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An Integrated Test For Exploitation and Discrimination in the National Basketball Association

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Abstract

Over the past thirty years, economists have become increasingly interested in the labor market for professional sports. These studies have focused primarily on exploitation, the difference between marginal revenue product and salary, or discrimination, salary differentials based on race, or ethnic background. This paper attempts to combine both areas of research, that is, to explain the systematic deviation of marginal revenue product from salary as a function of race, or ethnic background. Using NBA data collected over three seasons 1995-98, we specify a three-equation model, an enhancement of the Scully two-step method presented in 1976. We then ask if players are paid a salary equal to the revenue they generate, and if not, can the resulting differential be explained using a dummy variable for race and ethnic background.
INTRODUCTION

Previous studies on the labor market for professional sports have focused on exploitation and/or discrimination separately. Few efforts have been made to test for both simultaneously. This paper does just that. The model presented here attempts to explain the systematic deviation of NBA players' salaries from their marginal revenue products as a function of race or ethnic background.

Who cares? Economists have become increasingly interested in the labor market for professional sports. This arena provides an advantage over traditional labor studies, since more extensive, publicly kept measures of productivity are available. Even more enticing perhaps is the chance to shed light on a topic surrounded by misconceptions and controversy. The public as a whole tends to think that professional sports are perhaps the perfect equal economic employer, rewarding players on merit alone. This misconception is logical since the ratio of minority players to white players is greater than that same ratio for the labor force as a whole. Second, many of the highest paid athletes are black. For example in 1995, eighty percent of NBA players and thirteen of the highest paid players were black.

In general, the salary of athletes has been a controversial topic. For example, in the mid to late 90s, journalists and sports writers questioned whether college athletes should be compensated for the revenue they generated. The underlying theory behind the model estimated is if the NBA is a perfectly competitive market, players should be paid a salary equal to their productivity. This implies that athletes should be paid a salary equal to their marginal revenue product, a salary equal to the amount of revenue they generate. If they are not paid as much, are they being exploited? In the NBA however it is
important to note, the salary cap restricts the amount of revenue that can be paid out to the players. For example in 1995, players should have received about 39.26 percent of their MRPs.

Previous research has provided us with substantial evidence of exploitation in the four major sports leagues. This paper takes the difference between marginal revenue product and salary and attempts to explain the discrepancy as a function of race or ethnic background using the 1995-98 NBA seasons. The paper proceeds as such: first a look at previous literature written on the major professional sports and then specifically basketball, next I will take you through the model specification and provide details of the data, we will analyze the results, and finally I will offer some brief conclusions and possible extensions of the model.

LITERATURE REVIEW

Beginning in the early 1970s, labor economists became increasingly interested in studying exploitation and discrimination in the professional sports industry. As a labor market, professional sports provide elaborate, publicly available measures of performance and compensation. With such accurate measures of productivity and the nature of sports, researchers have been able to measure whether discrimination exists and in what forms. They have studied wage discrimination, hiring discrimination, exit discrimination or retention barriers, and positional segregation. As an extension, some economists have focused their efforts solely on identifying which of the three forms of discrimination present in the labor market, — employer discrimination, co-worker discrimination, and customer discrimination affect the professional sports industry (Gary Becker 1957).
Within the sports arena, economists cite the owners, the fans and occasionally teammates as the possible roots of discrimination. The fact that blacks were excluded from all major sports until after World War I, for example Jackie Robinson became the first black major league baseball player in 1947, is often used as the starting point for the owner discrimination argument (Okrent & Wulf 1989). Furthermore, sports leagues are virtually monopolies that do not have to contend with free entry, a market force that reduces employer discrimination. Several studies have been conducted on monopsony in professional sports, few by looking at the rise and fall of rival leagues, most recently by examining changes in free agency policy, and traditionally comparing marginal revenue with salary to test whether employer monopsony lowers worker's pay. The latter is the model typically used in tests for general exploitation, for example in the often-cited works, *Pay and Performance in Major League Baseball* be Gerald Scully or *On Monopsonistic Exploitation in Professional Baseball* by Marshall Medoff.

The second type of discrimination listed above receives less attention, — few studies have researched whether white players demand a premium for playing with blacks. This has become rather a moot point since the majority of players in the NBA (74.3% in the 1985-86 season) and NFL (56% in 1988) today are black, as well as a significant percent of MBL players (27.8% in 1987).

The third and final source is customer discrimination, which has proved to be a major source of discrimination in MLB and the NBA, where the majority of players are black and the majority of fans are white. Customer discrimination is of particular interest to economists since perfect competition will not eliminate this form. If it truly exists, then traditional market forces will not necessarily eliminate unequal treatment of equally
productive players. The sports industry is a customer-based service sector; a team, specifically the owners are rewarded through revenue for acquiring players that the fans are willing to pay to watch. In this section, I will use two papers written by Lawrence Kahn, *Monopsony and Player Salaries* and *Discrimination in Professional Sports: A Survey of the Literature* to present the general history of economic research on exploitation and discrimination in the four major sports leagues, the NBA, NFL, MLB and the NHL through the 1980s. I will then provide you with a closer look into the world of basketball, and the research previously done that served as the basis for this paper.

Traditionally, economists have defined discrimination as unequal treatment of equally productive workers (Becker 1971), measuring discrimination and productivity through wage regressions. The first models used in sports economics regress salary (or its log) on a host of productivity measures and on a dummy variable for race. The coefficient on this dummy is translated as an estimate of market discrimination. This method assumes that both white and black players receive the same returns to changes in performance level variables that influence salary. In 1974, Scully introduced a two-stage process that first estimated how players' performance statistics affected their team's winning percentage and second how winning percentage and other demand side variables affect team revenue. He then calculated a marginal revenue product by multiplying a player's contribution to win percentage by the contribution of win percentage on team revenue. From there economist can test for exploitation or the degree of exploitation in various ways. Scully (1974), Medoff (1976) and Hill (1983) measured exploitation as (MRP-Salary/MRP), Zimbalist (1992) as MRP/Salary, Sommers and Quinton (1982) as MRP-Salary.
Either approach explained above also allows an economist to test for salary discrimination. Beginning in 1972, economists found little evidence of wage discrimination in baseball (Pascal and Rapping). Based on data from 1968-71, calculated discrimination coefficients for blacks were not statistically significantly negative, rather some economists found a white shortfall in salary (Pascal and Rapping 1972; Christiano 1986, 1988). This suggested the possibility of omitted variables, which results in biased estimates of the parameters. Others economists found insignificant results in white-nonwhite wage equation differences (Medoff 1975; Mogull 1981; Cymrot 1983; Kahn 1989). Furthermore, Scully (1974) and Mogull (1975) found that black players received a higher return for experience, a finding that supports the theory that blacks faced retention barriers.

