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Abstract

Previous research finds that customer racial discrimination decreases the price of a non-white baseball player's card but does not decrease the price of a non-white basketball player's card. This paper seeks to examine if racial minority or league minority affects the value of a trading card. Using disaggregated player performance data from 1977 we explore this question with baseball cards (in which non-white players are the league minority) and basketball cards (in which white non-players are the league majority). Using Tobit regressions, we find that customer discrimination exists against non-white players in both baseball and basketball leagues.

I. Introduction

In an attempt to identify the roots of economic inequality in American society, many economists have turned their attention to racial discrimination. Becker (1971) defines discrimination in the market place as "voluntary relinquishing of profits, wages, or income in order to cater to prejudice." He cites three sources of discrimination: employers, co-workers, and consumers. According to Arrow (1972), natural economic forces within a competitive market reduce, if not eliminate, employer and co-worker discrimination. Employer discrimination forces employees seeking fair business practices to relocate while co-worker discrimination causes self-sorting among workers in a mobile economic environment. Therefore, if an economic imbalance exists between races, it comes as a consequence of consumer discrimination. However, the task of measuring consumer discrimination is not a simple one. The lack of a means to quantify and measure a worker's ability in most labor markets presents a formidable obstacle to economists. The professional sports labor market is a crucial exception to this standard.

Unlike other labor markets, where employee productivity is often blurred by extraneous variables, the professional sports labor market provides an isolated working arena in which uninhibited competition can take place. Thus, every worker's performance is a measure of individual ability, rather than a combination of skills and externalities.[1] Such a distinction is necessary when analyzing consumer discrimination. Take, for example, the case of two competing door-to-door salesmen. Both sales representatives are selling the same product, at the same exact price, in the same local area, at the same time. The only difference between the two salesmen is their race. After

[1] Here the term "externalities" is taken to mean any factor, which may affect the productivity of a worker, including job experience, age, sex, and education, among others.

a given period of time, one salesman sells more items than the other one. Is this because one sales representative has more experience than the other? Is this because one salesman is a better speaker than the other? Or, is one of the salesmen getting more sales because the consumer is racially discriminating against the other? None of these questions can be answered in a market open to externalities. However, in a relatively confined market, such as the sports labor market, consumer discrimination is identifiable because all extraneous factors can be controlled.

Professional sport trading cards, in particular, provide an ideal means of tracing consumer discrimination. The price of each card is derived from the entertainment value of the player represented on the card. Accordingly, the better a player's ability, the more entertainment they bring to the fans that in turn pay more for their card. Each player's ability is quantified in the form of disaggregated statistics, which appear on the back of each card. By analyzing the relative price a card sells for in the secondary market with respect to a player's race, one can show whether the price a consumer is willing to pay for a card is affected by the player's race.

This paper extends previous works but examines whether or not league status, more so than race, is the underlying variable influencing the price of a trading card. This paper seeks to answer whether card value is affected by the race of the player, or whether it is an issue of league minority. This paper uses two Tobit regression models: one for Major League Baseball (MLB), where non-white players are the league minority, and one for the National Basketball Association (NBA), where non-white players are the league majority. Therefore, the NBA provides a counterexample to the commonly studied MLB model, which may attribute lower minority prices to non-white players rather than league minority. The results of the regression models show that race impacts the trading price rather than league minority. That is, in both the MLB and the NBA non-white players' cards have significantly lower prices.

This paper proceeds as follows. Section II discusses the literature on the subject. Section III describes the data and methods. Section IV describes the specifications of the model. Section V presents the results. Section VI draws conclusions.

II. Literature

Previous research concerning consumer racial discrimination in the professional baseball memorabilia market has suggested that a player's race affects the value of their trading card. Nardinelli and Simon (1990) construct a model using the 1970 Topps Baseball Card Series as their dataset for players. Using player statistics from the Macmillan Baseball Encyclopedia and using *Beckett's Official 1989 Price Guide to Baseball Cards*, they determine card value. The results indicate that customer racial discrimination decreases a nonwhite baseball player's card value by approximately ten percent with respect to a comparable white player's card.

