Racial Discrimination Across Job Assignments: Theory and a Test from Major League Baseball

By

Őrn B. Bodvarsson
Department of Economics
St. Cloud State University
720 Fourth Avenue South
St. Cloud, MN 56301-4498 USA
(320)308-2225, FAX (320)255-2228
obbodvarsson@stcloudstate.edu

&

John G. Sessions
Department of Economics and International Development
University of Bath
Bath BA2 7AY, UK
+44(0) 1225 384517, FAX +44(0) 1225 383423
j.g.sessions@bath.ac.uk

ABSTRACT

The traditional model of taste discrimination in pay treats majority and minority workers as perfect substitutes. Consequently, the model is only appropriate for measuring majority/minority differences in pay for workers performing the same job assignment. In this study, the traditional model is extended to allow for the measurement of racial pay differences between majority workers performing a job different from the one performed by minority workers. We model an employer who hires workers for two complementary jobs. However, due to human capital and labor supply differences, majority workers are only suitable for job A, whereas minority workers are only suitable for job B. We extend Becker's *Market Discrimination Coefficient* to allow for the measurement of racial discrimination between job assignments, first under perfect competition and then under pure monopsony. We find that discrimination can vary in counterintuitive ways depending upon the structure of the labor market, technology, customer demand, industry size and productivity and labor supply differences. The model is tested using data on Major League Baseball hitters and pitchers for four different seasons during the 1990s, a period during which the Major League expanded in size. We test the perfect competition version of the model on free agents and players eligible for arbitration, whereas the monopsony version is tested on younger players subject to the reserve clause. We find strong evidence of *ceteris paribus* racial wage differences between hitters and pitchers.

We thank due Bree Dority O'Callaghan for assistance with the data collection.

Theme: Discrimination
Key Words: Wage Discrimination, Complementarity, Monopsony Power
JEL-Code: J7

I. Introduction

It is well understood by labor economists that one reason white earnings often exceed non-white earnings and males often earn more than females, is that there could be racial or gender differences in occupational distribution. According to the *occupational segregation hypothesis* applied to gender differences, for example, female earnings are often lower than male earnings because women, perhaps due to long term discrimination, are crowded into lower-paying occupations, whereas men face no occupational barriers to entry. It is easy to spot clear-cut cases where, for example, gender pay differentials between occupations are correlated with occupational segregation. Flight attendants, who are mostly female in the USA, have always earned substantially less than mostly male airline pilots. Secretaries, mostly female, have always earned considerably less than the executives they work for, who have been predominantly male. The median weekly pay of physicians and surgeons in the USA during 2003 was $1,405 and for registered nurses was $899, yet over 90% of nurses were female and nearly 70% of physicians and surgeons were male.[1] The median weekly pay of male physicians and surgeons was $1,677 in 2003, whereas it was $887 for female nurses.

Most of the literature in this area has focused on the linkage between occupational segregation and gender or racial pay differentials, i.e. determining how much these differentials are attributable to occupational segregation. For example, Polachek [1987] found that occupational segregation actually has less influence in explaining wage differentials than do traditional human capital variables. Very little attention has been given, though, to a related problem: to what extent are racial or gender differences in pay between occupations attributable to gender or racial discrimination? For example, how much of the pay gaps between male doctors and female nurses, or male pilots and female flight attendants, are attributable to discrimination? We will call between-occupation racial and gender wage differences the problem of *interoccupational wage discrimination.*

There is a small literature that provides some guidance to the understanding of interoccupational wage discrimination. Brown, Moon and Zoloth [1980] would argue, for example, that the gap in pay between male doctors and female nurses attributable to gender discrimination can be broken down into: (a) a portion resulting from female output being valued differently from male output (unequal pay for equal work); and (b) a portion resulting from women facing different occupational barriers from men (occupational segregation). They extended the original Blinder [1973] and Oaxaca [1973] wage decomposition methodology to allow for the separate estimation of each source of gender discrimination. Gill [1994] extended Brown, Moon and Zoloth's methodology to allow for the control of any differences in occupational segregation that may be due to men and women having different occupational preferences. Recent empirical studies that use these decomposition methodologies include Liu, Zhang and Chong [2004], Teo [2003] and Sung, Zhang and Chan [2001].

Missing from the literature is a theoretical measure of interoccupational wage discrimination, as well as a test based on this measure. The current theory of wage discrimination due to prejudice, beginning with Becker [1971] and Arrow [1985], is really a theory of *intra*occupational discrimination, where majority and minority workers are in the same occupation and are perfect substitutes. Since this theory assumes away productivity differences between workers, it is only appropriate for the measurement of discriminatory wage differentials within a particular occupation. There is no formal theory of *ceteris paribus* racial or gender differences in pay across occupations. Furthermore, the empirical approach usually taken to the study of occupational differences in pay has been to simply include occupation or industry dummies in wage regressions. Such an approach ignores the possibility that labor inputs across different occupational groups could be related in production in some way.

In this study, we develop and test a theory of interoccupational pay discrimination based on a novel approach. In our earlier examples from health care, airlines and corporate management, not only are there differences in occupational segregation, but the workers in each occupational group are employed in the same industry and perform services that are *complementary* in production. We contend that this complementarity is a potentially important factor in explaining wage discrimination between occupations. We show that if labor inputs in different occupation groups are related in production, technology can have an important influence on interoccupational wage discrimination.

This study is related to an earlier one by Bodvarsson and Partridge [2001], who tested a model of racial wage discrimination in the National Basketball Association. They used a quadratic production function where white and nonwhite players are imperfect substitutes and found that the race-specific labor demand and wage equations are not only complex, but influenced significantly by the parameters in the production function. Bodvarsson and Partridge demonstrated that when majority and minority workers are not perfect substitutes, the separation of racial pay differences attributable to productivity from differences due to prejudice may be a complicated exercise and will depend greatly on the chosen production function. They did not test for occupational (position) differences in wage discrimination, however. Our study is similar to the one by Bodvarsson and Partridge in that we build a model of pay based on a production function where two different labor inputs are not perfect substitutes, there is racial segregation and one of the racial groups is subject to customer prejudice. Our study is different, however, because it treats the labor inputs as imperfect complements, derives a theoretical measure of interoccupational wage discrimination and considers such discrimination under different types of labor market structure. Furthermore, we test our model on a clear-cut case of occupational complementarity in an environment of occupational segregation: Major League Baseball.

II. A Model of Interoccupational Wage Discrimination

We extend the Becker/Arrow wage discrimination model to the case where there are productivity differences between majority and minority workers and minority workers are subject to prejudice. Productivity differences occur because the worker groups are occupationally segregated, where each group supplies different skills and performs different tasks within the firm. The goal of the analysis is to derive a general equilibrium measure of pay discrimination between occupations. We derive and analyze this measure under two types of labor market structure: perfect competition and pure monopsony.

Perfect Competition

Suppose a firm is perfectly competitive in both the product and labor markets. Production requires the services of workers from two different occupations, where each worker is employed in one of the two occupations. The services supplied by these occupational groups are complementary, e.g. workers from occupation X assemble the good and those from occupation Y market it, and the complementarity is imperfect. We use a Cobb-Douglas production function to describe the relationship in production between the two labor services performed:

(1) $Q = AM^{\alpha}N^{\beta}$,

where Q is output, M is the quantity of labor service in one occupation and N is the quantity of labor service in the other occupation. Other inputs are fixed, so it is assumed that $\alpha + \beta < 1$.

