SEASON* variable accounts for any time trend in the data. It is also important to note that racial composition was calculated in terms of white players for the sake of simplicity.
[39] This model, as well as all others, will also be estimated using each of the alternative measures of racial composition. The results for all of these estimations are located in the attached appendix.

Variable Definitions and Descriptive Statistics[a]

Variables	Definition	Mean	Standard Deviation
ATT	Total home annual attendance	639,267.331	153,084.659
SEASON	Time trend (i.e. 1996 for 1996-1997 season)	1998	1.419
WIN	Winning percentage (in percent form)	49.930	17.052
STAR	Number of All-Star players on the roster	0.662	0.784
CAP	Arena capacity	19.296 759	1,935.054
POP[b]	Population of SMSA (in thousands)	3,415.655	2,527.872
INC[b]	Per capita income (in U.S. dollars)	16.320.069	2,272.622
PCTB[b]	Percentage of blacks in SMSA	26.414	19.256
ALLCOMP	Number of all professional teams in SMSA	2.166	1.736
TPR	Average ticket price	42.828	12.785
WPCTPLYRS	Percentage of white players on the roster	20.605	9.906
WPCTMIN	Percentage of total minutes played by white players	16.210	11.962
WPCTPTS	Percentage of total points scored by white players	5.906	4.691
WPCTSTARTS	Percentage of total starts started by white players	16.322	14.709
WPCTROTATION	Percentage of white players in the top nine roster spots (determined by points per game)	15.556	13.633
ROC	Race of head coach(s) (equal to one if team had a black coach at any point during the season and zero otherwise)	0.228	0.421

a The values listed are averages over the 1996-1997 to 2000-2001 seasons.
b Source: 2000 edition of the Statistical Abstract of the United States. Specifically, the values of population and the racial composition variables are 1990 values and per capita income data are in 1989 figures. It is important to note that this data for Toronto and Vancouver were collected from Statistics Canada (based on the 1996 Canadian census). Canada reports average total income of persons reporting income in Canadian dollars instead of per capita income. I used the 1996 U.S./Canadian exchange rate to convert this data into U.S. dollars.
Note: In the Appendix, there is a complete list of variable definitions and the sources from which the data to produce them was obtained.

Using a model almost identical to Kahn and Sherer (1988)[40], I obtain several different results for the period from 1996 to 2001. Table III presents the ordinary least squares results for this first set of equations. The coefficient for *SEASON* is negative and significant implying that attendance has decreased over the five-season sample period (1996-2001). More specifically, from one season to the next, total annual attendance decreases by 23,683.3. Contrary to theory, the coefficient of *WIN* is insignificant indicating that a team's winning percentage has no effect on attendance. However, this result may be due to the presence of multicollinearity between *WIN* and *STAR*. As noted earlier, a team's winning percentage may be a function of the number of All-Star players on the team, and if so, *STAR* may capture the effect of *WIN*, on attendance, and cause the insignificant t-statistic. In fact, the coefficient on *STAR* is positive and highly significant. Specifically, this coefficient indicates that the existence of an additional All-Star player on a team's roster causes total annual attendance to increase by 93,636.6.[41] The positive and significant coefficient on *TPR* is inconsistent with theory. An increase in ticket price should cause a decrease in attendance; however, the results suggest that a one-dollar increase in average ticket price causes total

[40] I use the number of All-Stars and average ticket price where they use the number of players on the first and second All-NBA teams and minimum ticket price, respectively.

annual attendance to increase by 2,862.59.[42] On the other hand, the results for *CAP* and *PCTB* are consistent with theory.[43] The positive and significant coefficient on *CAP* indicates that for each additional seat in an arena, total annual attendance increases by 40.298. There are 41 home games for each team in an NBA season; therefore, this result implies that the additional seat is filled by one person in each of those games, but one.[44] The negative and significant coefficient on *PCTB* implies that a one percent increase in the black population of an SMSA decreases attendance by 1,319.97.

The coefficients on *POP*, *INC*, and *ALLCOMP* are all insignificant. Specifically, a 1,000-person increase in an SMSA, a one-dollar increase in per capita income of an SMSA, or the presence of one additional professional sports team will not affect total annual attendance. Finally, the coefficient on *WPCTPLYRS* is insignificant indicating that a one-percent increase of white players on a team's roster has no effect on total annual attendance. Given this result, this equation provides no evidence of customer discrimination in the NBA. The results for the other five equations produce identical results. Specifically, none of the six equations indicates the existence of racial discrimination by spectators, no matter how the racial composition of a team is measured.

In addition to Kahn and Sherer (1988), McCormick and Tollison (2001) and Schollaert and Smith (1987) are key papers in the study of customer discrimination in the NBA. The results of both papers suggest that customer discrimination is non-existent, but I replicate them using similarly specified models to determine whether similar results occur using a more recent data set and alternative measures of racial composition.

Using ordinary least squares, McCormick and Tollison estimate attendance for the period from the 1980-1981 season to the 1986-1987 season. They obtain negative and significant coefficients for all of the season dummy variables (except the 1986-1987 coefficient is insignificant), ticket price, the number of other NBA teams in the SMSA, and the percentage of blacks in the SMSA. On the other hand, the coefficients on arena capacity, population of the SMSA, and total number of regular season games won are positive and significant. Finally, the number of

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[41] The simple correlation coefficient between *WIN* and *STAR* is 0.55275, another indication that some multicollinearity may exist.
[42] This result may be driven by a complicated relationship between ticket price, capacity, and population.
[43] The majority of previous literature suggests that attendance is negatively related to the percentage of blacks in the SMSA.
[44] It is important to note that the interpretation of this result strictly applies to teams for which arena capacity is a constraint (i.e. teams that sellout all or most of their games). By calculating the number of unsold seats in a season, I determined the teams for which this capacity constraint existed. Specifically, all of the following teams had zero or negative unsold seats (they sold additional standing tickets): Atlanta (97-98), Charlotte (96-97, 00-01), Chicago (96-97, 97-98), Houston (96-97, 97-98, 98-99), Indiana (99-00), New York (all seasons), Phoenix (96-97, 97-98),

other professional teams in the SMSA, per capita income in the SMSA, the interaction of regular season games won and population of SMSA, the number of All-Stars, the race of the coach variable, and the ratio of white to black players all have insignificant coefficients (all of them are negative except the number of All-Stars and the ratio of white to black players).[45] The key result is that the racial composition of the team has no effect on attendance implying that customer discrimination did not exist during this sample period.[46]

In order to replicate McCormick and Tollison, I estimate the following equation for each of the measures of racial composition:

$$(2.1) \quad ATT = \beta_0 + \beta_1 s97 + \beta_2 s98 + \beta_3 s99 + \beta_4 s00 + \beta_5 TPR + \beta_6 CAP + \beta_7 NBA + \beta_8 OTHERCOMP + \beta_9 INC + \beta_{10} POP + \beta_{11} PCTB - \beta_{12} NUMWIN + \beta_{13} NUMWINPOP + \beta_{14} STAR + \beta_{15} ROC + \beta_{16} WHITEBLACK + \varepsilon_1$$

where *s97*, *s98*, *s99*, and *s00* are dummy variables for the four seasons from 1997-1998 to 2000-2001 (1996-1997 is the reference season to which these variables are related); *NUMWIN* is the number of regular season wins; *NUMWINPOP* is the interaction of *NUMWIN* and *POP*; *WHITEBLACK* is the ratio of white to black players on the roster; and ε_1 is a random error term. Further, *ALLCOMP* is separated into *NBA* (the number of other NBA teams in the SMSA) and *OTHERCOMP* (the number of NFL, MLB, and NHL teams in the SMSA).[47]

Using this replication of the McCormick and Tollison model, I obtain several different results for the more recent period. Table IV presents the ordinary least squares results for this set of equations using the various measures of racial composition. The season dummy variable *s97* has a negative, but insignificant coefficient. Conversely, the other season dummy variables (*s98*, *s99*, and *s00*) all have negative and significant coefficients. This suggests that for the 1998-1999, 1999-2000, and 2000-2001 seasons, total annual attendance decreased by 289,234, 61,027.8, and 70,113.9, respectively. Contrary to theory, the coefficient on *TPR* is positive and significant indicating that a one-dollar increase in average ticket price causes total annual attendance to increase by 2,310.88. The coefficients on *CAP* and *POP* are positive and significant as theory suggests. This implies that for each

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Sacramento (96-97, 99-00, 00-01), San Antonio (98-99, 99-00, 00-01), and Seattle (96-97, 97-98). All of these teams were champions or strong contenders.

[45] It is important to note that McCormick and Tollison separate the number of NFL, MLB, and NHL teams into separate variables. The coefficient on the MLB variable was actually negative and significant where the others were insignificant. In addition, they address the issue of simultaneity between attendance and ticket price by producing two-stage least squares estimates.