Unlike the results from baseball, research on professional basketball players' salaries in the 1980s found clearly significant discrimination coefficients. "...several studies found statistically significant black salary shortfalls of 11-25 percent." (Kahn 2000, p. 84) Based on data from the 1984-85 and/or 1985-86 season (usually excluding rookies), the discrimination coefficients calculated were found to be positive and significant for white players and negative and significant for blacks. This was surprising to some since free agency had existed in basketball since 1970, not to mention that seventy-four percent of NBA player's were black in the 85-86 season, and just two years later four out of the five players making at least three million dollars were black. Recent studies, however, by Dey (1997) and Bodvarsson and Brastow (1998) do not find significant racial salary differences ceteris paribus; however, Hamilton (1997) gives us a
possible explanation for their results coupled with a way to improve the model. We will take a closer look a bit later in the paper at their work and its implications for this paper.

Finally, two other sports have received some attention in this area. The first being football which at the time of Kahn's literature survey 1991 had only been investigated twice, both over the 1970-71 season. In these two cases, discrimination coefficients were not calculated rather mean salaries by race were compared and the results did not indicate discrimination was an issue in the NFL. The problem economists faced in trying to specify early models of football or defense in the NHL was a lack of performance variables. Early work in hockey focused on discrimination against French-Canadians who faced generally negative stereotypes. To test for discrimination one had to look at individual performance numbers, which are more easily recorded for a goaltender or forward. Hence statistically significant discrimination against defensemen makes sense if owners/coaches determine pay according to both prior and predicted performance statistics and their own stereotypes. Recently more in-depth work has been possible on exploitation in the NHL (Nelson and Pearl 2001) that is an extension of the Scully model 1974. Nelson and Pearl find about thirty-five percent of their sample gets paid a salary equal to their marginal revenue product, thirty-seven percent are paid salaries above their MRP and twenty-eight percent are exploited. Unfortunately, little progress has been made in football since measuring a player's individual contribution to team level defense measures is still difficult based on the nature of defense in football.

Economists have spent considerable time testing for a second type of discrimination, hiring discrimination, to find out whether nonwhites face tougher admissions standards. Prior to World War I, there is no question racial barriers were in
place; rather, the question for economists in the 1980s was do they still exist? To understand these studies, I present you with a generally accepted definition of hiring discrimination: unequal job offer probabilities facing different applicants with the same ability. The majority of studies conducted on the NBA in the 1980s, did not find any such hiring barriers (Kahn, Sherer 1988, Brown, Spiro & Keenan 1988). They looked for racial differences in the order that players were drafted and at the performances of benchwarmers to hone in on differences among the marginal players accepted or rejected.

In general, hiring discrimination studies compare the performances of whites and nonwhites, which may indirectly signal hiring discrimination at the margin. In general, research done on the National League (Medoff 1975) and the NBA (Brown, Spiro, & Keenan 1988) suggests only that black players outperform whites. As such, the fact that there are more white players on a NBA bench than nonwhites is a hot topic under the heading of customer discrimination!

Similarly studies on the NHL suggest hiring discrimination against French-Canadians. The methods employed in these studies follow those done on the NBA. For example, Lavoie, Grenier, and Coulombe (1987) found that French-Canadians had to be even more qualified than English-Canadians to go as early in the draft. To further support their conclusions they examined the correlation of performance advantage and position with French-Canadian representation in that position.

As a third possibility, economists look at positional segregation on two levels. The first is that whites tend to occupy certain positions such as quarterback or pitcher, while fewer nonwhites hold or have held that position. This fact may be used as a defense for salary discrimination. Due to the importance and profile of these positions, the players
that hold them should be thus rewarded and so one may find white players tend to get paid a salary closer premium due to the nature of the position held. If so, then why are whites more likely to hold these positions? One explanation is owners wish to keep nonwhites out of positions that typically lead to managerial or executive positions. The second is that some owners make decisions based on negative stereotypes about nonwhites’ intellectual or leadership abilities. A third possibility is that whites are less willing to take orders or directions from nonwhite leaders. Finally, there are researchers who look at the early years, as far back as little league, high school teams and even training in college as the point of discrimination conception. The evidence concludes that few blacks baseball players are pitchers, catchers or hold positions in the infield. Fewer black football players are quarterbacks, linebackers or kickers. Fewer French-Canadians are defensemen. The evidence on basketball varies and is inconsistent. First, Kahn and Sherer (1988), contrary to theory, suggest that more blacks have played guard, a leadership position. On the flip side of the coin, Dey (1997) criticizes the work of Brown, Spiro, and Keenan for omitting a variable for the center position, which he concludes is key to a great team and crucial to measuring a white salary advantage since a significant number of whites play center.

Finally, retention and/or exit discrimination receives much less attention overall; yet, I will mention briefly a recent study on exit discrimination in the NBA because it lends itself as evidence of customer discrimination the next topic explored. The article entitled, The NBA, Exit Discrimination and Career Earnings, asserts that exit discrimination exists, — “involuntary dismissal of workers based on the preferences of employers, coworkers, or customers.” (Ha Hoang and Dan Rascher 1999, p. 69) Based on
data from eleven NBA seasons throughout the 1980s, the two men found first, that black players are cut more often than whites, whites have a thirty-six percent lower risk of being cut, which results, controlling for performance variables, in an average career length for whites of 7.5 years and 5.5 for blacks and second that the resulting career earnings decrease was greater than earning differentials due to wage discrimination. Most notably, they name customer discrimination as the fundamental cause by examining fan attendance and racial composition. Their data exhibits a positive relationship between the percentage of the population that is white and the number of white players on the home team.