Suppose there is complete occupational segregation by race or gender and this segregation is exogenous to the model.[2] For example, suppose that only white workers are available to assemble the good, whilst only non-white workers are available to do the marketing. Think of M, therefore, as the quantity of *majority* labor services and N as the quantity of *minority* labor services used in production. Furthermore, customers are prejudiced against minority workers. Customer prejudice may be viewed as a situation where customers discount the marginal revenue product (MRP) of minority workers and may be incorporated into the model through a relatively minor adjustment of the production function. We discount the minority occupation share parameter by a fraction D, such that the production function is now

(2) $Q = \psi M^{\alpha}N^{\beta D}$.

The lower is D, the more intense the prejudice and the lower is minority MRP. If D equals 1, the case of no prejudice, the production function reverts to equation (1). While it is traditional to think of customer discrimination as implying a price discount on the product of minority occupation workers, the approach above is equivalent: the parameter D reflects the idea that minority occupation output is valued less when customers are prejudiced compared to the case where customers are not prejudiced.[3]

Define W_M (W_N) as the market price of one unit of majority (minority) labor services. With p as product price, the employer's profits π are thus

(3) $\pi = pAM^{\alpha}N^{\beta D} - W_M M - W_N N$.

First and second order conditions yield the following demand functions for majority and minority labor services, respectively:

$$(4)\ M = \left(\frac{\beta D}{W_N}\right)^{\frac{\beta D}{\gamma}} \left(\frac{\alpha}{W_M}\right)^{\frac{1-\beta D}{\gamma}} (pA)^{\frac{1}{\gamma}},$$

$$(5)\ N = \left(\frac{\beta D}{W_N}\right)^{\frac{1-\alpha}{\gamma}} \left(\frac{\alpha}{W_M}\right)^{\frac{\alpha}{\gamma}} (pA)^{\frac{1}{\gamma}},$$

where $\gamma = 1-\alpha-\beta D$.

One important prediction from equations (4) and (5) is that an increase in customer prejudice (a reduction in D) will result in lower hiring from *both* occupations ($\partial M/\partial D > 0$, $\partial N/\partial D > 0$).[4] When customers become more prejudiced, this lowers the MRP of minority labor service and reduces its level of usage. Essentially, increased prejudice has the same effect on employment as a reduction in minority marginal product since a lower value of D reduces the minority share parameter (β). The employer responds not by increasing majority labor services, but rather by cutting the usage of *both* inputs; since both occupations are complementary, less quantity of majority labor service is needed when the usage of minority labor service falls.

On the supply side of the labor market, we assume upward sloping market supply curves for labor services in each occupation. The labor supply curve equations are, respectively,

(6) $W_M = \varepsilon\theta_M$

(7) $W_N = \lambda\theta_N$,

where θ_M and θ_N are the market supplies of the services of majority and minority workers, respectively, where $\varepsilon, \lambda > 0$.

The goal of our analysis is to derive a version of Becker's *Market Discrimination Coefficient* (MDC) that is an outcome of general equilibrium and the unique production conditions described here. The MDC derived here measures the *ceteris paribus* racial (or gender) gap between the two occupations, i.e. the *ceteris paribus* earnings difference between whites (or men) in one occupation and nonwhites (or women) in another occupation. The MDC is in its most general form:[5]

$$(8)\ MDC = \frac{W_M(D<1)}{W_N(D<1)} - \frac{W_M(D=1)}{W_N(D=1)}$$

The first term on the right side of (8) is the occupational wage ratio with customer prejudice, whereas the second term is the ratio in the absence of prejudice. The difference between the two ratios measures the *ceteris paribus* racial or gender interoccupational pay gap.

The first step in the derivation of a general equilibrium MDC is the derivation of the partial equilibrium wages for majority and minority labor. Suppose there are F employers. When the majority occupation worker market is in equilibrium, FM = θ_M, and when the minority occupation worker market is in equilibrium, FN = θ_N. We note from equation (6) that

$$(9)\ \theta_M = \frac{W_M}{\varepsilon}.$$

Now multiply equation (4) by F, set this equal to equation (9) and solve for the partial equilibrium majority wage:

$$(10)\ W_M = \left[\varepsilon F\left(\frac{\beta D}{W_N}\right)^{\frac{\beta D}{\gamma}} (pA)^{\frac{1}{\gamma}} (\alpha)^{\frac{1-\beta D}{\gamma}}\right]^{\frac{1}{1+\frac{1-\beta D}{\gamma}}}$$

From equation (7),

$$(11)\ \theta_N = \frac{W_N}{\lambda}.$$

Now multiply equation (5) by F, set this equal to equation (11) and solve for the partial equilibrium minority wage:

$$(12)\ W_N = \left[\lambda F\left(\frac{\alpha}{W_M}\right)^{\frac{\alpha}{\gamma}} (pA)^{\frac{1}{\gamma}} (\beta D)^{\frac{1-\alpha}{\gamma}}\right]^{\frac{1}{1+\frac{1-\alpha}{\gamma}}}$$

To obtain a general equilibrium (closed form) expression for the majority wage, we substitute expression (12) for W_N in expression (10) and solve again for W_M:

$$(13)\; W_M = \left[\frac{Z}{\alpha^{\theta}}\right]^{\frac{1}{1-\theta}}, \text{ where}$$

$$Z = \left[\varepsilon F\left(\frac{\beta D}{\left[(\lambda F (PA)^{\frac{1}{\gamma}}(\beta D)^{\frac{1-\alpha}{\gamma}})\right]^{\frac{\gamma}{\gamma+1-\alpha}}}\right)^{\frac{\beta D}{\gamma}} (PA)^{\frac{1}{\gamma}} (\alpha)^{\frac{1-\beta D}{\gamma}}\right]^{\frac{\gamma}{\gamma+1-\beta D}} \text{ and}$$

$$\theta = \left(\frac{\alpha}{\gamma+1-\alpha}\right)\left(\frac{\beta D}{\gamma+1-\beta D}\right).$$

To obtain the general equilibrium minority wage, substitute expression (10) for W_M in expression (12) and solve again for W_N:

$$(14)\; W_N = \left[\frac{X}{(\beta D)^{\theta}}\right]^{\frac{1}{1-\theta}}, \text{ where}$$

$$X = \left[\lambda F\left(\frac{\alpha}{\left[(\varepsilon F (PA)^{\frac{1}{\gamma}}(\alpha)^{\frac{1-\beta D}{\gamma}})\right]^{\frac{\gamma}{\gamma+1-\beta D}}}\right)^{\frac{\alpha}{\gamma}} (PA)^{\frac{1}{\gamma}} (\alpha)^{\frac{1-\alpha}{\gamma}}\right]^{\frac{\gamma}{\gamma+1-\alpha}}$$

In general equilibrium the minority and majority occupation wages depend upon the strength of customer demand for the product (p), the size of the industry (F), the intensity of customer prejudice against minority labor (D), the wage elasticities of labor supply (reflected in the values of ε and λ, respectively), the quantity of other input services used (reflected in the size of A), and the productivities of the labor inputs (reflected in the sizes of α and β, respectively).