Anderson and La Croix (1991) extend Nardinelli and Simon by examining baseball card data from 1977, rather than 1970 because the 1977 data has no supply differences in the amount of baseball cards produced per player. That is, each player has the same number of cards printed in that year. Additionally, rather than use disaggregated player performance data for hitters, Anderson and La Croix employ player performance indices. For hitters (non-pitchers) the performance index is measured as offensive average, which takes into account power, base hit frequency, and the effects of walks and stolen bases. A pitcher's performance index is based on two factors: earned run average (ERA) and the ratio of strikeouts to walks, both of which are independent of a player's team performance. The results of Anderson and La Croix's paper reinforce the conclusion of Nardinelli and Simon: customer discrimination exists against black hitters and pitchers.

Gabriel, Johnson, and Stanton (1995) investigate customer racial discrimination using rookie baseball cards for players entering major league baseball from 1984 to 1990. They examine if price is explained by expected future performance, as well as past performance and race. They find that price differences are not significantly influenced by race, contrasting the results found by Nardinelli and Simon (1990) and Andersen and La Croix (1991). Several factors may explain the difference in their results from those in previous studies. By using cards from active rookie players, racial discrimination may exist in both the current value of the card and the expectations about the future performance of a player. In addition, market segmentation in the baseball card market may occur such that those purchasing from the retired player's baseball card market (middle-aged white males) may have different racial preferences than those purchasing from the current card market (younger adults and children).

Brown and Jewell (1994) examine customer discrimination in college basketball. They find that customer discrimination affects the revenue-earning potential of white players relative to black players. Therefore, they conclude that college programs wish to discriminate against black recruits. Customer racial discrimination has also been explored in the basketball market through Trading Cards and Neilson Ratings. Using active players during the 1976-1977 season Stone and Warren (1999) use maximum-likelihood estimation to explore price discrimination in basketball trading cards taking into consideration position, years, and race. Overall they find no evidence of customer discrimination against black players. Using Neilson ratings, Kanazawa and Funk (2001) find that viewership increases when a higher percentage of white players are playing in a professional basketball game. Thus, explaining the salary gap in basketball as race-based.

III. Data and Methods

This paper extends the model of Nardinelli and Simon (1990) by using disaggregated player performance data. Furthermore, the same set of data as Anderson and La Croix (1991), 1977 Topps baseball cards, is used because of the uniform supply of cards. The paper differs from Stone and Warren (1999) in that only basketball cards issued in 1977 are used and that performance statistics are included in the regression models. The inclusion of both baseball and basketball cards allows determinations of whether racial minority or league minority determine card value, based on the fact that non-white players are a minority in baseball and white players are a minority in basketball.

Beckett's Price Guide determines the price data and RealLegends.com determines data on race.[2] In addition, each player's career statistics are gathered from various sources, including the CNN/Sports Illustrated archives and a downloadable sports database program.

Each year, when a new set of cards is released, professional sport card manufacturers insert unique groups of cards known as "subsets." These cards differ from the others in their appearance, their title, and the fact that they can depict multiple players

[2] RealLegends.com is an online website dedicated to tracking the market for professional sports memorabilia. The site houses complete checklists of all professional sport card sets and pictures of each individual card.

on one card. Every card manufacturer prints its own type of subset. In 1990, for example, Topps inserted a subset entitled "Record Breakers" while Fleer and Donruss included "Players of the Decade" and "Diamond Kings," respectively. Although these cards are considered part of the complete set, they present a problem when trying to collect a uniform dataset because they repeat players who already appear in the main set of cards.

The data include the 1977 set of Topps baseball cards, a total of 660 different cards. Of these, 314 cards are omitted. The majority of these cards fall into various subsets, including "Turn Back the Clock", "League Leaders", and "Big League Brothers". Team, coach, and manager cards are also left out along with the five checklist cards and the two world-series cards. Likewise, for the 1977 set of Topps basketball cards, 11 cards are omitted from the 144 card set. The omitted cards fall into the "All-Star" subset and the one checklist card.