[46] McCormick and Tollison also use the ratio of minutes played by white players to minutes played by black players to measure team racial composition, and they obtain the same results.

additional seat in an arena and for a 1,000-person increase in SMSA population, total annual attendance increases by 32.084 and 17.215, respectively. Although I do not separate NBA, NFL, MLB, and NHL teams as definitively as McCormick and Tollison, I obtain similar results. Specifically, the coefficient on *NBA* is negative and significant indicating that the existence of another NBA team causes total annual attendance to decrease by 128,013. Further, the coefficient on *OTHERCOMP* is positive and insignificant suggesting that the presence of other professional sports teams in the SMSA has no effect on attendance. Similarly, the coefficient on *INC* is negative and insignificant contrary to expectations. This result implies that per capita income of an SMSA also has no effect on total annual attendance. In addition, the coefficient on *PCTB* is negative and significant indicating that a one-percent increase in the number of blacks in an SMSA decreases total annual attendance by 1,413.14.

As expected, the coefficient on *NUMWIN* is positive and significant. This implies that one additional regular season win increases total annual attendance by 3,358.23. However, it is possible that the effect of the number of regular season wins is not entirely captured by this variable. Interestingly though, the coefficient on *NUMWINPOP* is negative and insignificant. This implies that the effect of regular season wins, on attendance, does not vary with the size of the SMSA population. Also consistent with theory, the coefficient on *STAR* is positive and significant indicating that the existence of an additional All-Star player on a team's roster causes total annual attendance to increase by 1,091.7. Lastly, the coefficients on *ROC* and *WHITEBLACK* are negative and positive, respectively, but insignificant. Specifically, the race of the head coach and team racial composition, measured as the ratio of white to black players on the roster, have no effect on attendance. Consistent with McCormick and Tollison, there is no evidence of racial discrimination using this specification or any of the alternative measures of racial composition.[48]

Finally, I replicate the model by Schollaert and Smith (1987) by estimating the following equation for every measure of racial composition:

$$\text{(3.1)} \quad ATT = \beta_0 + \beta_1 STAR + \beta_2 WIN + \beta_3 PRIORWIN + \beta_4 TPR + \beta_5 CAP + \beta_6 POP + \beta_7 INC + \beta_8 PCTB + \beta_9 NBA + \beta_{10} ALLCOMP + \beta_{11} WPCTPLYRS + \varepsilon_i$$

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[47] In this replication, I do not separate other professional sports teams into individual variables for NFL, MLB, and NHL teams. In addition, I use average ticket price where they use median ticket price.

[48] The results for this equation remain unchanged when using the alternative measures of racial composition with only one exception. In equation (2.5), using *WPCTROTATION*, *POP* is no longer significant and thus has no effect on attendance.

where *PRIORWIN* is a team's winning percentage in the previous season and ε_t is a random error term. Using generalized least squares to correct for serial correlation, Schollaert and Smith estimate a model similar to this, and obtain a number of interesting results.[49] Specifically, they find that the coefficients on the number of All-Stars, winning percentage, relative finishing position, prior season's winning percentage, high ticket price, facility size, SMSA population, and SMSA median income are positive and significant. They also find that the percentage of blacks in an SMSA has a negative and significant coefficient. Finally, they obtain negative, but insignificant coefficients for moderate ticket price, the number of competing franchises, and the percentage of black players on a team. Most importantly, their last observation implies that customer discrimination did not exist during the 1969-1982 sample and condensed period of 1977-1982.

Using equation (3.1), the ordinary least squares results in Table V are somewhat different than those found by Schollaert and Smith. The coefficients on *WIN* and *PRIORWIN* are positive and insignificant implying that the current and prior season's winning percentages have no effect on attendance. Although this result is not expected by theory, it may be due to multicollinearity. Specifically, the coefficient on *STAR* is positive and significant indicating that the existence of an additional All-Star player on a team's roster causes total annual attendance to increase by 89,372.7. If multicollinearity exists between any two or all three of these variables, it could be responsible for the insignificant t-statistics.[50] Also inconsistent with theory, the coefficient on *TPR* is positive and insignificant suggesting that average ticket price has no effect on total annual attendance. The law of demand suggests that there should be a negative relationship between ticket price and attendance, but it does not hold true in this model.

The coefficient on *POP* is negative and the coefficient on *INC* is positive, but both are insignificant. Consequently, changes in the population and in per capita income of an SMSA have no effect on total annual attendance. In addition, the coefficient on *ALLCOMP* (positive) is also insignificant implying that the existence of another professional sports team has no effect on total annual attendance. Although these market characteristics are not influential in determining attendance, the negative and significant coefficient on *PCTB* indicates that a one-percent increase in the number of blacks in an SMSA causes total annual attendance to decrease by 1,215.04.

[49] Schollaert and Smith use high and moderate ticket prices as separate explanatory variables where I only use average ticket price. Like Kahn and Sherer, they also combine *NBA* and *OTHERCOMP* into one variable. Further, they include relative finishing position from the prior season and a dummy variable equal to one for teams with a suburban facility. I do not use these variables in my replication of their model.

[50] In addition to the 0.55275 correlation coefficient between *WIN* and *STAR*, the correlation coefficient for *WIN* and *PRIORWIN* is 0.68951. It is highly likely that multicollinearity exists between these three variables.

Finally, the coefficient on *WPCTPLYRS* is positive and insignificant. This implies that the percentage of white players on a team's roster has no effect on total annual attendance.

After estimating the equation with the alternative measures of racial composition, the results are virtually unchanged. In fact, the only difference is that the positive coefficient on *PRIORWIN* only remains insignificant in equation (3.3) in which team racial composition is measured as the percentage of points scored by white players. For all the other alternative measures, a one-percent increase in the prior season's winning percentage causes attendance to increase. Most importantly, none of the coefficients on the measures of racial composition is significant; therefore, there is no evidence of customer discrimination using this model.

None of these three models produces evidence of customer discrimination. However, it is possible that these results are not entirely reliable since the 1998-1999 season was shortened to 50 games by a strike and there was no All-Star game.[51] Due to this abnormality, it is important to test if the 1998-1999 season can be pooled with the remaining four seasons. Specifically, I performed Chow tests for all equations in Tables III-V to determine if the explanatory variables have the same effect on total annual attendance for all the seasons in the sample period.[52] The Chow test consists of separating the data into two subsets, and then estimating the equation in question using the ordinary least squares method for each subset and a pooled set. Once these equations have been estimated, an F-statistic is calculated. If this F-statistic is greater than some critical value, one can reject the null hypothesis that the regression coefficients for each subset have the same effect on the dependent variable. Such a result indicates that samples of data cannot be pooled.

For my analysis, I create one subset for the 1998-1999 season (29 observations) and another for the remaining four seasons (116 observations). The pooled set consists of 145 observations. In order to perform the estimations, I have to remove *STAR* from every equation, *SEASON* from the Kahn and Sherer replication equations, and the season dummy variables (i.e. *s97*) from the McCormick and Tollison replication equations due to the singularity of this data. After estimating all the necessary equations for each model, I calculate the F-statistics and determine the results of the tests.

Using all six measures of racial composition for all three replication models, the calculated F-statistics are all greater than the critical values of the F-statistic at the 0.01 level of significance. Accordingly, I reject the null

[51] Since there was no All-Star game for the 1998-1999 season, I entered zero as the number of All-Star players on the roster for every team during this season.
[52] None of the replicated papers test for this potential pooling problem for their sample periods.

hypothesis and conclude that the data cannot be pooled for any of the models. As a result of separating the data into subsets, there are several interesting results for all three model replications (Table VI-Table XI).

In the Kahn and Sherer replication model for the 1998-1999 season, the coefficient on *POP* is positive and insignificant. Contrary to theory, this suggests that the population of an SMSA has no effect on attendance. Also inconsistent with theoretical expectations, the coefficient on *TPR* is positive and significant indicating that there is a positive relationship between average ticket price and attendance. In addition, the coefficient on *INC* is positive and significant indicating that an increase in per capita income causes attendance to increase. Although this result is consistent with theory, the coefficient is not significant when any of the alternative measures of racial composition is used.

Finally, the most interesting results are those of the various measures of racial composition. Specifically, the coefficients on *WPCTPLYRS*, *WPCTMIN*, *WPCTPTS*, and *WPCTROTATION* are positive and significant suggesting that a one-percent increase in each of these variables causes total annual attendance to increase by 1,720.84, 1,292.60, 3,038.24, and 820.590, respectively. On the other hand, the coefficients on *WPCTSTARTS* and *ROC* are insignificant implying that the percentage of starts by white players and the race of the head coach have no effect on attendance. Primarily, these results suggest that customer discrimination existed in the NBA during the 1998-1999 season. Fans prefer to see white players on the roster, on the court, scoring points, and in the nine-man rotation. Interestingly though, fans do not appear to have discriminatory preferences for the players in the starting line-up. This result may suggest that discriminatory customers are faced with a trade-off between their racial preferences and winning.