The above fore mentioned leads to our review of possible forms of discrimination in professional sports, a topic I propose is a logical follow-up to this paper. Already touched upon, discrimination may stem from the owners, teammates or fans. In terms of testing for owner discrimination specifically, my understanding is that economists look at salary and MRP differences before and after free agency. The reserve clause in most early professional sports contracts has often been given as a plausible explanation for salary discrimination before free agency gave a player greater mobility. The argument says that if some employers discriminated and others did not then the induction of free agency in 1976 (for both basketball and baseball) would reduce discrimination (Kahn 1991). In other words, there would be more salary discrimination for those not eligible for free agency than those with unlimited mobility.

Having said that, we move onto customer discrimination, which seems to be of particular interest to economists since market forces, increased competition, free agency, and free entry may not eliminate fan discrimination. Studies have found traces of
customer discrimination in basketball and baseball. Scully (1974a, 1974b) found that in the 1960s blacks players significantly lowered team revenue all else equal. However, by 1976-77, Sommers and Quinton (1982) found no evidence that the racial makeup of a team affects team revenue. On the other hand, evidence of customer discrimination in basketball appears in the 1980s. Kahn and Sherer (1988) found based on 1980-86 team data that white players raise attendance, -- replacing a black player with white player raises attendance by 5,700 to 13,000 fans per year. Brown, Spiro and Keenan (1988) found that replacing a fulltime white player with a black player leads to 8400 fewer fans attending. By the 1990s, conclusions are less striking. In 1997 Matthew Dey “found all else equal, white players added a statistically insignificant 60 fans apiece per season during the 1987-93 period (Kahn, 2000, p.85). In addition, research reveals a positive link between team racial composition and a similar racial composition in that team’s home city population. As previously mentioned, the fact that the NBA is predominantly black and the fans are predominantly white may serve as a plausible cause for discrimination. That is, as teams carried more nonwhite players, white fans put more and more value on an additional white player, even as a benchwarmer. “If NBA fans do have preferences for white players, having white benchwarmers may be a cheap way to satisfy such demands” (Kahn, 2000, p.85).

Whether or not white fans are appeased by white benchwarmers is up for grabs at this point in the game, as is whether salary differentials still exists. The most recent work on the NBA conducted by Barton H. Hamilton over the 1994-95 season used a new approach that looked at discrimination by salary percentiles. His theory stems from Becker’s hypothesis that consumer discrimination increases with the degree of contact
with the customer (Hamilton 1997). Meaning, players with the greatest visibility are subject to greater discrimination and as the number of white stars decrease the premiums paid for white stars will increase if demand remains constant.

First, he tested to see if population, percent of the population that is black, average income, or the number of white players affected home attendance; His results claim that white players increased home attendance by 3.9 percent. This led him to believe that customer discrimination existed. To discredit the possibility of employer discrimination he compared hiring and salary profiles of teams with black general managers with those of teams with white general managers and found the white-nonwhite salary gap the same in both cases. Next, he measures the mean difference in salaries of whites and nonwhites. To do so, he regresses, using OLS, a player’s salary on MRP controlling for games played, scoring averages, rebounds, assists per game and a dummy variable equal to one if the payer is white. His results imply that whites earn an insignificant 1 percent more than their black counterparts; if he takes out any team and city characteristics, he finds that whites earn 1.3 percent less.

Fearing that this approach hides substantial differences and that superstars’ salaries skew the means, he takes his work one step further. Dividing his dataset by salary percentiles, he compares the earnings of both groups at the .10, .25, .50, .75, and .90 quantiles of salary distribution. This eliminates the effect of outliers on the mean, a worthwhile exercise since by 1995 the thirteen highest paid ball players were black. His results find that whites get paid less than equally talented blacks at the lower end (though the coefficient on this is not significant), yet receive a twenty percent premium over blacks at the upper end of the distribution. The first result mentioned supports the idea
above that whites benchwarmers are a cheap way to increase the number of white players on a given team; yet, this study suggests that this alone is not sufficient to reduce customer discrimination.

Finally, I feel it is necessary to touch upon the most recent article that stands in opposition to all the evidence presented above. In an article entitled, *Racial Differences in National Basketball Association Players' Salaries: A New Look*, Matthew Dey says that changes in the structure of the league, specifically the addition of new franchises, increases in the amount of mobility a player has, and the institution of the salary cap have eliminated racial wage differences. Manipulating data collected over 5 seasons beginning in 1987 and omitting 1989, they find first that blacks outperform whites across the board, a finding that is consistent with previous studies, and second that mean real earnings of black players in this period is $110,000 greater than the mean for white players. This may be accurate to the extent that Dey allows superstars' salaries to skew his results. Next, Dey attempts to squash any lingering notions of consumer discrimination. He regresses home attendance on team and franchises variables paying particular attention to the sign and significance of the estimated coefficient on number of white players. He finds that not only is the coefficient insignificant, but that replacing an all-black team with an all white team increases attendance by 694 people. Compared with the results offered by Kahn and Sherer, Dey claims that customers no longer discriminate and therefore profit-maximizing entities, such as an NBA team, have no incentive to award unequal pay for equal productivity.

The discussion above has provided a general look at studies done on discrimination and/or exploitation. Few economists have successfully combined these
two hot areas of research. Based on the evidence I have presented thus far, one could connect persistent salary discrimination and customer discrimination in the NBA. Meaning, if fans are willing to pay more to see white players, white players may increase a team's revenue and thus will be given a bigger piece of the action for equal performances.

**BASKETBALL LITERATURE**

The model I present in the next section is modeled after the work found in two different articles specifically addressing the marginal revenue product and salary of basketball players in the NBA. The first entitled, *Salary Vs. Marginal Revenue Product Under Monopsony and Competition: The Case of Professional Basketball*, uses the salary-marginal revenue framework to look at racial discrimination. Scott, Long and Somppi test whether African American and/or European players receive a lower salary than whites for equal performance. The theory presented focuses on the elimination of the reserve clause, which prior to 1976 bound an athlete to his employer for his career and created owner monopsony power. They believed that if the NBA was a competitive market then any given player should receive a salary equal to his marginal revenue product (MRP). In other words, only if owners had monopsony power could salary be below MRP, and likewise only if the worker had monopoly power over the labor supply should salary be above MRP.