We first consider the separate effects of prejudice on each of the general equilibrium wages. The first two left-hand columns in Table 1 show Excel calculations for each wage at different levels of prejudice (D), assuming that A = 5, p = 2, F = 10, β and α are 0.4, and ε and λ are one. The subsequent columns to the right provide the same type of information, but for alternative product prices, industry sizes and minority labor share parameters. As the table shows, a decrease in customer prejudice will generally lead to higher wages in the minority occupation, and minorities will experience diminishing marginal benefits from reduced prejudice ($\partial W_N/\partial D > 0$, $\partial^2 W_N/\partial D^2 < 0$). This confirms intuition; a reduction in prejudice, by upgrading customer valuation of minority output, has the same effect on minority labor as an increase in its productivity. Minority labor demand rises, leading to higher wages for that group. The behavior of the majority wage in response to reduced prejudice can be under some circumstances, however, unexpected. In the first left-hand column of the table, notice that the majority wage *falls* with reduced prejudice! This is also the case when industry size doubles (from F = 10 firms to F = 20) and when the minority share parameter rises (from $\beta = 0.4$ to 0.5). According to the table, only at the higher product price of 4 will the majority wage rise in response to reduced prejudice.

The prediction that the majority wage falls when there is less prejudice clearly runs counter to intuition, as well as what a partial equilibrium analysis of the majority wage (equation (10)) would reveal (if one differentiates that equation with respect to D, the partial derivative is always positive). Intuition would suggest that the majority wage will always rise when there is reduced prejudice; since the two types of labor are complementary in production, the higher minority demand should trigger higher majority demand, hence a higher majority wage. However, that may not always be the case in general equilibrium. When the minority factor becomes more valuable, then the higher MRP could sometimes induce, through its interaction with other exogenous variables, an offsetting reduction in majority labor demand. Note, however, that the same thing happens when the minority share parameter rises; comparing columns 1 and 7 in the table, when β rises from 0.4 to 0.5, the majority wage is lower at each level of prejudice. Therefore, our finding that reduced prejudice lowers the majority wage stems from a more general feature of the Cobb-Douglas production function; when one class of labor becomes more productive the wage of the other class falls in general equilibrium. Our counterintuitive finding also illustrates an important implication; the effects of prejudice on occupational pay differences are sensitive to the choice of functional form, i.e. the production technology at hand.

Another important implication from table 1 is that the marginal effects of reduced prejudice on pay depend on the values of the other parameters, i.e. the effects of reduced prejudice on each wage interact with the other determinants of pay. For example, the marginal effect of reduced prejudice on minority pay is larger the higher is product price and the higher is the minority share parameter ($\partial^2 W_N/\partial D \partial p > 0$, $\partial^2 W_N/\partial D \partial \beta > 0$), but smaller the higher is industry size ($\partial^2 W_N/\partial D \partial F < 0$). The sensitivity of the majority wage to reduced prejudice will also depend on the values of the other exogenous variables. For example, the majority wage will fall more from a given reduction in prejudice the bigger is the industry ($\partial^2 W_M/\partial D \partial F > 0$).

Given the general equilibrium wages above, the derivation of the MDC is quite straightforward. Inserting equations (13) and (14) into equation (8), the MDC is

$$(15)\ MDC = \left[\left(\frac{Z(D<1)}{X(D<1)}\right)\left(\frac{\beta D}{\alpha}\right)^{\theta(D<1)} \right]^{\frac{1}{1-\theta(D<1)}} - \left[\left(\frac{Z(D=1)}{X(D=1)}\right)\left(\frac{\beta D}{\alpha}\right)^{\theta(D=1)} \right]^{\frac{1}{1-\theta(D=1)}}$$

We used Excel calculations to infer the signs of the marginal effects on MDC from changes in each of the exogenous variables. Table 2 shows specific calculations, the results of which are discussed below:

(i) *Heightened prejudice raises, at an increasing rate, the amount of interoccupational wage discrimination* ($\partial MDC/\partial D < 0$, $\partial^2 MDC/\partial D^2 > 0$).

Starting from the bottom of Table 2, notice that as D falls, the MDC rises at an increasing rate, regardless of the values of the other right-hand side variables. When customers become more prejudiced, employers reduce the usage of minority labor services, putting downward pressure on the minority occupation wage. While, as we saw earlier, the majority wage can rise or fall, the *ceteris paribus* racial (gender) pay gap between the occupations will always rise when prejudice rises;

(ii) *When minority occupation workers become more (less) productive relative to majority occupation workers, interoccupational wage discrimination falls (rises)* ($\partial MDC/\partial \beta < 0$).

As the second and third columns of Table 2 show, when the minority occupation share parameter rises from 0.4 to 0.5, the MDC falls at any level of customer prejudice. This illustrates a novel implication of the model; minority occupation workers can overcome the adverse effects of customer prejudice by becoming more productive. The reason is apparent from Table 1: when the minority occupation share parameter rises, the majority wage falls and the minority wage rises, which will reduce the MDC. This is in contrast to the traditional (within-occupations) model of wage discrimination, where the *ceteris paribus* pay gap is independent of worker productivity. We note that in the traditional model the discriminatory pay differential will rise when workers in the minority occupational group become relatively more abundant. However, in this model an opposite type of prediction is obtained: when minority occupation workers become more important in production, wage discrimination will decline.

(iii) *When majority occupation workers become more (less) productive relative to minority occupation workers, interoccupational wage discrimination rises (falls)* ($\partial MDC/\partial \alpha > 0$).

As the fourth and fifth columns of Table 2 show, when the majority occupation share parameter rises from 0.4 to 0.5, the MDC rises at any level of customer prejudice. This illustrates another novel implication; when majority occupation workers benefit from a technological advance in their occupation, this exacerbates wage discrimination against workers in the complementary occupation;

(iv) *When the minority occupation reservation wage rises (falls) wage discrimination against those workers falls (rises)* ($\partial MDC/\partial \lambda < 0$).

(v) *When the majority occupation reservation wage rises (falls) wage discrimination against minority occupation workers rises (falls)* ($\partial MDC/\partial \varepsilon > 0$).

These two last predictions illustrate the effects that labor supply differences have on interoccupational wage discrimination. When minority occupation workers' opportunity costs rise, that group's labor supply curve becomes steeper, raising the group's wage and resulting in lower employment. Majority labor usage falls, depressing the majority wage. The resulting increase in the relative minority occupation wage has the effect of reducing the MDC. Exactly the opposite is true if the majority occupation group's opportunity costs rise.

Finally, we find that changes in the number of employers, product price and the efficiency parameter (A) do not influence the MDC. For example, at each level of prejudice, a doubling of product price raises both occupations' wages, but they rise in the same proportion, causing the

MDC to be unchanged. The same result also occurs when industry size or the capital stock (reflected in A) double.

Monopsony

Suppose now our firm is a pure monopsony. As with the perfect competition case, we allow for labor supply differences between the two occupational groups, but for convenience we assume a constant wage elasticity of supply for each group. The labor supply curve equations are:

(16) $W_M = M^{\varepsilon\phi}$

(17) $W_N = N^{\lambda\phi}$,

where $\varepsilon\phi$ is the inverse of the wage elasticity of supply for majority occupation workers and $\lambda\phi$ is the inverse of the wage elasticity of supply for minority occupation workers. The inverse of the wage elasticity is a well accepted measure of the degree of monopsony power facing the firm and the greater the elasticity, the lower is the monopsony power possessed.[6] The firm's profits π are:

(18) $\pi = pAM^{\alpha}N^{\beta D} - M^{\varepsilon\phi+1} - N^{\lambda\phi+1}$.