With the remaining data, histograms are used to gain a better understanding of the price distribution of each card set with respect to a player's race. Figures 1 and 2 show the percentage of cards for white and non-white baseball non-pitchers and pitchers in specified price bins, while Figure 3 shows similar information for basketball players. Figures 1 – 3 show that in both sports, non-white players represent a substantial portion of the higher price cards. This is important because it suggests that any one card does not bias the results in favor of one race. Therefore, any conclusions reached as to the effect of race are a result of comparing cards of similar value.[3]

[3] The Tobit regression results are robust when price outliers are omitted.

To analyze the effect race and league percentage have on card value, Tobit regressions are run on the two different sports cards. For each set of cards there is a common card price representing the minimum observed value in the sample. This leads to the idea of a "common player" price. As described by Nardinelli and Simon (1991), the price of a common player's card is the absolute minimum value a card can take and is completely unrelated to the player performance. As illustrated in Tables 1 - 3, the descriptive statistic tables for baseball non-pitchers, baseball pitchers, and basketball players, respectively, the common player price for 1977 Topps baseball cards (both non-pitchers and pitchers) is $0.30 while the minimum value for a 1977 Topps basketball card is $1.75. Several reasons exist for the variation between the baseball and basketball card minimum values. First, there are fewer cards in the 1977 basketball set, 144 cards compared to 660. Furthermore, Topps began making baseball cards in 1952, but did not start making basketball cards until the 1957 - 1958 basketball season. As a result, basketball cards are harder to come by than baseball cards for this time period.

Therefore, Tobit regressions are used to generate unbiased regression estimates. For both leagues (MLB and the NBA), the price of the card is the dependent variable, while performance statistics and race serve as independent variables. The independent variable for non-white player is assigned a value of 1 for non-white players (black and Latino players) and a 0 for white players.

IV. Regression Equations and Hypotheses

A. Baseball Non-Pitchers

Table 1 summarizes the descriptive statistics for baseball non-pitchers. As illustrated, non-white players only account for 33.5% of the total number of hitters. The average prices for non-pitcher baseball cards are \$0.84 for white players and \$0.89 for non-white players. We specified the following model for non-pitchers:

$$P_{non-pitchers} = \beta_0 + \underset{(?)}{\beta_1 NON-WHITE} + \underset{(+)}{\beta_2 BAT\ AVERAGE} + \underset{(+)}{\beta_3 STOLENBASES} + \underset{(+)}{\beta_4 OFFENSIVE\ AVERAGE} \quad (1)$$

where $OFFENSIVE\ AVERAGE = \dfrac{(Total\ Bases\ Gained\ on Base\ Hits + Walks + Stolen\ Bases)}{At\ Bats + Walks}$, similar to Andersen and La Croix (1991). Expected signs on the coefficients are shown in parentheses. As long as the race variables are uncorrelated with omitted variables that measure athletic ability, the estimated coefficient on race will be an unbiased estimator of consumer discrimination.

Before settling on the regression model above, more traditional methods of measuring a player's performance were incorporated into the model, including hits, games, at-bats, and the remaining variables listed in the descriptive statistics (Table I). However, many of these disaggregated variables are eliminated based on their high correlation to each other. For example, "hits" takes into account the number of doubles, triples, and homeruns that a player gets. Additionally, the statistics "runs-batted-in" and "runs scored" are omitted because of their close relationship to hits. The more hits a player has, the more times they have the opportunity to score and the more teammates they help reach home plate. Because of the complex network of correlated variables, a new variable is sought to better account for a player's productivity. The variable "offensive average" is borrowed from Anderson and La Croix (1991) who borrowed the concept from Bennett and Flueck (1983).