The framework of their model relies on the work of Scully (1974) previously mentioned. Scully says a player's MRP is "the ability or performance that he contributes to the team and the effect of that performance on gate receipts" (Scott, Long & Somppi 1985, p.52). This ability to generate revenues can be direct through outstanding play or
indirect, -- a result of popularity, hype etc. One can measure the direct effect by relating individual performance statistics to team statistics and relating that to revenue. Inherent in this type of model is the assumption that an overall team’s performance is simply the summation of individual player performances. In specifying their actual model, Scott, Long and Sompii use a variation on the work done by Zak, Huang, and Siegfried (1979) with the Cobb-Douglas production function. First, they estimated winning percentage as a function of the field goal percentage and free throw percentage for both teams, and total rebounds, assists, and fouls for each team. They expected the winning percentage of a given team to be a positively affected an increase in its own field goal and free throw percentage, its total rebounds and assists, and the total number of fouls by their opponent. They expected the estimated coefficients on the opponents’ field goal and free throw percentages, the opponents’ total number of assists and rebounds, and its own level of fouls.

Next, they regressed team revenue, measured as gate receipts plus local and national broadcast revenue, on winning percentage, hometown population, stadium capacity, hometown population that was black, per capita income in hometown, number of years the team had been in the city, the number of players that made All-Pro team at least five times, a dummy variable for whether the team was a playoff contender and finally the percentage of players on that team that were black. They were interested in the sign of the coefficients on hometown black population and percentage of black players on the team as measures of racial preference for watching basketball and white fan discrimination against black player. They used data collected from 10 seasons, 1970-1980 for the winning percentage equation and data from the 1978-81 seasons in the
revenue equation. Next, they reasoned that the coefficients on the winning percentage equation variables were essentially elasticities, so if one multiplied them by the mean ratio of mean winning percentage to mean of the appropriate independent variable you have marginal physical product and if you then multiply that number by the coefficient on winning percentage in the revenue equation you would get marginal revenue product. They then converted this number to an individual marginal revenue product. In doing so they assumed that an individual’s total contribution was equal to the linear summation of his separate performance statistics. To account for a player’s responsibility for points give up to the other team, they divided up points scored by the number of minutes an individual played during the season. This adjustment will underestimate the MRP of a good defenseman and overestimate the MRP of a lousy defenseman.

Scott, Long and Sompilo offer two conclusions or results. First, they reject the null hypothesis of no difference between salary as a percentage of MRP for free agents and non free agents. Put differently, free agents are paid relatively higher percentages of their MRPs. Secondly, having regressed salary on MRP and a dummy for white/black they accepted the null hypothesis that the coefficient on the dummy was equal to zero. These results are consistent with those found in other studies previously mentioned; yet, these results were not included in Kahn’s work as significant since the sample size was too small. I simply present the model employed in this study as the starting point for the one in this paper.

The second article by David Berri, *Who is ‘Most Valuable’? Measuring the Player’s Production of Wins in the National Basketball Association*, also looks at player productivity and salary to test for racial discrimination. Specifically Berri wanted to
answer one question: Who is more valuable to his team Michael Jordan or Karl Malone?

To do this, Berri uses aggregate team data collected over four seasons 1994-1998, both regular and post-season play, to calculate per-game averages that will be used in his regressions. The model he uses is also based largely on Zak, Huang, and Siegried. (1979) ZHS proposed that the relationship between wins and the ratio of a team’s accumulation of specified statistics relative to its opponent follow the Cobb-Douglas functional form. However, Berri argues with their choice of the Cobb-Douglas functional form, the utilization of the opponent’s statistics, and raises the issue of team tempo as a significant factor. First, his argument against the Cobb-Douglas is for a linear form, that a player’s statistical value is independent of his teammates. Second, he disagrees with the adjustment made by Scott, Long, and Sompii to account for defensive play. He argues that such an approach implies that a point guard is equally responsibly for an opponent’s power forward as is his own forward or center.

Berri attempts to make some corrections for this in his estimation of winning percentage. Based on the issues just mentioned, Berri estimates wins as a function of points scored and points allowed which explains ninety-five percent of variation in team winning percentage. Points scored and points allowed are then defined as a function of how the team acquires the ball, efficiency in ball handling, and its ability to convert possession into points (Berri, 1999). A team’s points are a positive function of a team’s points per shot, free throw percentage, free throw attempts, offensive rebounds, defensive rebounds, assist to turnover ratio and its opponents turnovers. The opponent’s points are then assumed to be a positive function of the their free throw percentage and free throws attempted, their defensive and offensive rebounds, their field goals attempted, assist to
turnover ratio, and finally their opponent’s personal fouls, and a negative function of their own turnover ratio. Berri runs these two equations separately and simultaneously using three stage least squares an estimation method that I will get into in more detail in the next section. He finds each statistic to be significant at the 99% confidence interval and of the correct sign. From there he calculates the marginal value of each statistic; that is, he moves from two equations to one equation that relates the statistics to winning percentage.

Knowing the impact of each statistic on winning percentage allows him to calculate the number of wins a player produces individually. He does this in three steps. The first involves multiplying player’s accumulation of each statistic by the corresponding marginal value divided by the number of minutes played for a per-minute production measure. Next Berri attempts to construct some measure of a team’s tempo, which plays a role in the opponent’s ability to score as a team and the number of opportunities the players have to shot the ball. His theory is based on the idea that the number a shots a given team takes is equal to the number of opportunities the other team has to score ceteris paribus. To measure team tempo, Berri multiplies the values of the team tempo statistics by the total accumulation of these and then divides by the total minutes a team played that season. This per-minute tempo factor is added to the individual players per-minute production. To incorporate team defense, Berri decides that each player’s contribution to defense will be a function of minutes played; this is consistent with Scott, Long and Sompui. Finally, a player’s marginal value is calculated with two final tweaks; one for position played, the average production at each position is subtracted out from the player’s per minute production, and second values are adjusted to
reflect just regular season production. This last issue is not relevant in my study as all data is regular season figures. Berri goes on in his article to discuss whether Michael Jordan or Karl Malone is most valuable in the league; however, our discussion of the paper will end here.