First and second order conditions yield closed-form minority and majority occupation labor demand equations below:

$$(19)\ N = \left[\frac{\beta DpA}{(\lambda\phi+1)}\left(\frac{\alpha pA}{\varepsilon\phi+1}\right)^{\frac{\alpha}{\varepsilon\phi-(\alpha-1)}}\right]^{\frac{1}{\lambda\phi-\frac{\beta D\alpha}{\lambda\phi-(\alpha-1)}-(\beta D-1)}}$$

$$(20)\ M = \left[\left(\frac{\alpha pA}{\varepsilon\phi+1}\right)\left[\left[\frac{\beta DpA}{(\lambda\phi+1)}\left(\frac{\alpha pA}{\varepsilon\phi+1}\right)^{\frac{\alpha}{\varepsilon\phi-(\alpha-1)}}\right]^{\frac{1}{\lambda\phi-\frac{\beta D\alpha}{\lambda\phi-(\alpha-1)}-(\beta D-1)}}\right]^{\beta D}\right]^{\frac{1}{\varepsilon\phi-(\alpha-1)}}$$

The firm will pay a price of $W_M = [M]^{\varepsilon\phi}$ for each unit of majority labor services and $W_N = [N]^{\lambda\phi}$ for each unit of minority labor services. Inserting expressions (19) and (20) into the labor supply equations (expressions (16) and (17)), respectively, and then inserting the resulting labor supply equations into (10), the closed form solution for MDC is the following:

$$(21)MDC = \frac{\left[\left(\frac{\varepsilon \alpha p A}{\varepsilon\phi + 1}\right)\left[\left[\frac{\beta D p A}{(\lambda\phi+1)}\left(\frac{\alpha p A}{\varepsilon\phi+1}\right)^{\frac{\alpha}{\varepsilon\phi-(\alpha-1)}}\right]^{\frac{1}{\lambda\phi-\frac{\beta D\alpha}{\lambda\phi-(\alpha-1)}-(\beta D-1)}}\right]^{\beta D}\right]^{\frac{\varepsilon\phi}{\varepsilon\phi-(\alpha-1)}}}{\left[\frac{\beta D p A}{(\lambda\phi+1)}\left(\frac{\alpha p A}{(\varepsilon\phi+1)}\right)^{\frac{\alpha}{\varepsilon\phi-(\alpha-1)}}\right]^{\frac{\phi}{\lambda\phi-\frac{\beta D\alpha}{\lambda\phi-(\alpha-1)}-(\beta D-1)}}} - \frac{\left[\left(\frac{\alpha p A}{\varepsilon\phi + 1}\right)\left[\left[\frac{\beta p A}{(\lambda\phi+1)}\left(\frac{\alpha p A}{\varepsilon\phi+1}\right)^{\frac{\alpha}{\varepsilon\phi-(\alpha-1)}}\right]^{\frac{1}{\lambda\phi-\frac{\beta\alpha}{\lambda\phi-(\alpha-1)}-(\beta-1)}}\right]^{\beta}\right]^{\frac{\varepsilon\phi}{\varepsilon\phi-(\alpha-1)}}}{\left[\frac{\beta p A}{(\lambda\phi+1)}\left(\frac{\alpha p A}{(\varepsilon\phi+1)}\right)^{\frac{\alpha}{\varepsilon\phi-(\alpha-1)}}\right]^{\frac{\phi}{\lambda\phi-\frac{\beta\alpha}{\lambda\phi-(\alpha-1)}-(\beta-1)}}}$$

According to equation (21), the optimal value of MDC depends on the degree of customer prejudice, the amount of monopsony power possessed by the firm in the majority and minority occupation labor markets ($\varepsilon\phi$ and $\lambda\phi$, respectively), the relative productivities of the labor inputs and any labor supply differences.

Excel calculations were used to sign the marginal effects of the right-hand side variables on the MDC in equation (21). In all of the calculations discussed below, we assume away the possibility of monopsonistic wage discrimination due to differences in wage elasticities of supply, i.e $\varepsilon = \lambda$. Some of our results mirror what was found for perfect competition, others are unique to the pure monopsony case. Below is a summary of key findings from the numerical analysis:

(i) *An increase in customer prejudice will reduce employment and wages in both occupations, but will heighten the amount of interoccupational wage discrimination.*

Table 3 shows calculations for employment and wages for alternative values of the customer discrimination parameter (*D*). These calculations are done for three different sets of share parameters, assuming A = 5, p = 2 and a wage elasticity ($1/\phi$) equaling 1. We note that, given the labor supply curves assumed earlier, when the wage elasticity is unity wages are identical to employment levels. For all three sets of calculations, an increase in prejudice reduces employment and wages for both classes of labor, but raises the amount of wage discrimination. The reason is the same as for the perfect competition case: the minority occupation wage falls faster than the majority occupation wage, causing *MDC* to rise.

(ii) *The amount of interoccupational wage discrimination depends on productivity differences between occupations.*

The relative productivity of minority occupation labor will rise if the minority occupation worker group's partial elasticity of output rises relative to the majority occupation worker group's partial elasticity of output. Table 4 shows calculations of *MDC* for alternative pairs of the share parameters, assuming that the share parameters sum to 0.8. In these calculations, we assume that *D* = 0.9, ϕ = 1, A = 5 and p =2. At the same level of customer prejudice, *MDC* declines as the minority occupation elasticity rises and/or the majority occupation elasticity falls. This result is identical to what was found for the perfect competition case.

(iii) *When the labor market becomes less competitive, wage discrimination will not always rise. Greater monopsony power is capable of reducing discrimination under certain conditions.*

Table 5 shows calculations of *MDC* for values of the wage elasticity of supply ranging from 0.001 (almost pure monopsony) to infinity (perfect competition), assuming that A = 5, p = 2, *D* = 0.8 and the share parameters sum to 0.8. The calculations are performed for three cases: (a) the share parameters are equal; (b) the majority occupation share parameter is relatively large; and (c) the minority occupation share parameter is relatively large. As Table 5 shows, for cases (a) and (b) an increase in monopsony power unambiguously bolsters wage discrimination. For case (a), *MDC* nears 25% when the firm approaches the state of pure monopsony. For case (b), wage discrimination can be very substantial as the forces of competition lessen. Case (c) is perhaps the most interesting. For that case, *MDC* initially rises with an increase in monopsony power, but begins to decline for values of the wage elasticity below 1. However, it should be noted that a decline in *MDC* can only occur for a specific range of values for the wage elasticity and only if the minority occupation share parameter is sufficiently large.

Why are the effects of monopsony power on wage discrimination in case (c) different from the other two cases? When monopsony power rises, marginal and average costs of labor rise, inducing the firm to employ less labor services from each occupation (note that Excel calculations confirm that $\partial M/\partial \phi$ and $\partial N/\partial \phi < 0$) and pay lower wages. Common to the three cases above is that wages in both occupations with and without prejudice will decline when monopsony power rises. However, the occupational wage ratios with and without prejudice can rise, fall or stay the same, depending upon the sizes of the share parameters. Consequently, *MDC* can rise, fall or stay the same when monopsony power rises.

In case (a), an increase in monopsony power will raise *MDC* because the wage ratio with prejudice rises, whereas the wage ratio without prejudice stays even at 1. In case (b), both wage ratios rise, but the wage ratio with prejudice rises faster than the ratio without prejudice. In case (c), both wage ratios actually fall, but the wage ratio without prejudice declines faster. Note in case (c) that since the *MRP* of minority occupation workers is so large relative to majority occupation workers, the minority wage exceeds the majority wage. However, when equation (21) is used to control for these large productivity differences, the wage ratio attributable solely to prejudice is in favor of majority workers.