B. Baseball Pitchers

Table 2 summarizes the descriptive statistics for baseball pitchers. Once again, non-white players are also a league minority, only making up 9.2% of all pitchers in MLB. The average prices for pitcher baseball cards are $0.68 for white players and $0.52 for non-white players. We specified the following model for pitchers:

$$\begin{aligned} P_{pitchers} = \beta_0 + \overset{(?)}{\beta_1 NON-WHITE} + \overset{(+)}{\beta_2 WINS} + \overset{(+)}{\beta_3 SAVES} \\ + \overset{(?)}{\beta_4 INNINGS\ PITCHED} + \overset{(-)}{\beta_5 HITS\ GIVEN\ UP} \\ + \overset{(-)}{\beta_6 RUNS\ GIVENUP} + \overset{(+)}{\beta_7 PITCHING\ RATIO} \end{aligned} \qquad (2)$$

where *PITCHING RATIO* = $\frac{STRIKE\ OUTS}{WALKS}$, similar to Andersen and La Croix (1991).

Many of the variables excluded from this regression may provoke some controversy, particularly earned run average, or ERA. In order to understand the reason behind its omission, it is important to know how a pitcher's ERA is derived. The Official Homepage of Major League Baseball defines ERA as "the total number of earned runs allowed by a pitcher, divided by his total innings pitched, multiplied by nine." The flaw with using this variable as a means of measuring a pitcher's performance is that there are three distinct types of pitchers that serve three different functions: starters, relievers, and closers. In general, a starting pitcher begins the game and pitches until he is no longer effective in preventing the other team from getting on base and scoring. A reliever replaces a starting pitcher if the other team is earning runs against the starter. This can occur toward the beginning or end of the game. A closer is only used at the end of the game as a means of ensuring that the other team does not gain any more runs.

Accordingly, a pitcher's ERA often reflects his role as a starter, reliever, or closer. A starter's ERA, for example, varies less than a closer's ERA because of the number of innings pitched. Because a closer pitches far less innings than a starter, any runs scored in the last innings drastically increases a closer's ERA. As a result, a closing pitcher generally has a higher ERA than a starter. Likewise, the ERA of a reliever depends on how often and when they get into the game. Therefore, instead of using ERA we use *PITCHING RATIO.* Using pitching ratio in conjunction with wins, saves, innings pitched, hits, runs, accounts for relevant statistics for each type of pitcher.

C. Basketball

Table 3 summarizes the descriptive statistics for basketball players. In contrast to the baseball statistics, non-white players are a league majority in professional basketball. Non-white players represent approximately 70.7% of the entire NBA. The average prices for basketball cards are \$5.72 for white players and \$4.51 for non-white players. We specified the following model for basketball players:

$$\begin{aligned} P_{basketball} &= \beta_0 + \overset{(?)}{\beta_1 NON-WHITE} + \overset{(+)}{\beta_2 REBOUNDS} + \overset{(?)}{\beta_3 PERSONAL\ FOULS} \\ &\quad + \overset{(+)}{\beta_4 ASSISTS} + \overset{(+)}{\beta_5 AVERAGE\ POINTS\ PER\ GAME} \end{aligned} \tag{3}$$

Unlike baseball, where there are two distinct aspects of the game, pitching and hitting, basketball players must perform offensively and defensively. This allows for a much simpler analysis of each player's overall performance. Of the many disaggregated variables listed in the descriptive statistics, all of them can be accounted for using average points per game, rebounds, personal fouls, and assists. Free throws and field goals are both explained using the "points" variable. Moreover, points and games are used to calculate average points per game. "Minutes" is also eliminated as it is highly correlated to games. The more games a player appears in, the more minutes he has on the court.

V. Results

A. Baseball Non-Pitchers

The baseball non-pitcher sample consists of 346 non-pitchers: 230 white players and 116 non-white players. Equation (1) was estimated using Tobit regressions for linear and log prices, reported in Table 4. For non-pitchers, the coefficients on batting average, stolen bases, and offensive average are all positive, as expected, and significant. More importantly, the coefficient on non-white is negative with a t-ratio of –3.54 in the linear model and –3.00 in the log model.