Specifically, fans will discriminate against blacks as long as they are not important to the success of the team (i.e. players on the bench). Although this is an interesting interpretation of the results, it is not likely since fans prefer white players play more minutes and score more points, both of which are very good gauges of the importance and productivity of players. In fact, the magnitudes of the parameter estimates suggest that fans are most sensitive to changes in the percentage of points scored by white players, and consequently, attendance increases by the greatest magnitude. Specifically, a one-percent increase in *WPCTPTS* causes attendance to increase by almost twice as much as a one-percent increase in *WPCTPLYRS* (3,038.24 and 1,720.84, respectively). This implies that fans are more interested in observing teams on which white players are not only members who play, but also members who have the ball and score points. In particular, the players who score are the most visible and contribute significantly to winning; fans preferred to see white players fulfill this role during the 1998-1999 season.[53]

The results are slightly different for the remaining four seasons in the sample period. For this subset, the coefficients on *STAR* and *POP* are both insignificant indicating that the number of All-Stars on the roster and the SMSA population have no effect on attendance.[54] Like the 1998-1999 season, the coefficient on *INC* is positive and significant for some, but not all, of the estimated equations. Specifically, the coefficient on *INC* is insignificant in equations (5.3), (5.4), and (5.6) in which race is examined by *WPCTPTS*, *WPCTSTARTS*, and *ROC* respectively. More importantly, the coefficients on all of the racial composition variables (excluding *ROC*) are positive and significant indicating the presence of customer discrimination for this sample.[55] Again, it is important to note the magnitudes of the coefficients on these variables. Specifically, a one-percent increase in the percentage of white players on the roster causes total annual attendance to increase by 1,356.40 where a one-percent increase in the percentage of starts by white players only causes total annual attendance to increase by 792.835. This result suggests that it is more important for teams to have white players on the roster than to have white players be starters. This is another indication that there is a trade-off between discrimination and winning, but the coefficient on *WPCTPTS* remains the largest, contradicting this theory. However, the results clearly indicate that customer discrimination exists.

Using the McCormick and Tollison replication for the two subsets of data, the general results are somewhat similar to those of the Kahn and Sherer replications. In this model, average ticket price and population of the SMSA also cause total annual attendance to increase for the 1998-1999 season. In contrast to theory, the coefficient on *INC* is negative and insignificant for every equation indicating that there is no relationship between per capita income and attendance. Further, the coefficient on *NUMWIN* is positive and insignificant for every equation except (6.2) in which team racial composition is measured by the percentage of minutes played by white players. This suggests that

[53] The examination of attendance for a single season (i.e. 1998-1999) is similar to the study by Brown, Spiro, and Keenan (1991). They estimate home attendance using winning percentage, average ticket price, the number of All-Star players, SMSA population, SMSA per capita income, the number of other professional teams in the SMSA, the number of years a team has been in its city, and the percentage of total minutes played by black players.
[54] *STAR* and *SEASON* are estimated for the non-strike season subset, but not for the 1998-1999 season due to the singularity of the data.
[55] It is interesting that the results for both subsets in this replication indicate the existence of customer discrimination, however, the chow test suggested that they could not be pooled. Since *STAR* and *SEASON* were omitted from the 1998-1999 season subset, it is possible that they could be the source of inconsistency in the data set. Thus, I estimate the four non-strike seasons without these variables to see if the results for the racial

one additional regular season win has no effect on total annual attendance. Most importantly, however, the results pertaining to discrimination are substantially different than those produced by the Kahn and Sherer replication. Specifically, *WPCTMIN* and *WPCTPTS* are the only measures of racial composition with positive and significant coefficients indicating that a one-percent increase in minutes played and points scored by white players cause total annual attendance to increase by 934.414 and 2,160.09, respectively. Like the Kahn and Sherer replication, these results suggest that fans had racial preferences during the 1998-1999 season. These results are interesting not only because they suggest discriminatory behavior by fans, but because of the way in which fans discriminate.

In particular, fans are not interested in seeing white players merely on the rosters of NBA teams, white players must be highly visible and contribute significantly to their teams. Specifically, the ratio of white to black players on a roster changes frequently during the course of an NBA season as a result of short-term personnel changes. For instance, a white player can be added to a roster for a ten-day period increasing the white to black ratio, but never play a single minute. Thus, this player is never exposed to the spectators and bares little importance to the success of the team. On the other hand, the players who play more minutes and score more points are highly exposed to the fans and of the utmost importance to winning, and the results suggest that fans prefer these players to be white. Given these results, it is clear that the alternative measures of racial composition, like the percentage of points scored by white players, can have an effect on attendance when the percentage of white players on the roster does not. As a result, it is possible that customer discrimination can be overlooked if the racial composition of a team is only measured as a percentage, fraction, or ratio of white players on the roster.

When examining the remaining four seasons, it is obvious that there are several different results. Although the coefficients on *TPR* and INC remain insignificant and consequently have no effect on attendance, the coefficients on *POP* and *NUMWIN* become positive and significant. Thus, a 1,000-person increase in SMSA population and an additional regular season win cause total annual attendance to increase by 17.225 and 3,726.30, respectively. However, changes in all the measures of racial composition now have no effect on attendance contrary to all replications for both the strike and non-strike seasons. This inconsistency suggests that the specification of the model can significantly alter the results, providing contradicting evidence in regards to discrimination.

In the last replications of Schollaert and Smith, there are some additional interesting results. Specifically, the replication for the 1998-1999 strike season indicates that *INC* and *PRIORWIN* are positively related to total

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compositions variables change. Interestingly, they do not, suggesting that these variables are not the problem in the annual attendance for some of the equations.[56] Contrary to previous results, average ticket price has no effect on the dependent variable. The key information, however, is that the coefficients on *WPCTPLYRS*, *WPCTMIN*, and *WPCTPTS* are positive and significant providing evidence of customer discrimination for this season. The results for the subset of the four remaining seasons are very similar. Specifically, *INC* and *PRIORWIN* have positive and significant coefficients in every equation, and average ticket price has no effect on attendance.

Lastly, all of the coefficients on the racial composition variables are positive and significant, thus providing further evidence of customer discrimination in the NBA. Similar to previous findings in this paper, the coefficient on *WPCTPLYRS* is larger than the coefficients on the other racial composition variables. Again, this is an indication that fans are most concerned with the visibility, productivity, and importance of white players. It is important that white players are on the roster, but the effect of discrimination, on attendance, is the greatest when white players are on the court scoring points more frequently.

In addition to replicating the models from previous literature, I specified a new model in which I include the number of years a team has been in the SMSA (*YEARS*) as an explanatory variable:

$$(10.1)\quad ATT = \beta_0 + \beta_1 WIN + \beta_2 PRIORWIN + \beta_3 TPR + \beta_4 CAP + \beta_5 POP + \beta_6 INC + \beta_7 PCTB + \beta_8 NBA + \beta_9 OTHERCOMP + \beta_{10} YEARS + \beta_{11} WPCTPLYRS + \varepsilon_1$$

where ε_1 is a random error term. The results of this model strongly resemble those produced by the Schollaert and Smith replications including evidence of customer discrimination. For the 1998-1999 season, the coefficient on *YEARS* is insignificant indicating that the number of years a team has been in its SMSA has no effect on attendance. More pertinent to the issue of discrimination, the coefficient on *WPCTMIN* is positive and significant indicating that a one-percent increase in the percentage of minutes played by white players causes total annual attendance to increase by 765,242. However, all of the other measures of racial composition have no effect on attendance. Like the 1998-1999 replication of McCormick and Tollison, this result suggests that fans are not concerned with the racial composition of the roster, but rather, the racial composition of the players on the court who are the most visible and the most vital to winning. For the remaining four seasons, the results are significantly different. Specifically, the coefficient on *YEARS* is positive and significant indicating that one additional year in an SMSA causes a team's total annual attendance to increase by 1,275.96. This result supports the theory that a team's

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pooled set.

tradition and longevity increase attendance. In addition, all of the racial composition variables are positively related to total annual attendance except for the percentage of points scored by white players (equation 11.3). In total, this model, consistent with the results produced by the replications, provides evidence of customer discrimination in the NBA.

V. Additional Results

In addition to testing for discrimination, it is important to further explore the findings of this paper and to discuss other interesting results. Thus far, the majority of results have suggested that customer discrimination is a real phenomenon in the NBA. Specifically, several model specifications have produced results indicating that increases in one, some, or all of the measures of racial composition cause attendance to increase.[57] For instance, the coefficient on *WPCTSTARTS* in equation (11.4) is positive and significant indicating that a one-percent increase in the percentage of starts by white players causes total annual attendance to increase by 826.293. Using the mean average ticket price from this data ($42.83), this change in attendance increases team revenue by $35,390. Distributed over 41 games, these figures appear to be insignificant, however, what happens when a team acquires a player like Larry Bird? Larry Bird did not play during the five seasons from 1996-2001, but when he did play, he was one of the most dominant players in the game and undoubtedly the most recognizable white player in the history of the sport. Although there is no "Larry Bird" in the NBA currently, there are highly skilled and accomplished veterans, like John Stockton, and rising stars like Keith Van Horn (both are white). Assuming that he is healthy for an entire season, John Stockton will start all 82 games. Since there are five starters in a game, the acquisition of Stockton would increase the number of starts by white players by 20 percent.[58] Consequently, total annual attendance does not increase by 826.293 (as stated above), but by 16,525.86, causing team revenue to increase by $707,802.58! This impact also holds true for the other measures of racial composition. For instance, assume a team with all black players makes a trade for a white player who scores 1,000 points. If this team scores 8,000 points in

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[56] Specifically, the coefficient on per capita income is positive and significant in equations (8.1) and (8.2), in contrast to prior season's winning percentage which is positive and significant in equations (8.4), (8.5), and (8.6). See Table X in the Appendix for specifications of the equations.