Cases (a) and (b) are similar to what Becker (1971, pp. 43-47) found in his model of employer discrimination. Becker's model, however, is very different from the one presented here for several reasons. First, his model is not of a single firm, but of an economy with a perfectly competitive labor market in which firms can indulge prejudicial tastes only by adjusting the minority shares of their workforces. The wage differential in Becker's model is the same for all firms and reflects a diffuse distribution of prejudicial tastes across firms. Second, Becker studied the relationship between employer prejudice and the degree of competition in the product market, whereas the model above examines how the amount of labor market power possessed by one firm influences the strength of wage discrimination within that firm. Cases (a) and (b) also are similar to the findings of Fujii and Trapani (1978), who hypothesized that when a firm possesses monopsony power, wage discrimination varies inversely with the wage elasticity of supply. However, Fujii and Trapani assume perfect substitution.

The above analysis has two novel implications. First, as case (c) shows, competition in the labor market is not guaranteed to alleviate interoccupational wage discrimination ($\partial MDC/\partial\phi$ is not always positive). In fact, it is possible that under certain conditions, a more competitive labor market could augment the amount of discrimination! This implication is novel because it has been considered conventional wisdom in the discrimination literature, beginning with Alchian and Kessel (1962) and Becker (1971), that competition is always an effective remedy for alleviating wage discrimination. Second, the degree to which monopsony power can affect wage discrimination depends partly on how important minority occupation workers are in production. For cases (a) and (b), for example, as minority occupation workers become more important in production, the marginal effect of an increase in monopsony power on wage discrimination will lessen ($\partial^2 MDC/\partial\beta\partial\phi < 0$).[7]

III. A Test Case: Major League Baseball During the 1990s

In testing our two models above, we sought an industry where: (a) production requires the employment of labor from complementary occupations or skill groups and the production function is compatible with the Cobb-Douglas case developed above; (b) the pay of some members of the labor force is competitively determined, whilst the pay of others is determined under conditions resembling monopsony; (c) accurate data on worker-specific productivity, personal characteristics and contract status are readily available; (d) there is some degree of racial or gender segregation between occupations and a long term history of discrimination in the industry; (e) customers can observe worker performance, hence they are a potential source of racial or gender discrimination in salaries; and (f) there have been changes in the number of employers in the industry, allowing for a natural experiment of the effects of changes in the degree of monopsony power over time.

One industry conveniently satisfying these criteria is Major League Baseball (MLB) in the USA.[8] In MLB, each team (firm) requires, in addition to other skills, two distinctly complementary types of player skill – hitting (an offensive skill) and pitching (a defensive skill). Thus, hitting and pitching services are complementary in the production of baseball entertainment. Furthermore, Woolway [1997] and Zech [1981] have argued that the Cobb-Douglas function, with its feature of imperfect complementarity, is an entirely appropriate form for the analysis of production in MLB.[9]

In MLB player salaries are set under two different regimes, one competitive, the other monopsonistic. The monopsonistic regime applies to players with fewer than six years of MLB experience. These players are subject to the *reserve clause* and are constrained to negotiate their pay with only one team. The competitive regime applies to players with at least 6 years of MLB experience. They are eligible to file for *free agency* and may negotiate with any team in the league. Monopsony power effectively begins to erode, however, as early as the fourth year because then a player is eligible for *final offer arbitration*. Arbitration rights tend to relieve players of monopsonistic exploitation because arbitrators strive to award competitive salaries. Pitchers have historically been disproportionately white, whereas the pool of hitters has tended to be more racially balanced. The Major League added new teams (called "expansion teams") since the early 1990s, leading to a reduction in each team's degree of monopsony power held over reserve clause players. Therefore, MLB is a very attractive candidate for the study of interoccupational wage discrimination.[10]

The ideal way to measure a Major League player's marginal revenue product (MRP) is by his contribution to the team's ticket, broadcasting and merchandise revenues. Because of the team production nature of baseball, however, it is impossible to directly measure a player's revenue contribution. We thus proxy MRP by the player's years of Major League experience, tenure with his current club, and various career statistics (computed on a game-by-game basis since the beginning of the player's Major League career) that proxy his ability and skills. The career statistics we use to measure a hitter's productivity include *at bats*, *stolen bases*, *bases on balls*, *total bases*, *slugging average* and *batting average*.[10] We distinguish between hitters that are "designated hitters" from those who are not. A designated hitter is a player who is chosen at the start of the game to bat in lieu of the pitcher in the lineup. We also distinguish, using dummies, between hitters that serve other types of positions. These include whether the hitter served as an infielder or a catcher.[11] We measure a pitcher's productivity by use of the following career statistics: *Wins*, *Losses*, *Games Started, Complete Games, Saves, Homeruns, Walks, Strikeouts, Innings Pitched, Earned Run Average (ERA) and Strikeout Rate.*[12]

IV. A Preliminary Empirical Analysis

Our preliminary empirical analysis is set out in Tables 6-12. Tables 6 and 7 present descriptive statistics for hitters and pitchers, respectively. The full sample includes 1093 hitters (549 white and 544 non-white) and 1204 pitchers (948 white and 256 non-white). Salary, experience, performance and position data were drawn from the *Lahman Baseball Database* (www.baseball1.com) over four seasons -1992, 1993, 1997 and 1998. The Major League expanded by two teams between 1992 and 1993 and again by two teams between 1997 and 1998. The salary data do not include information about contract length, bonus clauses or endorsements. Salaries for players on the Canadian teams were converted to U.S. dollars. The experience data were used to determine the player's eligibility for free agency and final offer arbitration and the player's race was inferred from inspection of *Topps* baseball cards for all four seasons. For the U.S. teams, metropolitan area population and per-capita income were obtained from the website of the Bureau of Economic Analysis (www.bea.gov). For the Canadian teams, similar data were obtained from the Statistics Canada website (www.statcan.ca). Per-capita income data for the Canadian cities were converted to U.S. dollars.

From Table 6, one can see that there are no major differences between the personal and professional characteristics of white and non-white hitters, nor in the characteristics of the greater metro area in which they play. In terms of career characteristics, however, it is apparent that non-white hitters record significantly more *At Bats* and *Stolen Bases* than whites, *vis*. 2593.9 and 2419.7 and 94.9 and 44.8, respectively. Whites are, however, significantly more likely than non-whites to play as an infielder or catcher and less likely to play as an outfielder or designated hitter. In Table 7, the domination of white pitchers is immediately apparent. It is evident that white pitchers are on average older than non-white pitchers, over whom they also enjoy higher average earnings. In terms of career characteristics, white pitchers record significantly higher *Wins*, *Losses*, *Games Started*, *Complete Games*, *Shutouts*, *Saves*, *Homeruns*, *Walks*, *Strikeouts* and *Innings Pitched* than their non-white counterparts. Non-whites do, however, record relatively higher *ERA's* and *Strikeout Rates*.