DATA

Data for this paper is collected over three consecutive NBA seasons stating with the 1995-96 season and covers only the regular seasons. Salary figures for a particular year are regressed against team and player statistics from that same year. In other words, Michael Jordan’s salary from the 1995-96 season is regressed against a MRP constructed from his performance measures and statistics for the Chicago Bulls from 1995-96 season. Some economists prefer to regress salary against productivity measures from the previous season arguing that salary is based on last season’s performance. However, based on varying lengths of contracts and a belief that salaries are indeed based on predicted MRPs, this paper uses team statistics and player performance and compensation all from the same season.

Team and individual performance measures and financials were gathered from three main sources: www.basketball.com, Rodney Fort’s Sport’s Business Pages, and Stats Pro Basketball Handbooks 1996-97, 1997-98, 1998-99. www.dfw.net/~patricia/ was used in cases were additional salary figures were needed. Population figures for each metropolitan area corresponding with a team’s home city came from table K.1 of the Survey of Current Business, September 2000. Per capita income figures were collected from the Bureau of Economic Analysis, Regional Accounts Data- Local Area Personal Income by Metropolitan Statistical Areas. Stadium capacity was found on
Finally, race or ethnic background was ascertained from players’ profiles and pictures found in the NBA registers for 1996-97, 97-98, and 98-99 housed in the NBA Hall of Fame. Note that information was collected for all eligible players, including rookies, who played for one team during a given season. Players who played for more than one team during a season were not included, as was not, injured players or players for whom data was missing. Given these limitations, this paper proceeds with a rather large sample, approximately 900 players and 29 teams/season. The racial and ethnic composition of the sample reflects the NBA as a whole, twenty percent of the players from the sample period are white, and eighty percent are black, and about five percent of the entire sample are of European or other backgrounds. Furthermore, the dataset shows that eight out of ten of the highest paid players are black, one is white and one is European or other.

THE MODEL

To test for both exploitation and discrimination, we have specified a unique three-equation model that follows the early work of Sully (1974), and, in terms of manipulating basketball statistics, the two papers presented above. The first two specifications are the Scully two-equation model. First, we regress revenue on winning percentage and a host of demand-side variables, such as population or per-capita income, that affect a team’s revenue.

\[
REV = \alpha_0 + \alpha_1 WINPCT + \sum \alpha_i X_i + \epsilon_1
\]

where the \(X_i\) are the demand-side variables and \(\epsilon_1\) is the random error term. Next we set winning percentage equal to several team level performance statistics:

\[
WINPCT = \beta_0 + \sum \beta_i Z_i + \epsilon_2
\]
where the $Z_i$ are the team level performance measures that influence points scored and points surrendered, which explains ninety five percent of the winning percentage (Berri 1999). The third and unique step that sets this paper apart from previous work is to regress salary as a function of these estimated parameters and other explanatory variables, for example, race or ethnic background. The equation takes this form:

$$\text{SALARY} = (\gamma_0 + \gamma_1 D_i) [\alpha_1 \times (\sum \beta_i V_j)] + \varepsilon_3$$

where $D_i$ are the possible explanations for salary/MRP differences not explained by the salary cap. If players are paid their estimated MRPs we would expect $\gamma_0$ to equal one and the $D_i$ to equal zero. Because of the salary cap, however, which limits the total salaries paid to a team’s players to a fixed amount, we expect $\gamma_0$ to equal the fraction of a team’s revenue allocated to the salary cap. During the 1995-96, 1996-97, and 1997-98 seasons the salary cap averaged forty percent of a team’s revenues, implying $\gamma_0$ equal forty percent. T-tests are performed on the estimated parameters to determine if we can reject the null hypothesis that $D_i=0$. $\alpha_1$ as you recall is the percent change in revenue for a one percent change in a team’s winning percentage. $\beta_i$ are the percent changes in winning percent given a one percent increase in any given team level performance measure. Finally, the $V_i$ are the individual contributions a player makes to the team level performance. Therefore $\alpha_1 \times \sum \beta_i V_i$ is equal to a player’s marginal revenue product.

The theory of perfect markets dictates MRP must equal salary. If MRP differs from salary then that group is treated unfavorably. This paper tests to see if systematic departures of salary from MRP are a function of race, ethnic background, number of years in the NBA, minutes played, or a rookie year. In our analysis of the results, we recall that the salary cap limits the amount of revenue appropriated for players. This
particular model is unique in that we use an integrated system of equations, rather than a two-step process and as a result our estimates are more efficient. Previous studies, using the two-equation model, take the estimated parameters from the revenue and winning percentage equations and calculate MRP, which, in turn, is compared to salary. This is the test for exploitation and if found, dummy variables are then added to explain the difference. Since MRP, a right-hand side variable is the product of estimated parameters, it is not exogenous and as a result the estimates are inefficient. Our model avoids this problem by estimating MRP and tests for discrimination in one equation.

Before we discuss the exact specifications of revenue and winning percent, one more issue needs to be addressed. That is, estimated coefficients obtained using OLS, ordinary least squares regression method, will be both biased and inefficient for two reasons. First off, the winning percent variable appears a dependent variable in the revenue equation and as the dependant variable in the second equation. Therefore, winning percent is not an exogenous variable and is correlated with the disturbance term in the revenue equation. Since these two are simultaneous equations, that is, there is feedback between the equations; OLS will generate biased, inefficient estimated coefficients. If this was the end of the story one could use two stage least squares to get biased but consistent estimates. However, it has been suggested by Medoff that the disturbance terms are correlated if we allow for the possibility of omitted variables “if any of the excluded variables from equation (1) [the winning percent equation for our purposes] also influence equation (2) [the revenue equation], then $u_1 [e_2]$ and $u_2 [e_1]$ are not serially independent. Yet it seems extremely plausible that some of the omitted variables from equation (1) [winning percent], such as managerial, quality, fan
enthusiasm, entrepreneurial ability in player acquisitions and commercial promotions to attract fans, and stadium constraints such as playing field configuration and capacity do in fact influence team revenue.” (Medoff, 1976, p.114) If this is indeed true and \( \varepsilon_1, \varepsilon_2 \neq 0 \) then we have violated one of the five classical assumptions. In this case, we must employ three stage least squares. “The 3SLS estimator is consistent and in general is asymptotically more efficient than the 2SLS estimator”(Kennedy, p.167)

Three stage least squares as the name suggests involves three steps. The first two are the same as using two stage least squares. Since \( Z_i \varepsilon_1 = 0 \) and \( X_i \varepsilon_2 = 0 \), that is, each of the other variables are exogenous and are not correlated with the error term of their given equation, we can estimate winning percentage using OLS. Next we take our estimated values of the endogenous variable, winning percentage, and plug them into the right hand side of the revenue equation. The estimated coefficients are now biased and consistent. The third step involved calculating the variance and covariance of the estimated error terms to transform the original variables to which we apply generalized least squares. In our case we allow the computer to estimate the parameters using three stage least squares. These parameters are biased but consistent and more efficient than two stage least squares.