[57] It is important to note that the coefficient on *ROC* was never significant in any model indicating that the race of the head coach has no effect on total annual attendance. In addition, all of the models were estimated using two-stage least squares to account for the simultaneous nature of attendance and ticket price. The results are more or less unchanged.

[58] This increase in the percentage of starts by whites assumes that Stockton is replacing a black player in the starting line-up.

the season, the addition of this one player increases *WPCTPTS* by 12.5%. Using the coefficient on *WPCTPTS* in equation (4.3) (3,038.24), the addition of this white player will cause total annual attendance to increase by 37,978 and a subsequent increase in revenue of $1,626,597.74. Although it is disturbing to find evidence of customer discrimination, the results are even more staggering when examining the possibility of the "Bird Effect".

Given the evidence that customer discrimination exists in the NBA, it is important to examine if other factors affect the results. Specifically, interacting the measures of racial composition with the percentage of blacks in the SMSA tests to see if the effects of those variables, on attendance, vary with the racial composition of the market. As shown in Tables XIV and XV, none of the interaction variables are significant indicating that the effects of the racial composition variables on total annual attendance do not vary with the racial composition of the SMSA.[59] Despite these results, an anecdotal analysis of the data suggests that the racial composition of teams is representative of the racial composition of the SMSA. In particular, Washington, D.C., Detroit, Sacramento, and Utah exhibit this quality over the sample period. For instance, Salt Lake City (in Utah) is only 1.7 percent black[60], and for one season in the sample, the Jazz had white players start 70.976 percent of the time, the maximum value for all five seasons. On the other hand, Detroit has the highest percentage of blacks in the SMSA, 75.7. For one season, the Pistons had zero for all of the measures of racial composition. In fact, the largest percentage of white players on the roster for the Pistons during this period was approximately 27 percent.[61] Although these examples suggest that the racial composition of the SMSA may influence the racial composition of the market's team, it is possible that these are the results of random distribution.

In several of the models, the coefficient on *STAR* is large, positive, and significant indicating the existence of an additional All-Star player on a team's roster causes total annual attendance to increase. In order to more closely examine the effect of star power in the NBA, I reestimate the models including a dummy variable, *MJ*, equal to one if Michael Jordan, the quintessential superstar, played in the season and zero otherwise. Consistent throughout all the models, the coefficient on *MJ* is positive and significant (i.e. 67,010) indicating that total annual attendance increased by 67,010 for any season in which he played.[62] Further, the inclusion of this variable does not alter the significance of any of the racial composition variables, indicating that customer discrimination was a

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[59] In addition, all of the measures of racial composition lose significance except for *WPCTPLYRS* during the non-strike seasons.

[60] Only Vancouver had a lower percentage of blacks in the SMSA, 0.9.

[61] Washington, D.C. is predominantly black and Sacramento is not; the racial composition of the Wizards and Kings over the sample period was similar to that of the Pistons and Jazz, respectively.

problem even when Michael Jordan (who is black) was playing. Despite the discrimination, Michael Jordan had a tremendously positive effect on league attendance and revenues. Using the mean value of average ticket price, $42.83, it can be inferred that Michael Jordan increased each team's revenue by $2,870,038.30. In total, Michael Jordan produced $83,231,110.70 in additional revenue throughout the league.[63] Apparently, fans did not discriminate against Michael Jordan!

VI. Conclusions

In this paper, I categorize the league into two groups: white and black players. Specifically, I identified any non-black player as white. However, the NBA has become even more diverse recently, and there are players of many nationalities from all over the world. In fact, many of these international players, like Dirk Nowitzki of the Dallas Mavericks, have risen to stardom. An interesting extension of this paper would be to examine the effects these foreign players have on the NBA and if those players face discrimination similar to blacks.

In a time when racism is not in the forefront of our culture and in a sport dominated by black individuals, the existence of discrimination is perplexing, yet a reality. In a recent article in the *Boston Herald*, Gerry Callahan writes, "These days sports fans set a wonderful example because they just don't care [about race]. The only dividing most fans do is wins from losses, good effort from bad, the Troy Browns from the Randy Mosses." However, using several models and alternative measures of racial composition to estimate total annual attendance, I mostly find that racial preferences influenced individuals' decisions to attend NBA games during the five-season period from 1996-2001. Specifically, I find that at least one, but never all, of the racial composition variables for each model has a positive and significant coefficient for the 1998-1999 strike season providing evidence of customer discrimination. Further, I find evidence of discrimination for the non-strike seasons for every model, but the McCormick and Tollison replication.[64] These results are interesting because they suggest that the sample period and the specification of the model can alter the results relevant to customer discrimination.

Although it was surprising to find discrimination, it was more interesting to see the different ways in which the racial composition of a team affected attendance. Specifically, there were a variety of results suggesting

[62] In this sample period, Michael Jordan only played in the 1996-1997 and 1997-1998 seasons.
[63] The product of the change in attendance and average ticket price (67,010 x $42.83) equals $2,870,038.30. Multiplying this value by 29 equals total league revenue produced by Michael Jordan.
[64] For each model, other than McCormick and Tollison, all of the racial composition variables have positive and significant coefficients, except for *WPCTPTS* in the Tugberk model, equation (11.3).

different methods of discrimination. For instance, it is possible that fans faced a trade-off in which they were willing to set aside racial preferences in order not to compromise winning. On the other hand, spectators could have preferred to see white players play more minutes, score more points, start more often, and be a part of the rotation (overall more visible, more productive, and more important to team success) while being indifferent to the race of the players on the bench. This result is interesting because it suggests that it is possible that discrimination can go undetected if a model excludes the alternative measures of racial composition and only examines the racial composition of the roster. Lastly, it is quite possible that fans simply discriminate against black players period. Regardless of the motivation, customer discrimination is a very real issue in the NBA.

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APPENDIX

TABLE I
Variable Definitions

Variables	Definition
ATT	Total annual attendance
SEASON	Time trend (i.e. 1996 for 1996-1997 season)
s97	Equal to one if 1997-1998 season and zero otherwise
s98	Equal to one if 1998-1999 season and zero otherwise
s99	Equal to one if 1999-2000 season and zero otherwise
s00	Equal to one if 2000-2001 season and zero otherwise
WIN	Winning percentage (in percent form)
PRIORWIN	Winning percentage in the prior season (in percent form)
NUMWIN	Number of regular season wins
STAR	Number of All-Star players on the roster
TPR	Average ticket price
CAP	Arena capacity
POP[a]	Population of SMSA (in thousands)
INC[a]	Per capita income (in U.S. dollars)
PCTB[a]	Percentage of blacks in SMSA
NBA	Number of other NBA teams in SMSA
OTHERCOMP	Number of other professional teams in SMSA (i.e. NFL, MLB, and NHL)
ALLCOMP	Number of all professional teams in SMSA (*NBA* plus *OTHERCOMP*)
YEARS	Number of years team has been in city (SMSA)
WPCTPLYRS	Percentage of white players on the roster
WPCTMIN	Percentage of total minutes played by white players
WPCTPTS	Percentage of total points scored by white players
WPCTSTARTS	Percentage of total starts started by white players
WPCTROTATION	Percentage of white players in the top nine roster spots (determined by points per game)
WHITEBLACK	Ratio of white players to black players on the roster
ROC	Race of head coach(s) (equal to one if team had a black coach at any point during the season and zero otherwise)

a: It is important to note that SMSA data for Toronto and Vancouver were collected from Statistics Canada (based on the 1996 Canadian census). Canada reports average total income of persons reporting income in Canadian dollars instead of per capita income. I used the 1996 U.S./Canadian exchange rate to convert this data into U.S. dollars.