Tables 8 and 9 set out our preliminary earnings regressions for Hitters and Pitchers, respectively. We estimate seven specifications *vis*. (1) All; (2) Whites; (3) Non-Whites; (4) Early Period (1992-1993); (5) Latter Period (1997-1998); (6) Competitive (i.e. Hitters or Pitchers who are *Free Agents* or *Eligible for Final Offer Arbitration)*; and (7) Non-Competitive (i.e. Hitters or Pitchers who are neither *Free Agents* nor *Eligible for Final Offer Arbitration*). Looking at Hitters first (Table 8), it is evident that the regressions are generally well specified, and that the coefficients on the explanatory variables are generally robust, across all the various specifications. Earnings are negatively related to *Age* but positively and concavely related to *MLB Experience*. It would appear that the negative coefficient on *Age* is reflecting the player's physical depreciation, whilst the positive coefficient on experience is reflecting rewards to greater human capital – indeed when we experimented with dropping age from our regressions we found that the coefficient on *MLB Experience* declined by almost exactly the size of the coefficient on *Age*. Earnings are also positively and significantly related to *Tenure with Current Club* and also to whether the player is a *Free Agent* or *Eligible for Final Offer Arbitration*. Career characteristics are dominated by the effects of a player's *Slugging* and *Batting Average*, although *At Bats* and *Stolen Bases* exert small, but significant effects on earnings. Somewhat surprisingly, *Slugging Average* and *At Bats* impact negatively on earnings when attention is confined to "monopsonised" players – i.e. those who are neither *Free Agents* nor *Eligible for Final Offer Arbitration*.

In terms of the *Greater Metro Area Characteristics* that we incorporate as proxies for customer discrimination, it is evident that there was a dramatic shift in the relationship between Hispanic populations and the earnings of hitters over the periods 1992-1993 and 1997-1998, a significantly negative correlation in the former becoming significantly positive in the latter. There was both an increase in the number of teams and a general decline in monopsony power over this period, either of which could have been at work here, and we explore this issue in more detail in Table 12 following.

Turning to our preliminary regressions for the earnings of pitchers (Table 9), we find that whilst *MLB Experience* and *Tenure with Current Club* impact relatively similarly upon the earnings of both white and non-white pitchers, *Age* impacts negatively on the earnings of the latter but has no effect on the earnings of the former. There is also a racial effect in terms of "competitive" and "non-competitive" players – white, but not non-white, pitchers who are either *Free Agents* or *Eligible for Final Offer Arbitration* enjoy significantly higher earnings. The premium to all competitive players, however, declined over the two periods 1992-1993 and 1997-1998.

The coefficients on the productivity variables generally accord to *a priori* expectations, although there are some noticeable discrepancies across the various sub-sample regressions. For example, the pay of non-white, but not white, pitchers is significantly and positively related to *Wins*, and significantly and negatively related to *Games Started* and *Complete Games*. White, but not non-white, pitcher pay is significantly and positively related to *Saves*, and significantly and negatively related to *Shut Outs*, *Walks*, *Home Runs*, and *ERA's*. Very surprisingly, the earnings of white pitchers are positively related to *Strikeouts*, whilst that of non-white pitchers are negatively related. Other discrepancies are apparent across the *Early Period* and *Latter Pe*riod regressions and across the *Competitive* and *Non-Competitive* regressions – interestingly, in the latter case many of the productivity variables become insignificant when attention is restricted to pitchers who are neither *Free Agents* nor *Eligible for Final Offer Arbitration*. In terms of the *Greater Metro Area Characteristics*, there again appears to have been an impact from Hispanic populations, this time correlating positively with the earnings of white pitchers over the whole sample period and with all pitchers over the latter half of the period (1997-1998).

In Tables 10 and 11, our aim is a preliminary assessment of interoccupational pay discrimination, specifically whether there are any *ceteris paribus* racial differences in pay between hitters and pitchers. In both tables, hitters and pitchers are combined, but the *Career Characteristics* variables are dropped since they are specific to position. The remaining controls for pay include

Personal, *Professional*, and *Greater Metro Area Characteristics* only. There is of course the danger of omitted variables bias resulting from the deletion of the career characteristics variables, but keep in mind that two key traditional human capital variables (experience and tenure), as well as contractual status, age, race and market-wide controls are included.

In Table 10, we break our sample down by racial, sample period and contractual status category. The results from this table suggest that, ignoring the effects of productivity, pitchers earn less than hitters, *ceteris paribus*. The differential is, however, largely attributable to race – the differential is enhanced considerably when one compares non-white pitchers to non-white hitters, but disappears completely when one compares white pitchers to white hitters. The differential has also worsened over time – there was no significant differential in the two seasons 1992 and 1993. Monopsony power declined over the two periods (1992-1993 and 1997-1998), and there is again evidence of a positive relationship between Hispanic populations and earnings, especially in the years 1997-1998.

In Table 11, we test for interoccupational wage discrimination by including interactions between the occupational and racial controls. Note first in column (1), where there are no interactions, that there appear to be no racial differences in pay, but pitchers earn nearly 10% less, all other things equal, than hitters. However, once we add race x occupation interactions, we do find racial differences in pay between occupations. Equations (2) – (5) provide estimates of interoccupational wage discrimination for four different default categories – white hitters, non-white hitters, white pitchers and non-white pitchers. We find that *ceteris paribus* and ignoring position-specific productivity indicators, that: (a) non-white pitchers earn 12.5% less than white hitters; but (b) non-white hitters earn 12.8% *more* than white pitchers. Note that the magnitudes of these differentials are roughly the same. These estimated racial pay differentials across positions may be taken as preliminary estimates of interoccupational wage discrimination. Note that non-white hitters are estimated to earn 9.1% more than white hitters, whereas non-white pitchers earn 21.6% less than non-white hitters. Furthermore, there appears to be no significant difference between white and non-white pitcher salaries.

Finally, in Table 12 we explore the combined effects of customer discrimination and declining monopsony power on the earnings of both white and non-white hitters and pitchers. Focusing on hitters first, it is apparent that non-white earnings were negatively related to the size of the Hispanic population in the *Greater Metro Area* in which they played over the period 1992-1993, but not during the period 1997-1998. In contrast, the earnings of white hitters were positively related to the size of the Hispanic population in the *Greater Metro Area* in which they played over the period 1997-1998, but not 1992-1993. As regards pitchers, the higher the percentage of the *Greater Metro Population* that was white, the lower the earnings of non-white pitchers over the years 1992-1993, but not 1997-1998, whereas the higher the percentage of the *Greater Metro Population* that was Hispanic, the higher were the earnings of white pitchers in 1997-1998, but not 1992-1993. It would seem then that discrimination against minority (non-white) labour did decline as the industry became more competitive.

V. Concluding Remarks

When it comes to the study of occupational differences, most of the interest in the wage discrimination literature has been on the role of occupational segregation in accounting for gender or racial wage differences. Quite another problem, previously unresearched, is ascertaining the extent to which racial or gender differences in pay across particular occupations are attributable to prejudice. In this study, we developed and tested a theory of interoccupational wage discrimination. Nearly all wage discrimination studies have focused on discrimination within the same occupation and have treated majority and minority workers as perfect substitutes. We extend the theory of wage discrimination to the case of interoccupational discrimination where occupation groups are imperfect complements in production. Wage discrimination between occupations was found to depend on majority/minority productivity differences, as well as other variables. Furthermore, it was found that heightened competition in the labor market may not always produce the desired effects on discrimination. Our theoretical findings underscore the importance of considering the role of technology as a key to understanding pay discrimination across occupations. We tested our model on the case of complementary hitters and pitchers in Major League Baseball, an industry characterized by racial segregation between positions, fan discrimination and a dual labor structure. We found preliminary evidence of racial differences in pay between these positions.