AN APPLICATION TO THE NBA

Based on the theory presented above, we now turn to the actual specifications of the model. First, the variable team revenue measured in millions of dollars is the summation of gate, media and venue revenue plus other revenue such as licensing and merchandise for both the regular season and postseason play. Although not every team plays in the post season, or in the same number of rounds, we proceed with the
assumption that winning percentage is indicative of postseason play. Team revenue is then assumed to be positively related to the population (POP) and per capita income (INC) of the SMSA in which the team is located, and the capacity of the home stadium (CAP). Two dummy variables are included Y96 which is equal to one for the 1996-97 season and zero otherwise, and Y97 equal to one for the 1997-98 season and zero otherwise. In addition, a dummy variable for competition was considered, the theory being that competition for revenue may exist if a NBA team is located in a city with an NHL team. However, the inclusion of this variable did not increase the explanatory power of our equation. Hence we estimate revenue to be:

\[ REV = \alpha_0 + \alpha_1 \text{WINPCT} + \alpha_2 \text{CAP} + \alpha_3 \text{INC} + \alpha_4 \text{POP} + Y96 + Y97 + \varepsilon_1 \]

I have not included variables for percent of the population that is nonwhite, or the number of white players as this is not a test specifically for customer discrimination. Also, I did not include a measure for the increase in revenue due to the number of superstars a team has.

The second equation specified looks like this:

\[ \text{WINPCT} = \beta_0 + \beta_1 \text{OEGPCT} + \beta_2 \text{DEFGPCT} + \beta_3 \text{FGA} + \beta_4 \text{DIFFTREB} + \beta_5 \text{FTPCT} + \beta_6 \text{DIFFTFO} + \varepsilon_2 \]

The dependent variable winning percentage is the number of games won in a given season divided by the number of games played; teams in the NBA play 82 games a year in the regular season. OEGPCT is the offensive effective field goal percentage. This is calculated as \(2 \text{PFGM} + 1.5(3 \text{PFGM})/\text{FGA} \times 100\) where \(2 \text{PFGM}\) is two point field goals made, \(3 \text{PFGM}\) is three point field goals made, and \(\text{FGA}\) is total free throws attempted. This variable allows us to minimize the number of variables used. DEFGPCT is
calculated the same way for the opponent. FGA is field goals attempted; DIFFREB is the total rebounds for offensive team less total rebounds for the opponent; FTPCT is free throw percentage; and DIFFTO is the difference between a team’s total number of turnovers and his opponent’s total number of turnovers. We expect OEFGPCT, FGA, DIFFREB, FTPCT to have a positive influence on a team’s winning percentage and DEFGPCT and DIFFTO to have negative signs.

Finally, equation three is specified below:

\[
(1) \quad (3) \quad \text{SALARY} = (\gamma_0 + \gamma_1 \text{RACE} + \gamma_2 \text{OTHER} + \gamma_3 \text{YEARS} + \gamma_4 \text{MIN} + \gamma_5 \text{ROOKIE}) \times \\
[\alpha_1 (\beta_1 V_1 + \beta_2 V_2 + \beta_3 V_3 + \beta_4 V_4 + \beta_5 V_5 + \beta_6 V_6) + \epsilon_3]
\]

Salary is measured in millions of dollars and in some cases is taken as an average salary for a year of a given contract, the figure listed on the cap for that season, not necessarily what the player made since bonuses are for accounting purposes spread over the life of the contract. The dummy variable RACE is equal to one if black, and 0 otherwise. OTHER is equal to one if player is European or other. Rookie equals one for a player’s rookie season, 0 otherwise. Negative and significant values for \( \gamma_1, \gamma_2, \gamma_3 \) would indicate that black players, non-US players, and rookies are discriminated against in the sense that their MRPs are less than their MRPS. YEARS and MIN are continuous variables; their estimated coefficients may be interpreted as indicating the change in the percent of a player’s MRP he receives as the number of years of NBA experience or minutes played changes. If \( \gamma_3 \) and \( \gamma_4 \) are positive, more experienced players with greater playing time receive a larger fraction of their MRP in the form of salary than less experienced players who sit on the bench.
As explained above, \( \alpha_1 (\beta_1 V_1 + \beta_2 V_2 + \beta_3 V_3 + \beta_4 V_4 + \beta_5 V_5 + \beta_6 V_6) \) is equal to a player’s marginal revenue product. In the table below you will find the formulas for calculating each player’s contribution. Notice that defensive contributions are assumed to be a function of the number of minutes played divided by the total number of minutes played by the team. So, if a player plays 100 percent of the time, he is responsible for one-fifth of the points given up and the consequent revenue lost. In a world of perfect knowledge, you would be able to deduct from an individual’s MRP each rebound given up, or every shot taken by the opposing player he was guarding, but these statistics are not available. As a result the MRPs will understate the value of good defensive players and overestimate the value of poor defensive players. (Scott, Long, Somppi) MRP is thus equal to a player’s contribution to team level performance offensively and defensively, multiplied by that performance measure’s contribution to team winning percentage, which is then multiplied by the percent change in revenue from a one percent change in winning percentage, the estimated coefficient \( \alpha_1 \).