TABLE II
Summary Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
ATT	639.267.331	153.084.659	256,568	985,722
SEASON	1998	1.419	1996	2000
s97	0.20	0.401	0	1
s98	0.20	0.401	0	1
s99	0.20	0.401	0	1
s00	0.20	0.401	0	1
WIN	49.930	17.052	13.40	84.10
PRIORWIN	49.932	17.315	13.40	87.80
NUMWIN	40.943	13.983	10.988	68.962
STAR	0.662	0.784	0	4
TPR	42.828	12.785	23.690	91.150
CAP	19,296.759	1,935.054	16.021	24,042
POP	3,415.655	2,527.872	1,072	8,863
INC	16,320.069	2,272.622	11,828	21,416
PCTB	26.414	19.256	0.90	75.70
NBA	0.138	0.346	0	1
OTHERCOMP	2.028	1.532	0	6
ALLCOMP	2.166	1.736	0	7
YEARS	25.172	12.690	1	54
WPCTPLYRS	20.605	9.906	0	50
WPCTMIN	16.210	11.962	0	57.410
WPCTPTS	5.906	4.691	0	22.052
WPCTSTARTS	16.322	14.709	0	70.976
WPCTROTATION	15.556	13.633	0	66.667
WHITEBLACK	0.281	0.179	0	1
ROC	0.228	0.421	0	1

Note. The values listed are for the five-season period from 1996-2001.

TABLE III
Ordinary Least Squares Estimations of Kahn and Sherer Replication Equations

Independent Variables	**(1.1)**	**(1.2)**	**(1.3)**	**(1.4)**	**(1.5)**	**(1.6)**
INTERCEPT	0.470e8***	0.472e8***	0.471e8***	0.473e8***	0.478e8***	0.473e8***
	(2.97)	(2.98)	(2.97)	(2.98)	(3.02)	(2.98)
SEASON	-23,683.3***	-23,789.5***	-23,727.1***	-23,824.5***	-24,083.1***	-23,849.3***
	(2.99)	(3.00)	(3.00)	(3.00)	(3.03)	(3.00)
WIN	328.985	303.121	294.710	284.944	286.416	282.350
	(0.43)	(0.40)	(0.39)	(0.37)	(0.38)	(0.37)
STAR	93,636.6***	93,973.0***	93,826.9***	94,158.8***	93,336.9***	94,466.4***
	(6.57)	(8.13)	(6.59)	(6.61)	(6.65)	(6.64)
CAP	40.298***	40.248***	40.321***	40.258***	40.064***	40.200***
	(8.14)	(8.13)	(8.14)	(8.11)	(8.09)	(8.12)
PCTB	-1,319.97***	-1,319.79***	-1,316.92***	-1,319.02***	-1,329.07***	-1,332.87***
	(2.60)	(2.60)	(2.59)	(2.56)	(2.62)	(2.50)
POP	-4.300	-4.184	-4.251	-4.208	-4.170	-4.367
	(0.72)	(0.70)	(0.71)	(0.70)	(0.70)	(0.73)
INC	3.450	3.036	3.004	2.652	3.077	2.528
	(0.68)	(0.61)	(0.61)	(0.54)	(0.62)	(0.50)
ALLCOMP	468.600	686.413	840.383	551.274	757.104	611.140
	(0.05)	(0.08)	(0.10)	(0.06)	(0.09)	(0.07)
TPR	2,862.59***	2,905.13***	2,915.87***	2,920.85***	2,929.58***	2,919.49***
	(2.91)	(2.97)	(2.98)	(2.98)	(3.00)	(2.97)
WPCTPLYRS	636.384					
	(0.65)					
WPCTMIN		388.029				
		(0.48)				
WPCTPTS			1,173.43			
			(0.57)			
WPCTSTARTS				156.126		
				(0.23)		
WPCTROTATION					421.657	
					(0.60)	
ROC						-1,228.25
						(0.05)
Adj R^2	0.49	0.49	0.49	0.49	0.49	0.49
F	14.7	14.7	14.7	14.6	14.7	14.6
S_ε	109,552	109,630	109,590	109,700	109,577	109,722
N	145	145	145	145	145	145

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE IV
Ordinary Least Squares Estimations of McCormick and Tollison Replication Equations

Independent Variables	**(2.1)**	**(2.2)**	**(2.3)**	**(2.4)**	**(2.5)**
INTERCEPT	-158,461**	-150,458**	-142,053*	-141,022*	-146,282**
	(1.80)	(1.73)	(1.64)	(1.64)	(1.70)
s97	-1,262.67	-1,402.10	-2,030.91	-2,058.62	-1,590.59
	(0.08)	(0.09)	(0.13)	(0.13)	(0.10)
s98	-289,234***	-288,878***	-288,497***	-289,088***	-289,635***
	(16.69)	(16.65)	(16.58)	(16.66)	(16.70)
s99	-61,027.8***	-60,681.0***	-61,361.9***	-61,659.7***	-61,293.7***
	(3.52)	(3.50)	(3.52)	(3.48)	(3.53)
s00	-70,113.9***	-70,057.4***	-70,364.9***	-69,908.2***	-71,583.4***
	(3.89)	(3.88)	(3.88)	(3.86)	(3.97)
TPR	2,310.88***	2,348.82***	2,373.19***	2,356.21***	2,373.73***
	(4.34)	(4.43)	(4.47)	(4.44)	(4.49)
CAP	32.084***	32.064***	32.013***	32.090***	31.900***
	(11.63)	(11.61)	(11.54)	(11.60)	(11.59)
NBA	-128,013***	-131,947***	-135,446***	-135,022***	-129,287***
	(3.88)	(4.08)	(4.21)	(4.24)	(3.96)
OTHERCOMP	927.405	1,112.35	1,255.33	771.106	1,094.20
	(0.20)	(0.24)	(0.27)	(0.16)	(0.23)
INC	1.046	0.636	0.296	0.249	0.693
	(0.34)	(0.21)	(0.10)	(0.08)	(0.23)
POP	17.215***	17.476***	18.130***	17.499***	17.109
	(2.43)	(2.47)	(2.55)	(2.47)	(1.10)
PCTB	-1,413.14***	-1,428.18***	-1,443.81***	-1,406.70***	-1,428.98***
	(4.55)	(4.61)	(4.65)	(4.50)	(4.62)
NUMWIN	3,358.23***	3,289.12***	3,296.14***	3,206.04***	3,260.38***
	(4.47)	(4.35)	(4.32)	(4.16)	(4.30)
NUMWINPOP	-0.104	-0.093	-0.103	-0.079	-0.091
	(0.78)	(0.68)	(0.75)	(0.56)	(0.67)
STAR	1,091.7*	14,466.5*	15,006.4**	14,281.4*	14,863.6**
	(1.59)	(1.63)	(1.69)	(1.61)	(1.69)
ROC	-8,513.57	-7,789.46	-9,057.19	-8,078.15	-8,296.67
	(0.63)	(0.57)	(0.66)	(0.59)	(0.61)
WHITEBLACK	37,145.5				
	(1.20)				
WPCTMIN		514.435			
		(1.09)			
WPCTPTS			854.779		
			(0.72)		
WPCTSTARTS				414.393	
				(1.06)	
WPCTROTATION					493.311
					(1.21)
Adj R^2	0.86	0.86	0.86	0.87	0.86
F	54.9	54.8	54.5	54.8	54.9
S_ε	57,904.9	57,958.6	58,109.9	57,973.3	57,897.4
N	145	145	145	145	145

Notes. * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE V
Ordinary Least Squares Estimations of Schollaert and Smith Replication Equations

Independent Variables	**(3.1)**	**(3.2)**	**(3.3)**	**(3.4)**	**(3.5)**	**(3.6)**
INTERCEPT	-328,656**	-314,694**	-316,461**	-304,793**	-307,236**	-304,423**
	(2.21)	(2.16)	(2.19)	(2.11)	(2.15)	(2.13)
STAR	89,372.7***	89,715.9***	89,572.4***	89,876.8***	90,080.3***	90,471.6***
	(6.14)	(6.16)	(6.15)	(6.17)	(6.20)	(6.22)
WIN	259.497	225.801	221.347	204.161	208.229	165.398
	(0.29)	(0.26)	(0.25)	(0.23)	(0.24)	(0.19)
PRIORWIN	1,019.93	1,034.84*	1,024.59	1,041.11*	1,042.99*	1,081.38*
	(1.27)	(1.29)	(1.27)	(1.29)	(1.30)	(1.33)
TPR	886.895	920.029	938.911	932.013	924.250	899.871
	(1.03)	(1.07)	(1.09)	(1.08)	(1.07)	(1.04)
CAP	37.888***	37.821***	37.906***	37.834***	37.644***	37.816***
	(7.55)	(7.53)	(7.55)	(7.52)	(7.49)	(7.53)
POP	-1.120	-0.986	-1.063	-0.991	-1.004	-1.077
	(0.19)	(0.16)	(0.18)	(0.16)	(0.17)	(0.18)
INC	6.186	5.763	5.715	5.392	5.642	5.770
	(1.16)	(1.09)	(1.10)	(1.04)	(1.07)	(1.07)
PCTB	-1,415.04***	-1,416.74***	-1,412.51***	-1,414.49***	-1,430.79***	-1,383.26***
	(2.69)	(2.68)	(2.68)	(2.64)	(2.72)	(2.52)
ALLCOMP	945.745	1,185.61	1,342.29	1,035.11	1,243.01	632.928
	(0.11)	(0.13)	(0.15)	(0.12)	(0.14)	(0.07)
WPCTPLYRS	677.498					
	(0.67)					
WPCTMIN		404.639				
		(0.48)				
WPCTPTS			1,236.06			
			(0.58)			
WPCTSTARTS				177.335		
				(0.26)		
WPCTROTATION					312.801	
					(0.43)	
ROC						-9,032.02
						(0.35)
Adj R^2	0.46	0.46	0.46	0.46	0.46	0.46
F	13.3	13.2	13.3	13.2	13.2	13.2
S_e	112,466	112,556	112,511	112,626	112,576	112,602
N	145	145	145	145	145	145