This study can be seen as making three contributions. First, we extend the traditional theory of within-occupation wage discrimination to the case of discrimination across occupations. It was found that when the traditional wage discrimination model was extended in this manner, some novel predictions were obtained. Second, our study extends the classical theory of monopsony to the case where the firm practices wage discrimination due to prejudice using a particular type of technology. Third, the study presented a preliminary test of interoccupational pay discrimination based on our theoretical model. One potentially fruitful extension of the above model would be a general equilibrium approach in which occupational segregation and wage discrimination are both endogenous. A worthwhile extension of our test would be an extension of the Blinder/Oaxaca decomposition technique to the case of discrimination between occupations.

Endnotes

1 From the Bureau of Labor Statistics website (www.bls.gov)

2 The reasons for the segregation are beyond the scope of this paper.

3 Kahn (1991) took a similar approach. In his model of affirmative action when there is customer discrimination, the fraction D is used to discount minority labor input, whereas in the model above D discounts output. Both approaches have the same implication, namely that majority customers value the output of minority workers by a fraction of what they do majority workers.

4 The signs of these partial derivatives were obtained from numerical analysis. Using Excel, we calculated the values of M and N for different values of D, assuming different sets of values for the other parameters in the demand equations. For example, assuming $A = 5$, $p = 2$, $F = 10$ and α and β are both 0.4, majority (minority) labor usage falls from 275.39 (247.85) to 109.51 (87.61) when D falls from 0.9 to 0.8. These and other calculations are available from the authors upon request.

5 This expression is identical to Becker's (1971, pg. 17) general expression for the MDC, which he treats as the economy-wide wage gap when there is employment discrimination.

6 For example, Sullivan (1989) estimated a hospital's monopsony power using the inverse elasticity of wage supply for nursing services.

7 As with perfect competition, changes in product price or the efficiency parameter were found to have no effect on wage discrimination.

8 Wage discrimination in professional sports has received considerable attention among labor economists because of the abundant statistical evidence on a player's personal attributes, compensation and productivity. Most studies of wage discrimination in professional sports have focused on racial discrimination with respect to pay, hiring, retention and positional segregation. For a relatively recent examination of the research in this area, see Kahn's [2000] expository survey.

[9] Woolway and Zech both estimated Cobb-Douglas functions where the dependent variable is team winning percentage and the independent variables are player or team career statistics.

[10] A player has an *at bat* every time he comes to bat, except in certain circumstances, e.g. if he is awarded first base due to interference or obstruction or the inning ends while he is still at bat. A hitter is assigned a stolen base (also called a "steal") when he reaches an extra base on a hit from another player. For example, suppose that hitter A is at first base when hitter B hits the ball. Hitter B reaches first base (he would be assigned a "single"), but hitter A reaches third base. Hitter A would be assigned a stolen base because he reached an extra base. A base on balls (also called a "walk") is assigned when the batter receives four pitches which the umpire determines is a "ball." A ball is any pitch at which the batter does not swing and is out of the "strike zone" (which means it would not qualify to be a strike). When the hitter is assigned a base on balls, he is entitled to walk to first base. Total bases are the number of bases a player has gained through hitting. It is the sum of his hits weighted by 1 for a single, 2 for a double (if he gets to second base as a result of his hit), 3 for a triple (if he gets to third base) and 4 for a home run. A hitter's batting average is the ratio of hits to at bats; this measures the hitter's success rate. Slugging percentage, a related measure, reflects his hitting power. It is calculated as total bases divided by at bats.

[11] An infielder is a defensive player who plays on the "infield," the dirt portion of a baseball diamond between first and third bases. The specific infielder positions are first baseman, second baseman, shortstop (which is between second and third bases) and third baseman. In contrast, an "outfielder" plays farthest from the batter and his primary role is to catch long fly balls. Outfielder positions include left fielder, center fielder and right fielder. The catcher crouches behind home plate and receives the ball from the pitcher. Because the catcher can see the whole field, he is best positioned to lead and direct his fellow players in play. He typically calls the pitches by means of hand signals, hence requires awareness of both the pitcher's mechanics and strengths and the weaknesses of the batter.

[12] A pitcher is assigned a *win* or a *loss* depending on whether he was the *pitcher of record* when the decisive run was scored. One is the pitcher of record if one is the pitcher at the point when the player who scores the decisive run is allowed to reach a base. *Games started* is the number of times the pitcher was given the ball to start a game, whereas *games finished* is the number of times the pitcher was throwing on the mound during the final *out* (which is any failed attempt by a hitter to advance to a base). A *shutout* is a game in which one team does not score any runs. A pitcher earns a *save* if he is able to hold a lead for his team at the end of the game. Pitchers who earn saves, called *relievers*, tend not to gain wins, so it is customary to treat saves and wins equally, especially when studying pitcher salaries. Number of *home runs*, which is assumed to be negatively related to salary, is the number of pitches that were hit by batters which were scored as a home run. A pitcher is assigned a *walk*, which is assumed to be negatively related to salary, if he allows a batter to reach base after pitching him four balls. He is assigned a *strikeout* if he pitches three *strikes* (pitched balls counted against the batter, typically swung at and missed or fouled off) in a row. An *inning* is one of nine periods in a MLB game in which each team has a turn at bat; *innings pitched* is the number of such periods when the pitcher was working. *Earned run average* is negatively correlated with the pitcher's ability to prevent the opposing team from scoring. It equals the number of times the pitcher allows a batter to score a *run* (where the batter scores a point by advancing around the bases and reaching home plate safely) x 9, divided by the number of innings pitched. Finally the *strikeout rate* is the percentage of times the pitcher has succeeded in striking a batter out.

References

Alchian, A. A. and R.A. Kessel. (1962). "Competition, Monopoly and the Pursuit of Money." In *Aspects of Labor Economics*. Princeton, NJ: National Bureau of Economic Research, pp. 157-183.

Arrow, K. J. (1985). "Some Mathematical Models of Race Discrimination in the Labor Market." In Kenneth J. Arrow (Ed.), *Collected Papers of Kenneth J. Arrow, Applied Economics, Volume 6*. Cambridge, MA: The Belknap Press of Harvard University Press, pp. 112-129.

Becker, G. S. (1971). *The Economics of Discrimination, Second Edition.* Chicago: University of Chicago Press.

Blinder, A.S. (1973). "Wage Discrimination: Reduced Form and Structural Estimations," *Journal of Human Resources* (8), pp. 436-55.

Bodvarsson, Ö. B. and M. D. Partridge. (2001). "A Supply and Demand Model of Employer, Customer and Coworker Discrimination." *Labor Economics*, 8, June, pp. 389-416.

Brown, R.S., M. Moon and B.S. Zoloth (1980). "Incorporating Occupational Attainment in Studies of Male/Female Earnings Differentials," *Journal of Human Resources* (15), pp. 3-28.

Fujii, E. and J. J. Trapani. (1978). "On Estimating the Relationship Between Discrimination and Market Structure." *Southern Economic Journal*, January, 44 (3), pp. 556-567.

Gill, A. (1994). "Incorporating the Causes of Occupational Differences in Studies of Racial Wage Differentials"' *Journal of Human Resources*, 29, Winter, pp. 20-41.

Kahn, L. M. (1991). "Customer Discrimination and Affirmative Action." *Economic Inquiry*, 29, July, pp. 555-571.

__________(2000). "A Level Playing Field? Sports and Discrimination." In William S. Kern (ed.), *The Economics of Sports*, W.E. Upjohn Institute, Kalamazoo, MI.

Liu, P-W, J. Zhang and S-C. Chong (2004). "Occupational Segregation and Wage Differentials Between Natives and Immigrants: Evidence from Hong Kong." *Journal of Development Economics*, 73, pp. 395-413.