<table>
<thead>
<tr>
<th>Formula</th>
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<tbody>
<tr>
<td>( V_1 = \frac{\text{FGA (player)} \cdot \text{OEFGPCT}}{\text{FGA (team)}} )</td>
</tr>
<tr>
<td>( V_2 = \frac{\text{Player minutes played} \cdot \text{DEFGPCT}}{\text{Team minutes played}} )</td>
</tr>
<tr>
<td>( V_3 = \text{FGA for the player} )</td>
</tr>
<tr>
<td>( V_4 = \frac{\text{Total Rebounds (player) - minutes played (player) \cdot total defensive rebounds minutes played (team)}}{\text{minutes played (team)}} )</td>
</tr>
<tr>
<td>( V_5 = \frac{\text{Free throw percentage (player) \cdot Free throws attempted (player)}}{\text{Free throws attempted (team)}} )</td>
</tr>
<tr>
<td>( V_6 = \frac{\text{Turnovers (player) - minutes played (player) \cdot total defensive turnovers minutes played (team)}}{\text{minutes played (team)}} )</td>
</tr>
</tbody>
</table>

RESULTS

Having applied three stage least squares to the model explained in detail in the above section, we find that no significant racial wage difference exists in the 1990s. Rather, we find that black players may be paid more than equally productive white
players, and that being European/Other is insignificant as a plausible explanation. In
equation one, the estimated parameters on population, capacity and winning percentage
are of the correct sign and are significant at the 5 percent confidence level. Specifically,
we find that one unit increases in population and stadium capacity increase team revenue
by $1,778.33 and $1,187.76 respectively. More importantly, we find that a one
percentage point increase in winning percentage increases revenue by approximately
$490,678.00. The estimated parameter on per capita income is positive, but insignificant
at the ten percent confidence level. The dummy variables for the seasons 1996 and 1997
are significant and of the correct sign, reflecting increases in revenue based on other
economic factors such as inflation. The R squared for the revenue equation is .4666, a
reasonable fit if one takes into account the omission of a variable for number of
superstars, and proxies for customer discrimination. All the results and implications of
the revenue equation along t-stats are summarized in Table 1.

The second equation is also consistent with theory. We find that increases in
offensive effective field goal percentage and free throw percentage increases winning
percentage while increases in the opponents' effective field goal percentages decreases
winning percentage. In numeric terms, a one percentage point increase in a team's
effective field goal percentage, free throw percentage increases win percentage 4.78 and
.478 percentage points respectively. Likewise a one percentage point increase in your
opponents effective field goal percentage decreases your win percent by 2.74 percentage
points. Furthermore, getting more rebounds than your opponents increases the number of
chances you have to shoot and therefore increases your winning percentage, while
turning over the ball more times than your opponents deceases winning percentage. The
results imply a one-unit increase in net rebounds (team-opponent rebounds) increases win percent by .027 percentage points. In the opposite direction, a one-unit increase in a team’s turnovers less his opponents’ turnovers decreases win percent by .038 percentage points. The estimated coefficients on each of these variables are significant at the one percent confidence interval and the R-squared is .8746, suggesting a reasonably good fit. All the estimated coefficients and asymptotic t-statistics for equation 2 can be found in Table 1.

We now take a look at the third equation, which tells a rather interesting story. I recall for you the integrated equation used to estimated exploitation and discrimination.

\[
(3) \text{SALARY} = (\gamma_0 + \gamma_1 \text{RACE} + \gamma_2 \text{OTHER} + \gamma_3 \text{YEARS} + \gamma_4 \text{MIN} + \gamma_5 \text{ROOKIE}) \times \left[ \alpha_1 \right.
\left. (\beta_1 V_1 + \beta_2 V_2 + \beta_3 V_3 + \beta_4 V_4 + \beta_5 V_5 + \beta_6 V_6) \right] + \epsilon_3
\]

In the absence of the salary cap and discrimination a player should receive a salary equal to his marginal revenue product, implying that \(\gamma_0 = 1\), \(\gamma_1 = \ldots = \gamma_5 = 0\).

Because of the salary cap, however, players will receive a salary less than their estimated MRP, implying that \(\gamma_0 < 1\). During the 1995-96, 1996-97, and 1997-98 seasons the salary cap was set at $23 million, $24.4 million, and $26.9 million, respectively; the corresponding average team revenues were $58.59 million, $58 million, and $64.6 million, respectively. The salary cap was thus equal to 39.26%, 42.07%, and 41.64% of average team revenues during the 1995-96, 1996-97, and 1997-98 seasons, respectively, with an average of 40.00% over the 3 seasons. As a result of the salary cap, we thus expect players to receive a salary roughly equal to 40% of their estimated MRPs.

The estimate of \(\gamma_3\) is positive and significant, implying that more experienced players receive a larger percentage of the estimated MRPs in salary than less experienced
players, while the estimate of $\gamma_4$ is negative and significant, implying that players who receive little playing time receive a higher fraction of their estimated MRP than players who log a lot of minutes. One possible explanation is that the NBA and the players’ union have established minimum and maximum salary levels that vary by experience. During the 1989-90 season rookies had a minimum salary of $287,500 and a maximum of $9 million, while players with ten or more years of experience had minimums and maximums of $1 million and $14 million, respectively. More experienced players may receive a larger percentage of their estimated MRP because their minimum and maximum salaries are higher than less experienced players. Alternatively, older players may have established a proven track record over a number of years, making it possible for teams to more accurately assess their contribution to the team and their MRPs. Teams may be willing to pay a higher percentage of this estimated MRP in salary because they are more confident of their prediction of the player’s MRP.

The minimum salary scale may also explain why players who play very little receive a higher percentage of their estimated MRP in salaries than players who play a lot. Approximately 9% of the players of the players in our sample played fewer than 100 minutes in a season, which over an eighty-two game season means that they played less than 1.22 minutes per game. Presumably their MRPs are very low, but teams may be prevented from paying them a salary commensurate with their MRP because of the minimum salary requirement. On the other hand, players who log a lot of minutes may have very high MRPs, but teams may be prevented from paying them a commensurately high salary because of the salary maximums.
The estimated coefficient for EURO is positive or negative, but insignificant, implying no discrimination against non-U.S. players. The estimated coefficient for ROOKIE is negative and significant at the 10% level, implying that rookies receive a smaller percentage of their estimated MRPs than more experienced players with similar playing time and productivity. Finally, the coefficient of RACE is positive and significant at the 10% level, implying that Black players receive a larger share of their estimated MRPs than white players with similar tenure and productivity. This finding is consistent with Matthew Dey's findings of a one percent bonus for blacks in his recent regressions over the early 1990s. The above findings are summarized in Table 1.