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE VI
Ordinary Least Squares Estimations of Kahn and Sherer Replication: 1998-1999 Season

Independent Variables	**(4.1)**	**(4.2)**	**(4.3)**	**(4.4)**	**(4.5)**	**(4.6)**
INTERCEPT	-291,237**	-258,229**	-231,714**	-202,139**	-223,249**	-103,445
	(2.45)	(2.31)	(2.08)	(1.70)	(1.90)	(0.77)
WIN	2,092.16***	2,095.35***	1,995.79***	1,727.54***	2,023.00***	1,302 74**
	(3.21)	(3.20)	(3.01)	(2.55)	(2.81)	(1.72)
CAP	23.184***	22.452***	22.408***	23.022***	22.354***	22.115***
	(7.31)	(7.08)	(6.89)	(6.69)	(6.65)	(5.90)
PCTB	-1,201.63***	-1,152.04***	-1,126.20***	-1,097.56***	-1,225.67***	-1,324.34***
	(3.42)	(3.26)	(3.10)	(2.80)	(3.28)	(2.83)
POP	2.660	1.882	1.552	1.450	2.046	0.254
	(0.64)	(0.46)	(0.37)	(0.32)	(0.46)	(0.06)
INC	6.195*	5.628	4.543	2.766	4.043	-0.982
	(1.36)	(1.26)	(1.03)	(0.61)	(0.87)	(0.19)
ALLCOMP	1,162.77	1,174.53	1,181.11	-47.388	1,114.50	569.354
	(0.19)	(0.19)	(0.19)	(0.71e-2)	(0.17)	(0.08)
TPR	1,094.97*	1,221.54**	1,253.42**	1,508.34**	1,356.62**	1,919.15**
	(1.54)	(1.76)	(1.76)	(2.06)	(1.85)	(2.31)
WPCTPLYRS	1,720.84**					
	(2.30)					
WPCTMIN		1,292.60**				
		(2.28)				
WPCTPTS			3,038.24**			
			(2.00)			
WPCTSTARTS				595.136		
				(1.22)		
WPCTROTATION					820.590*	
					(1.57)	
ROC						14,012.7
						(0.47)
Adj R^2	0.74	0.74	0.73	0.69	0.71	0.67
F	10.9	10.9	10.2	8.9	9.4	8.2
S_ε	34,146.2	34,208.9	35,061.6	37,037.4	36,216.3	38,190.7
N	29	29	29	29	29	29

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE VII
Ordinary Least Squares Estimations of Kahn and Sherer Replication:
1996-1997, 1997-1998, 1999-2000, and 2000-2001 Seasons

Independent Variables	**(5.1)**	**(5.2)**	**(5.3)**	**(5.4)**	**(5.5)**	**(5.6)**
INTERCEPT	0.411e8***	0.418e8***	0.418e8***	0.415e8***	0.436e8***	0.413e8***
	(4.20)	(4.24)	(4.22)	(4.22)	(4.44)	(4.14)
SEASON	-20,783.7***	-21,084.7***	-21,084.8***	-20,963.7***	-22,006.8***	-20,846.4***
	(4.23)	(4.27)	(4.25)	(4.24)	(4.47)	(4.17)
WIN	2,937.94***	2,837.03***	2,800.91***	2,811.83***	2,732.59***	2,810.17***
	(5.44)	(5.24)	(5.13)	(5.18)	(5.05)	(5.08)
STAR	5,708.64	7,052.82	7,702.16	6,540.07	8,742.85	8,723.39
	(0.54)	(0.67)	(0.73)	(0.62)	(0.83)	(0.81)
CAP	38.966***	39.054***	39.194***	39.071***	38.594***	38.781***
	(11.63)	(11.59)	(11.54)	(11.58)	(11.53)	(11.36)
PCTB	-881.303***	-885.381***	-905.595***	-835.200***	-911.985***	-877.162***
	(2.62)	(2.62)	(2.67)	(2.44)	(2.73)	(2.48)
POP	-2.891	-2.348	-2.676	-1.915	-2.531	-2.633
	(0.73)	(0.59)	(0.67)	(0.48)	(0.64)	(0.65)
INC	5.143*	4.464*	4.010	3.986	4.524*	3.866
	(1.59)	(1.40)	(1.26)	(1.26)	(1.43)	(1.17)
ALLCOMP	-3,226.57	-2,597.79	-2,279.77	-3,248.38	-2,287.66	-3,346.48
	(0.57)	(0.46)	(0.40)	(0.57)	(0.41)	(0.57)
TPR	2,291.78***	2,389.84***	2,428.82***	2,408.69***	2,491.80**	2,351.22***
	(3.46)	(3.60)	(3.63)	(3.62)	(2.17)	(3.49)
WPCTPLYRS	1,356.40**					
	(2.08)					
WPCTMIN		1,005.58**				
		(1.81)				
WPCTPTS			1,983.96*			
			(1.42)			
WPCTSTARTS				792.835**		
				(1.73)		
WPCTROTATION					1,053.80**	
					(2.17)	
ROC						-9,409.16
						(0.59)
Adj R^2	0.68	0.68	0.68	0.68	0.68	0.67
F	25.9	25.5	25.1	25.4	26.0	24.6
S_ε	63,933.3	64,243.6	64,624.7	64,326.9	63,829.2	65,134.6
N	116	116	116	116	116	116

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE VIII
Ordinary Least Squares Estimations of McCormick and Tollison Replication: 1998-1999 Season

Independent Variables	**(6.1)**	**(6.2)**	**(6.3)**	**(6.4)**	**(6.5)**
INTERCEPT	-73,279.7	-75,199.7	-45,180.0	-23,521.0	-47,187.5
	(0.47)	(0.51)	(0.31)	(0.15)	(0.30)
TPR	1,606.21**	1,630.81**	1,662.81**	1,856.30**	1,746.70**
	(2.06)	(2.24)	(2.23)	(2.44)	(2.24)
CAP	19.377***	19.049***	18.939***	19.070***	18.892***
	(5.54)	(5.68)	(5.54)	(5.31)	(5.35)
NBA	-99,608.7**	-93,982.2**	-97,120.8**	-108,317.0***	-103,793.0**
	(2.33)	(2.26)	(2.29)	(2.51)	(2.37)
OTHERCOMP	3,192.64	3,265.63	3,197.14	2,900.32	3,490.51
	(0.52)	(0.54)	(0.52)	(0.45)	(0.55)
INC	-1.564	-1.205	-2.340	-3.717	-2.594
	(0.26)	(0.22)	(0.43)	(0.66)	(0.43)
POP	10.286	9.110	8.483	10.831	11.204
	(1.18)	(1.07)	(0.96)	(1.20)	(1.26)
PCTB	-1,739.10***	-1,727.34***	-1,723.70***	-1,749.91***	-1,787.15***
	(3.86)	(3.97)	(3.87)	(3.71)	(3.92)
NUMWIN	1,638.52	1,693.53*	1,498.16	1,424.17	1,710.30
	(1.30)	(1.39)	(1.22)	(1.11)	(1.29)
NUMWINPOP	0.089	0.097	0.119	0.080	0.066
	(0.44)	(0.50)	(0.59)	(0.39)	(0.32)
STAR	10,934.2	11,893.1	12,420.5	11,535.8	12,642.2
	(1.06)	(1.17)	(1.22)	(1.13)	(1.25)
ROC	20,266.5	24,062.7	24,360.2	23,297.1	20,964.3
	(0.76)	(0.94)	(0.93)	(0.85)	(0.77)
WHITEBLACK	54,474.5				
	(1.24)				
WPCTMIN		934.414*			
		(1.66)			
WPCTPTS			2,160.09*		
			(1.42)		
WPCTSTARTS				333.490	
				(0.72)	
WPCTROTATION					449.884
					(0.88)
Adj R^2	0.77	0.77	0.76	0.74	0.75
F	8.9	9.6	9.2	8.3	8.5
S_ε	33,007.6	31,980.7	32,606.0	33,964.6	33,707.1
N	29	29	29	29	29

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE IX
Ordinary Least Squares Estimations of McCormick and Tollison Replication:
1996-1997, 1997-1998, 1999-2000, and 2000-2001 Seasons