B. Baseball Pitchers

The baseball pitcher sample consists of 238 pitchers: 216 white players and 22 non-white players. Equation (2) was estimated using Tobit regressions for linear and log prices, reported in Table 5. Using the linear model for pitchers, the coefficients on wins, saves, and the pitching ratio are not significant. The insignificant impact of wins and saves on the price of a pitcher's card is also found in Andersen and La Croix (1991) depending on the model. However, the most surprising of these results is the pitching ratio. In the linear model, the coefficient on innings pitched is positive and significant, as is the coefficient on runs given up, contradicting the hypothesis. As predicted, the coefficient on hits given up is negative and significant. More importantly in the linear model, the coefficient on non-white is negative with a t-ratio of –2.95.

Using the log model for pitchers, the coefficients on innings pitched and runs given up are not significant. The coefficient on wins, saves, and pitching ratio are positive and significant as expected. Also as predicted, the coefficient on hits given up is negative and significant. More importantly in the linear model, the coefficient on non-white is negative with a t-ratio of –1.73.

C. Basketball

The basketball sample consists of 133 players: 39 white players and 94 non-white players. Equation (3) was estimated using Tobit regressions for linear and log prices, reported in Table 6. In the linear model, the coefficients on rebounds, assists, and average points per game are all positive and significant, as expected. The coefficient on personal fouls is not significant. More importantly, the coefficient on non-white is negative with a t-ratio of –2.17.

In the log model, the coefficients on rebounds and average points per game are positive and significant, as expected. The coefficient on personal fouls and assists are not significant. Again, the coefficient on non-white is negative with a t-ratio of -1.06.

VI. Conclusions

Racial minority has a significant impact on the value of a professional sports card. Consumers discriminate more against racial minorities rather than league minorities. Accordingly, this paper supports the findings of Nardinelli and Simon (1990) and Anderson and La Croix (1991) and finds results that differ from the findings in Stone and Warren (1999). Thus, professional sports cards depicting racial minorities sell for significantly less than racial majorities of equal ability.

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[5 May 2002 and 6 May 2002]