We employ two different definitions of exploitation in our attempts to test whether or not NBA players are exploited. First, if one adopts a Marxian, labor theory of value interpretation, workers are the ultimate source of all wealth and thus are responsible for all of the revenues generated by the NBA. Under this theory a player's salary should be equal to his estimated MRP, implying that

\[(\gamma_0 + \gamma_1 \text{RACE} + \gamma_2 \text{OTHER} + \gamma_3 \text{YEARS} + \gamma_4 \text{MIN} + \gamma_5 \text{ROOKIE}) = 1.\]

Bowing to the realities of the NBA salary cap, however, we recognize that teams are limited in the salaries that they can pay. As a result, players will receive only a fraction of a team's total revenues in the form of compensation. Under this more realistic interpretation, we argue that players are exploited if the fraction of their estimated MRP that they receive in salaries is less than the fraction of the salary cap as a proportion of a team's revenues. During the 1995-96 through 1997-98 seasons the ratio of the salary cap to average team revenues was .4, implying that

\[(\gamma_0 + \gamma_1 \text{RACE} + \gamma_2 \text{OTHER} + \gamma_3 \text{YEARS} + \gamma_4 \text{MIN} + \gamma_5 \text{ROOKIE}) = .4\]
We test these hypotheses by computing the asymptotic t-statistics for the expressions with the parentheses, and then testing to see if the differences between the estimated and hypothesized values (1 and .4) are statistically different. We test the hypotheses for four different groups of players, White, Black, European, and rookies while holding the variables YEARS and MIN at the average values.

The test statistics and corresponding significance levels for the tests are presented in Table 2. If we take the Marxian point of view, we find that black players are getting 46.17% of their MRP, whites get just over 40%, Europeans and other non-US players 41%, and rookie 31% of their MRP. In every case we can reject the null hypothesis that they are getting their full MRP at the 1% level. If we are testing for exploitation while acknowledging that a salary cap does exist, the estimates for blacks, whites and Europeans are positive implying they get more than 40%, but the results are insignificant at the 10% level. The estimate for rookies is negative, implying they get less than 40%, but once again it is not significant at the 10% confidence level.

CONCLUSIONS

Based on NBA player and team data collected over the 1995-96, 1996-97, 1997-98 seasons, regression analysis, using three stage least squares on simultaneous equations, suggests that racial wage differences no longer exist. Gone are the white salary advantages in the area of twenty percent found in the 1980s. Rather, our enhanced model, which produces more efficient estimates than those of the 1980s, finds that players are not exploited by team owners. However, if one proposes that the salary cap was established to make the league more competitive and inherently exploit players by keeping their salaries below their MRP, one can look at the first chart in Table 2 and say
that players of any race or nationality are paid a salary less than their MRP, and are thus by definition exploited. In addition, we find that more experienced players get a higher percentage of their MRPs in salary, while rookies receive a smaller percentage of their estimated MRPs than those more experienced players with similar playing time and productivity. Also, players who play fewer minutes receive a greater portion of their MRP. Finally, our evidence reveals that non-U.S. players are not discriminated against; however, black players receive a larger share of their estimated MRPs than white players with similar tenure and productivity.
<table>
<thead>
<tr>
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<th>ESTIMATE</th>
<th>T-STAT</th>
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<tr>
<td>WINPCT</td>
<td>0.490678</td>
<td>20.5998*</td>
</tr>
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<td>CAP</td>
<td>0.00177833</td>
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<td>POP</td>
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<tr>
<td>Y97</td>
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<td>12.7090*</td>
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<td>-26.8936*</td>
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<td>0.027206</td>
<td>27.2124*</td>
</tr>
<tr>
<td>DIFFTO</td>
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</tr>
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<td>G0</td>
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<tr>
<td>RACE</td>
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<td>OTHER</td>
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<td>0.057302</td>
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<tr>
<td>YEARS</td>
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<td>6.74728*</td>
</tr>
<tr>
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<td>-3.54256*</td>
</tr>
<tr>
<td>ROOKIE</td>
<td>-0.089714</td>
<td>-1.70305**</td>
</tr>
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</table>

* SIGNIFICANT AT THE ONE PERCENT CONFIDENCE LEVEL
** SIGNIFICANT AT THE TEN PERCENT CONFIDENCE LEVEL
Table 2

Null Hypothesis: (1) based on a Marxian labor theory of value

\[(\gamma_0 + \gamma_1 RACE + \gamma_2 OTHER + \gamma_3 YEARS + \gamma_4 MIN + \gamma_5 ROOKIE) = 1.\]

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</tr>
<tr>
<td>BLACK</td>
<td>-12.9778</td>
<td>1%</td>
</tr>
<tr>
<td>EURO</td>
<td>-10.9359</td>
<td>1%</td>
</tr>
<tr>
<td>ROOKIE</td>
<td>-10.7129</td>
<td>1%</td>
</tr>
</tbody>
</table>

Null Hypothesis: (2) taking into account the realities of the NBA salary cap

\[(\gamma_0 + \gamma_1 RACE + \gamma_2 OTHER + \gamma_3 YEARS + \gamma_4 MIN + \gamma_5 ROOKIE) = .4\]

<table>
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<td>WHITE</td>
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<td>EURO</td>
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<td>92.4%</td>
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<tr>
<td>ROOKIE</td>
<td>-.087418</td>
<td>17.3%</td>
</tr>
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Data Appendix

Data for WINPCT, OEFGPCT, DEFGPCT, FGA, FTPCT, DIFFTO, and DIFFTREB for each player were taken from *Stats Inc. NBA Handbook*, 1996-97, 1997-98, 1998-99.

Team data for the WINPCT equation were taken from [www.basketball.com](http://www.basketball.com) basketball database.

Data for POP appears in *The Survey of Current Business*, September 2000 table K.1

Data for per capita income was found on the Bureau of Economic Analysis website, Local Area Personal Income by Metropolitan Statistical Areas.

Data on stadium capacity were taken from Ballparks by Munsey & Suppes at [www.ballparks.com](http://www.ballparks.com)

Revenue data were found on Rodney Fort’s Sport’s Business Pages on the web.

Salary data were found on Rodney Fort’s Business Pages and [www.dfw.net/~patricia/](http://www.dfw.net/~patricia/). The figures from the latter were taken from the Dallas Morning News.
References


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