Independent Variables	**(7.1)**	**(7.2)**	**(7.3)**	**(7.4)**	**(7.5)**
INTERCEPT	-250,681.0***	-241,546.0***	-235,462.0***	-230,751.0**	-237,248.0***
	(2.46)	(2.39)	(2.34)	(2.31)	(2.37)
s97	-2,287.39	-2,571.69	-3,177.59	-3,132.94	-2,708.12
	(0.14)	(0.16)	(0.20)	(0.19)	(0.17)
s99	-68,685.7***	-68,832.9***	-69,330.6***	-68,336.0***	-69,381.9***
	(3.61)	(3.61)	(3.63)	(3.58)	(3.65)
s00	-78,934.3***	-79,208.0***	-79,512.1***	-78,739.5***	-80,925.8***
	(3.95)	(3.96)	(3.97)	(3.93)	(4.05)
TPR	2,665.12***	2,717.88***	2,741.90***	2,714.37***	2,755.70***
	(4.11)	(4.20)	(4.23)	(4.20)	(4.26)
CAP	35.778***	35.806***	35.766***	35.767***	35.658***
	(10.74)	(10.70)	(10.64)	(10.71)	(10.72)
NBA	-133,181.0***	-139,299.0***	-142,348.0***	-141,966.0***	-135,703.0***
	(3.42)	(3.68)	(3.79)	(3.81)	(3.54)
OTHERCOMP	644.431	912.538	1,055.52	600.866	938.140
	(0.12)	(0.16)	(0.19)	(0.11)	(0.17)
INC	1.042	0.525	0.283	0.153	0.639
	(0.30)	(0.15)	(0.08)	(0.04)	(0.18)
POP	17.225**	17.964**	18.611**	17.770**	17.181**
	(2.01)	(2.12)	(2.19)	(2.08)	(2.00)
PCTB	-1,377.64***	-1,404.81***	-1,420.77***	-1,385.30***	-1,402.77***
	(3.77)	(3.86)	(3.91)	(3.79)	(3.86)
NUMWIN	3,726.30***	3,626.92***	3,641.22***	3,531.76***	3,539.73***
	(4.23)	(4.05)	(4.02)	(3.85)	(3.90)
NUMWINPOP	-0.130	-0.121	-0.132	-0.102	-0.113
	(0.83)	(0.76)	(0.82)	(0.62)	(0.71)
ROC	-4,873.62	-4,647.10	-5,815.57	-4,752.84	-5,100.67
	(0.32)	(0.30)	(0.37)	(0.31)	(0.33)
WPCTPLYRS	38,737.2				
	(1.05)				
WPCTMIN		501.599			
		(0.87)			
WPCTPTS			864.624		
			(0.61)		
WPCTSTARTS				431.099	
				(0.89)	
WPCTROTATION					516.848
					(1.02)
Adj R^2	0.71	0.71	0.71	0.71	0.71
F	20.1	20.0	19.9	20.0	20.0
S_e	60,906.9	61,011.7	61,131.7	61,000.9	60,930.1
N	116	116	116	116	116

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE X
Ordinary Least Squares Estimations of Schollaert and Smith Replication: 1998-1999 Season

Independent Variables	**(8.1)**	**(8.2)**	**(8.3)**	**(8.4)**	**(8.5)**	**(8.6)**
INTERCEPT	-273,507.0**	-255,389.0**	-229,076.0**	-196,802.0**	-218,507.0**	-151,065.0
	(2.25)	(2.32)	(2.08)	(1.69)	(1.89)	(1.14)
WIN	1,810.84**	1,775.26***	1,665.95**	1,362.66**	1,630.83**	1,117.20*
	(2.44)	(2.56)	(2.35)	(1.91)	(2.12)	(1.52)
PRIORWIN	490.151	676.151	683.475	805.503*	751.831*	931.440*
	(0.82)	(1.25)	(1.22)	(1.36)	(1.31)	(1.60)
TPR	863.151	812.625	854.681	1,013.24	912.701	1,110.43
	(1.12)	(1.07)	(1.10)	(1.26)	(1.14)	(1.17)
CAP	22.337***	21.445***	21.409***	21.661***	21.281***	21.122***
	(6.64)	(6.64)	(6.46)	(6.16)	(6.25)	(5.76)
POP	2.134	1.504	1.179	0.906	1.468	0.230
	(0.50)	(0.37)	(0.28)	(0.21)	(0.34)	(0.05)
INC	6.609*	6.917*	5.842	4.367	5.422	2.932
	(1.43)	(1.53)	(1.30)	(0.95)	(1.16)	(0.52)
PCTB	-1,214.42***	-1,176.53***	-1,158.01***	-1,156.65***	-1,39.09***	-1,256.57***
	(3.42)	(3.37)	(3.22)	(3.00)	(3.38)	(2.77)
ALLCOMP	1,155.93	1,257.48	1,228.85	332.986	1,146.33	660.005
	(0.19)	(0.21)	(0.20)	(0.05)	(0.18)	(0.10)
WPCTPLYRS	1,399.35*					
	(1.64)					
WPCTMIN		1,101.84**				
		(1.90)				
WPCTPTS			2,462.76*			
			(1.56)			
WPCTSTARTS				378.808		
				(0.75)		
WPCTROTATION					614.440	
					(1.15)	
ROC						3,297.00
						(0.11)
Adj R^2	0.74	0.75	0.73	0.71	0.72	0.70
F	9.6	10.1	9.5	8.5	8.9	8.2
S_e	34,433.1	33,733.0	34,643.5	36,263.4	35,590.9	36,790.4
N	29	29	29	29	29	29

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE XI
Ordinary Least Squares Estimations of Schollaert and Smith Replication:
1996-1997, 1997-1998, 1999-2000, and 2000-2001 Seasons

Independent Variables	**(9.1)**	**(9.2)**	**(9.3)**	**(9.4)**	**(9.5)**	**(9.6)**
INTERCEPT	-360,974.0***	-338,958.0***	-327,615.0***	-330,840.0***	-323,081***	-301,905***
	(3.61)	(3.42)	(3.30)	(3.38)	(3.33)	(3.10)
STAR	-572.715	863.721	1,565.66	243.424	2,377.02	3,158.67
	(0.05)	(0.08)	(0.14)	(0.02)	(0.22)	(0.28)
WIN	2,638.97***	2,530.99***	2,505.35**	2,486.54***	2,436.48***	2,470.10***
	(4.08)	(3.88)	(3.81)	(3.80)	(3.71)	(3.68)
PRIORWIN	1,448.49***	1,456.13***	1,433.29***	1,474.29***	1,491.43***	1,444.27***
	(2.54)	(2.53)	(2.48)	(2.56)	(2.59)	(2.47)
TPR	205.060	284.112	331.688	314.507	296.105	262.985
	(0.37)	(0.51)	(0.59)	(0.56)	(0.53)	(0.47)
CAP	36.702***	36.752***	36.897***	36.810***	36.183***	36.465***
	(10.62)	(10.56)	(10.51)	(10.58)	(10.40)	(10.37)
POP	0.817	1.471	1.114	1.974	1.388	1.201
	(0.20)	(0.36)	(0.27)	(0.48)	(0.34)	(0.29)
INC	8.099**	7.330**	6.805**	6.870**	7.299**	7.034**
	(2.31)	(2.12)	(1.97)	(2.01)	(2.11)	(1.96)
PCTB	-1,027.84***	-1,034.21***	-1,053.37***	-975.911***	-1,069.33***	-984.641***
	(2.86)	(2.86)	(2.90)	(2.68)	(2.96)	(2.62)
ALLCOMP	-2,968.73	-2,278.66	-1,942.51	-2,997.21	-2,015.13	-3,541.30
	(0.50)	(0.38)	(0.32)	(0.50)	(0.34)	(0.58)
WPCTPLYRS	1,516.52**					
	(2.21)					
WPCTMIN		1,095.85**				
		(1.87)				
WPCTPTS			2,165.39*			
			(1.47)			
WPCTSTARTS				913.815**		
				(1.89)		
WPCTROTATION					991.94**	
					(1.93)	
ROC						-17,139.7
						(1.01)
Adj R^2	0.65	0.65	0.64	0.65	0.65	0.63
F	22.5	22.1	21.7	22.1	22.1	21.3
S_e	67,140.6	67,570.9	67,995.2	67,545.5	67,507.3	67,356.0
N	116	116	116	116	116	116

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE XII
Ordinary Least Squares Estimations: Tugberk Model
1998-1999 Season