Figures

Figure 1. Distribution of Non-Pitcher Baseball Card Prices by Race

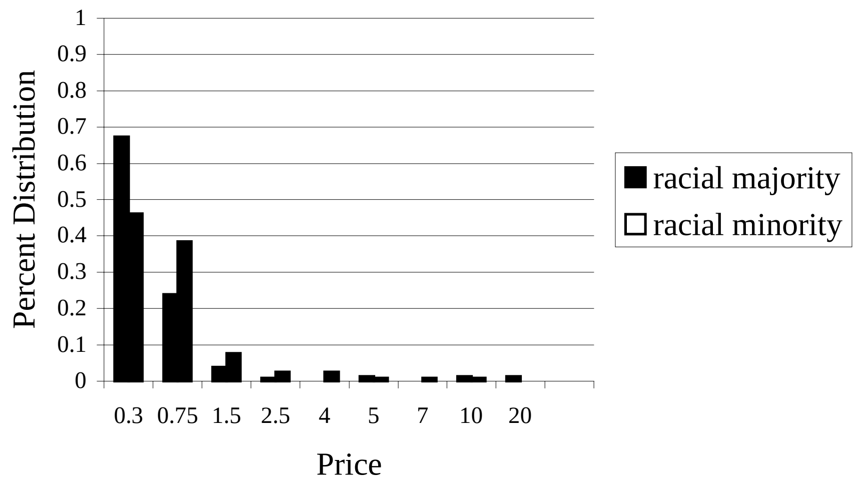


Figure 2. Distribution of Pitcher Baseball Card Prices by Race

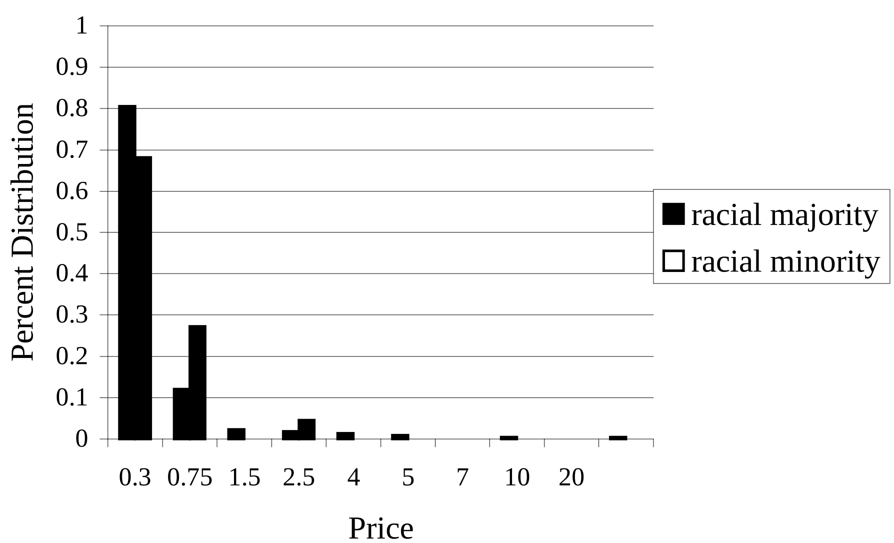
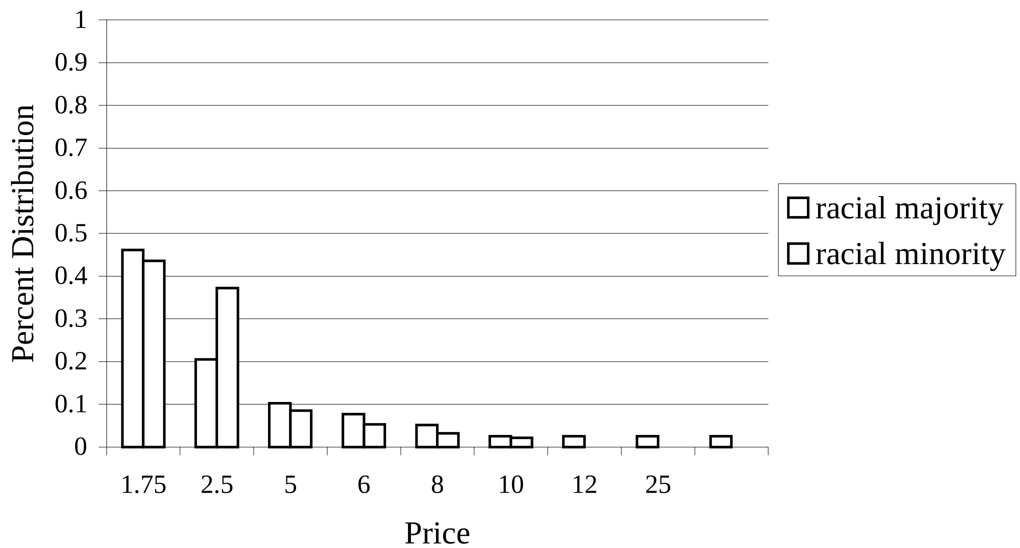


Figure 3. Distribution of Basketball Card Prices by Race



Tables

Table 1. Descriptive Statistics for Baseball Non-Pitchers

Variables	Observations	Mean	Minimum	Maximum
Price	346	0.86	0.30	30
Non-white	346	0.34	0	1
Batting Average	346	0.26	0.18	0.33
Games	346	1310.15	42	3562
At-Bats	346	4250.82	67	14053
Runs	346	544.95	6	2165
Hits	346	1131.82	14	4256
Doubles	346	186.81	1	746
Triples	346	29.90	0	141
Homeruns	346	105.61	0	563
Runs-Batted-In	346	521.99	3	1844
Walks	346	427.99	7	1865
Strike Outs	346	598.39	9	2597
On-Base %	346	0.32	0.23	0.40
Slugging %	346	0.48	1.86	35
Stolen Bases	346	81.32	0	938
Offensive Average*	346	0.45	0.29	0.89

***** Offensive Average = $\frac{\text{Total Bases Gained on Base Hits + Walks + Stolen Bases}}{\text{At Bats + Walks}}$

Table 2. Descriptive Statistics for Baseball Pitchers

Variables	Observations	Mean	Minimum	Maximum
Price	238	0.67	0.30	20
Non-white	238	0.09	0	1
ERA	238	3.75	2.83	5.85
Wins	238	84.60	1	329
Losses	238	79.88	3	292
Saves	238	30.72	0	390
Games Pitched	238	367.21	13	1071
Innings Pitched	238	1461.60	46.2	5404
Hits Given Up	238	1404.20	58	5044
Runs Given In	238	655.58	29	2337
Errors	238	581.47	28	2012
Bases-On-Balls	238	498.90	20	2795
Strike Outs (Ks)	238	862.72	20	5714
Pitching Ratio*	238	1.58	0.84	3.25
Average Against	238	0.26	0.20	0.33

***** Pitching Ratio = $\frac{\text{Strike Outs}}{\text{Walks}}$

Table 3. Descriptive Statistics for Basketball Players

Variables	Observations	Mean	Minimum	Maximum
Price	133	5.05	1.75	60
Non-white	133	0.71	0	1
Games	133	733.69	134	1560
Minutes	133	21828.11	1493	57446
Field Goals	133	4326.74	269	15837
Free Throws	133	2195.34	71	9018
Rebounds	133	4344.88	215	17834
Assists	133	2257.69	99	6476
Personal Fouls	133	2055.80	192	4657
Points	133	10876.36	609	38387
Average PPG	133	14.00	4.2	25.1

Table 4. Tobit Regressions for Baseball Non-Pitchers, N = 346

Variable	**Linear Price** Coefficient **(t-stat)**	**Log Price** Coefficient **(t-stat)**
Non-white	**-0.76** **(-3.54***)**	**-0.82** **(-3.00***)**
Batting Average	13.33 (2.80***)	35.17 (4.59***)
Stolen Bases	0.00 (3.07***)	0.00 (2.12**)
Offensive Average	**6.37** (3.73***)	**12.97** (5.24***)
Constant	**-5.37** (-5.04***)	**-16.63** (-5.89***)
Log-Likelihood Function	-670.75	-104.52

KEY:

* = Significance level of 10% or better
** = Significance level of 5% or better
*** = Significance level of 1% or better

Table 5. Tobit Regressions for Baseball Pitchers, N = 238

Variable	Linear Price Coefficient (t-stat)	Log Price Coefficient (t-stat)
Non-white	-0.92 (-2.95***)	-0.79 (-1.73*)
Wins	0.00 (0.25)	0.02 (1.80*)
Saves	0.00 (0.30)	0.00 (2.05**)
Innings Pitched	0.01 (7.72***)	0.00 (0.99)
Hits Given Up	-0.01 (-13.39***)	-0.00 (-3.70***)
Runs Given Up	0.01 (3.23***)	-0.00 (-0.09)
Pitching Ratio	-0.23 (-0.75)	0.50 (1.84*)
Constant	0.37 (0.87)	-2.51 (-3.76***)
Log-Likelihood Function	-409.60	-26.47

KEY:

* = Significance level of 10% or better

** = Significance level of 5% or better

*** = Significance level of 1% or better

Table 6. Tobit Regressions for Basketball Players, N = 133

Variables	Linear Price Coefficient (t-stat)	Log Price Coefficient (t-stat)
Non-white	-3.69 (-2.17**)	-1.06 (-2.98***)
Rebounds	0.01 (2.70***)	0.00 (1.87*)
Personal Fouls	-0.00 (-1.47)	-0.00 (-0.65)
Assists	0.00 (2.12**)	0.00 (0.42)
Average PPG	1.20 (5.90***)	0.17 (3.85***)
Constant	-15.14 (-4.61***)	-1.62 (-1.82*)
Log-Likelihood Function	-333.60	-50.72

KEY:

* = Significance level of 10% or better

** = Significance level of 5% or better

*** = Significance level of 1% or better