Independent Variables	(10.1)	(10.2)	(10.3)	(10.4)	(10.5)	(10.6)
INTERCEPT	-175,684.0*	-171,088*	-144,184	-109,272	-128,550	-53,703
	(1.42)	(1.53)	(1.30)	(0.96)	(1.12)	(0.43)
WIN	1,740.88***	1,735.94***	1,636.82**	1,417.62**	1,578.39**	1,184.07**
	(2.49)	(2.65)	(2.45)	(2.14)	(2.20)	(1.73)
PRIORWIN	459.948	579.368	588.083	675.825	637.550	661.666
	(0.81)	(1.13)	(1.11)	(1.23)	(1.18)	(1.23)
TPR	989.028	916.904	1,002.32	1,127.20*	1,059.95	1,335.80*
	(1.22)	(1.14)	(1.23)	(1.36)	(1.28)	(1.49)
CAP	19.885***	19.388***	19.262***	19.108***	19.063***	18.297***
	(5.94)	(6.08)	(5.90)	(5.61)	(5.76)	(5.23)
POP	12.089**	11.354**	11.553**	12.313**	12.219**	12.494**
	(1.98)	(1.88)	(1.86)	(1.96)	(1.96)	(2.00)
INC	2.981	3.500	2.359	0.919	1.743	-1.203
	(0.63)	(0.75)	(0.51)	(0.20)	(0.37)	(0.23)
PCTB	-1,558.71***	-1,527.47***	-1,523.80***	-1,571.78***	-1,590.71***	-1,758.97***
	(4.07)	(4.03)	(3.88)	(3.83)	(4.08)	(3.61)
NBA	-87,799.0**	-84,433.2**	-88,673.9**	-98,189.8**	-93,829.0**	-103,634.0***
	(2.10)	(2.04)	(2.10)	(2.32)	(2.21)	(2.50)
OTHERCOMP	3,060.40	2,926.34	3,184.64	2,975.29	3,226.39	3,164.72
	(0.49)	(0.47)	(0.50)	(0.46)	(0.50)	(0.49)
YEARS	66.174	113.400	42.980	28.992	38.175	130.482
	(0.10)	(0.17)	(0.06)	(0.04)	(0.05)	(0.18)
WPCTPLYRS	904.273					
	(1.09)					
WPCTMIN		765.242*				
		(1.34)				
WPCTPTS			1,519.58			
			(0.99)			
WPCTSTARTS				141.779		
				(0.30)		
WPCTROTATION					318.723	
					(0.62)	
ROC						14,617.4
						(0.52)
Adj R^2	0.77	0.77	0.76	0.75	0.76	0.76
F	9.4	9.8	9.3	8.7	8.9	8.8
S_ε	32,268.5	31,743.6	32,455.8	33,283.0	33,000.2	33,110.7
N	29	29	29	29	29	29

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses

TABLE XIII
Ordinary Least Squares Estimations: Tugberk Model
1996-1997, 1997-1998, 1999-2000, and 2000-2001 Seasons

Independent Variables	**(11.1)**	**(11.2)**	**(11.3)**	**(11.4)**	**(11.5)**	**(11.6)**
INTERCEPT	-269,437.0***	-253,074***	-241,061***	-249,360***	-238,324***	-206,909**
	(2.55)	(2.49)	(2.38)	(2.51)	(2.38)	(2.13)
WIN	2,553.69***	2,463.34***	2,432.96***	2,413.76***	2,405.35***	2,419.56***
	(4.14)	(4.00)	(3.92)	(3.92)	(3.87)	(3.81)
PRIORWIN	1,328.04***	1,339.03***	1,321.56***	1,364.04***	1,355.72***	1,309.04***
	(2.45)	(2.47)	(2.43)	(2.52)	(2.48)	(2.37)
STAR	440.888	1,481.31	2,170.98	794.552	2,665.69	3,759.52
	(0.04)	(0.14)	(0.21)	(0.08)	(0.25)	(0.35)
TPR	-90.010	-27.020	25.917	-5.225	-11.620	54.051
	(0.16)	(0.05)	(0.05)	(0.92e-2)	(0.02)	(0.09)
CAP	34.033***	33.925***	33.931***	33.948***	33.543***	33.339***
	(9.88)	(9.87)	(9.81)	(9.93)	(9.79)	(9.67)
POP	15.413***	16.711***	16.967***	17.530***	16.372***	17.779***
	(2.53)	(2.82)	(2.85)	(2.98)	(2.73)	(2.99)
INC	4.873*	4.247	3.687	3.919	4.129	3.165
	(1.30)	(1.17)	(1.03)	(1.11)	(1.13)	(0.87)
PCTB	-1,708.57***	-1,734.83***	-1,763.04***	-1,691.39***	-1,751.79***	-1,726.05***
	(4.42)	(4.51)	(4.58)	(4.39)	(4.55)	(4.29)
NBA	-123,985.0***	-130,252.0***	-134,584.0***	-133,477.0***	-128,149.0***	-142,867.0***
	(3.06)	(3.30)	(3.42)	(3.44)	(3.18)	(3.66)
OTHERCOMP	-4,525.45	-3,835.07	-3,335.00	-4,476.48	-3,632.84	-3,438.03
	(0.72)	(0.62)	(0.54)	(0.72)	(0.58)	(0.55)
YEARS	1,275.96**	1,273.61**	1,248.99**	1,295.65**	1,249.55**	1,052.72*
	(2.01)	(2.01)	(1.97)	(2.05)	(1.97)	(1.63)
WPCTPLYRS	1,062.51*					
	(1.54)					
WPCTMIN		871.129*				
		(1.53)				
WPCTPTS			1,792.81			
			(1.26)			
WPCTSTARTS				826.293**		
				(1.79)		
WPCTROTATION					690.319*	
					(1.35)	
ROC						-9,511.07
						(0.59)
Adj R^2	0.67	0.69	0.68	0.69	0.69	0.68
F	22.0	22.0	21.8	22.3	21.9	21.4
S_e	63,634.6	63,644.0	63,869.0	63,387.3	63,797.0	64,255.1
N	116	116	116	116	116	116

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses.

TABLE XIV
Ordinary Least Squares Estimations: Tugberk Model with Interaction Variables
1998-1999 Season

Independent Variables	**(12.1)**	**(12.2)**	**(12.3)**	**(12.4)**	**(12.5)**
WPCTPLYRS	774.622				
	(0.59)				
PCTBWPCTPLYRS	5.089				
	(0.13)				
WPCTMIN		585.608			
		(0.73)			
PCTBWPCTMIN		10.632			
		(0.33)			
WPCTPTS			1,028.14		
			(0.45)		
PCTBWPCTPTS			28.864		
			(0.30)		
WPCTSTARTS				199.347	
				(0.33)	
PCTBWPCTSTARTS				-4.139	
				(0.16)	
WPCTROTATION					243.785
					(0.31)
PCTBWPCTROTATION					3.452
					(0.13)
Adj R^2	0.75	0.76	0.75	0.74	0.74
F	8.1	8.5	8.0	7.6	7.7
S_ε	33,243.4	32,610.8	33,363.7	34,279.2	33,997.4
N	29	29	29	29	29

Notes: * indicates $p < 0.10$; ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses. The interaction variables equal the percentage of blacks in SMSA times each racial composition measure (i.e. *PCTBWPCTPLYRS = PCTB*WPCTPLYRS*).

TABLE XV

Ordinary Least Squares Estimations: Tugberk Model with Interaction Variables
1996-1997, 1997-1998, 1999-2000, and 2000-2001 Seasons

Independent Variables	**(13.1)**	**(13.2)**	**(13.3)**	**(13.4)**	**(13.5)**
WPCTPLYRS	1,429.57* (1.31)				
PCTBWPCTPLYRS	-13.830 (0.43)				
WPCTMIN		1,043.58 (1.16)			
PCTBWPCTMIN		-7.143 (0.25)			
WPCTPTS			2,127.60 (0.92)		
PCTBWPCTPTS			-14.009 (0.18)		
WPCTSTARTS				342.411 (0.51)	
PCTBWPCTSTARTS				25.311 (1.00)	
WPCTROTATION					867.892 (0.97)
PCTBWPCTROTATION					-6.529 (0.24)
Adj R^2	0.68	0.68	0.68	0.69	0.68
F	20.2	20.1	19.9	20.6	20.0
S_ε	63,887.1	63,936.1	64,170.7	63,390.3	64,090.3
N	116	116	116	116	116

Notes: * indicates $p < 0.10$, ** indicates $p < 0.05$; and *** indicates $p < 0.01$. I use one-tail significance tests for each of the estimated coefficients. The absolute values of the t-statistic for each coefficient are in parentheses. The interaction variables equal the percentage of blacks in SMSA times each racial composition measure (i.e. *PCTBWPCTPLYRS = PCTB*WPCTPLYRS*).

TABLE XVI

Sources of Data

Ballparks by Munsey and Suppes (http://www.sfo.com/~csuppes/NBA/misc/index.htm)
Doug's NBA and MLB Statistics (http://www.rmi.net/~doug/)
http://www.infoplease.com/ipsa/A0105554.html
http://www.mlb.com
http://www.nba.com
http://www.nfl.com
http://www.nhl.com
Sporting New Official NBA Register (Editions: 1996-97, 1997-98, 1998-99, 1999-2000, 2000-2001, and 2001-2002)
Statistics Canada (ww2.statcan.ca)
The Association for Professional Basketball Research (http://members.aol.com/bradleyrd/apbr.html)
TMR's Fan Cost Index (http://www.teammarketing.com/fci.cfm)
U.S. Census Bureau (www.census.gov)
U.S. Census Bureau, Statistical Abstract of the United States: 2000