Oaxaca, R. (1973). "Male-Female Wage Differentials in Urban Labour Markets." *International Economic Review*, (14), 693-709.

Polachek, S. (1987). "Occupational Segregation and the Gender Wage Gap." *Population Research and Policy Review*, (6), 47-67.

Sullivan, D. (1989). "Monopsony Power in the Market for Nurses." *Journal of Law and Economics*, 32, October, pp. 135-178.

Sung, Y.-W., J. Zhang and C.-S. Chian (2001). "Gender Wage Differentials and Occupational Segregation in Hong Kong, 1981-96." *Pacific Economic Review*, 6, October, pp. 345-59.

Teo, S.Y. (2003). "Occupational Segregation and its Effect on Estimates of the Gender Wage Differential: Evidence from Brunei." *Asian Economic Journal*, 17, December, pp. 341-60.

Woolway, M.D. (1997). "Using an Empirically Estimated Production Function for Major League Baseball to Examine Worker Disincentives Associated with Multi-Year Contracts." *The American Economist*, 41, No. 2, 77-84.

Zech, C.E. (1981). "An Empirical Estimation of a Production Function: The Case of Major League Baseball." *The American Economist*, 25, No. 2, 19-23.

Table 1
The effects of prejudice on wages under perfect competition[i]

D	W_M (p=2,F=10, β=0.4)	W_N (p=2,F=10, β=0.4)	W_M (p=4,F=10, β=0.4)	W_N (p=4,F=10, β=0.4)	W_M (p=2,F=20, β=0.4)	W_N (p=2,F=20, β=0.4)	W_M (p=2,F=10, β=0.5)	W_N (p=2,F=10, β=0.5)
0.5	4.94601	3.497357	8.114774	5.738012	6.029254	4.26333	4.85657	3.83946
0.6	4.873289	3.774833	8.112744	6.284104	5.8454726	4.53505	4.78053	4.14006
0.7	4.809515	4.023929	8.131194	6.803034	5.68956	4.76022	4.71552	4.41096
0.8	4.753304	4.251485	8.16912	7.306683	5.53154	4.94756	4.65997	4.65997
0.9	4.703687	4.462309	8.2263	7.804153	5.37901	5.10298	4.61289	4.89271
1	4.659972	4.659972	8.303127	8.303127	5.23064	5.23064	4.57363	5.11345

[i] Calculations assume values of A = 5, α = 0.4 and ε and λ both one.

Table 2
The effects of prejudice on interoccupational wage discrimination under perfect competition[i]

D	MDC (β=0.4)	MDC (β=0.5)	MDC (α=0.4)	MDC (α=0.5)	MDC (λ=1)	MDC (λ=1.5)	MDC (ε=1)	MDC (ε=1.5)
0.5	0.4142	0.3705	0.4142	0.4631	0.4142	0.3382	0.4142	0.5073
0.6	0.2910	0.2603	0.2910	0.3253	0.2910	0.2376	0.2910	0.3564
0.7	0.1952	0.1746	0.1952	0.2183	0.1952	0.1594	0.1952	0.2392
0.8	0.1180	0.1006	0.1180	0.1397	0.1180	0.0964	0.1180	0.1446
0.9	0.0541	0.0484	0.0541	0.0648	0.0541	0.0442	0.0541	0.0662
1	0	0	0	0	0	0	0	0

[i] All calculations assume values of A = 5, p =2, F = 10. The second and third columns assume values of α = 0.4, λ = 1 and ε = 1, the fourth and fifth columns assume values of β = 0.4, λ = 1 and ε = 1, the sixth and seventh columns assume values of α = 0.4, β = 0.4 and ε = 1, and the last two columns assume values of α = 0.4, β = 0.4 and λ = 1.

Table 3

The Effects of Prejudice on Employment, Wages and Discrimination

pA	ϕ	α	β	*D*	*M*	*N*	*MDC*
10	1	0.4	0.4	0.9	1.72	1.63	0.054
10	1	0.4	0.4	0.8	1.67	1.49	0.118
10	1	0.4	0.4	0.7	1.63	1.36	0.195
10	1	0.6	0.3	0.9	1.63	2.18	0.038
10	1	0.6	0.3	0.8	1.53	1.93	0.083
10	1	0.6	0.3	0.7	1.45	1.72	0.138
10	1	0.3	0.6	0.9	2.40	1.61	0.076
10	1	0.3	0.6	0.8	2.34	1.48	0.167
10	1	0.3	0.6	0.7	2.29	1.36	0.276

Table 4

The Effects of Majority / Minority Productivity Differences on Employment, Wages and Discrimination

pA	ϕ	α	β	*D*	*M*	*N*	*MDC*
10	1	0.7	0.1	0.9	2.61	0.94	0.143
10	1	0.6	0.2	0.9	2.25	1.23	0.094
10	1	0.5	0.3	0.9	1.99	1.45	0.069
10	1	0.4	0.4	0.9	1.72	1.63	0.054
10	1	0.3	0.5	0.9	1.48	1.82	0.042
10	1	0.2	0.6	0.9	1.24	2.03	0.031
10	1	0.1	0.7	0.9	0.915	2.30	0.02

Table 5

Wage Discrimination When Monopsony Power Varies

D	pA	*1/ϕ*	*MDC* $\alpha = \beta = 0.4$	*MDC* $\alpha = 0.7, \beta = 0.1$	*MDC* $\alpha = 0.1, \beta = 0.7$
0.8	10	∞	0	0	0
0.8	10	10	0.0205	0.0245	0.0172
0.8	10	4	0.0456	0.0674	0.0309
0.8	10	2	0.0772	0.1477	0.0404
0.8	10	1	0.1180	0.3123	0.0446
0.8	10	0.5	0.1604	0.5869	0.0438
0.8	10	0.1	0.2249	1.6190	0.0383
0.8	10	0.04	0.2445	1.6477	0.0363
0.8	10	0.01	0.2472	1.6977	0.036
0.8	10	0.001	0.2497	1.7447	0.0357

Table 6: Descriptive Statistics: Hitters

	All (N =1093)		White (N =549)		Non-Whites (N = 544)	
Variable	*Mean*	*Std. Dev*	*Mean*	*Std. Dev*	*Mean*	*Std. Dev*
Personal Characteristics						
Log Annual Salary	13.890	1.13	13.865	1.10	13.914	1.16
Age	30.304	3.70	30.596	3.49	30.011	3.88
White	0.502	0.500	-	-	-	-
Non-White	0.498	0.500	-	-	-	-
Professional Characteristics						
MLB Experience	7.061	3.89	7.062	3.87	7.061	3.91
MLB Experience-Squared	64.957	69.31	64.785	70.06	65.131	68.61
Tenure with Current Club	2.673	3.00	3.062	3.38	2.279	2.50
Free Agent	0.600	0.49	0.598	0.49	0.603	0.49
Eligible for Final Offer Arbitration	0.296	0.46	0.304	0.46	0.287	0.45
American League	7.061	3.89	0.521	0.50	0.507	0.50
National League	0.486	0.50	0.479	0.50	0.493	0.50
Canadian Team	0.073	0.26	0.067	0.25	0.079	0.27
Performance						
At Bats	2506.414	2001.58	2419.738	1940.51	2593.888	2059.46
Stolen Bases	69.746	112.52	44.800	72.35	94.925	137.54
Bases on Balls	254.275	247.74	253.131	233.32	255.428	261.69
Total Bases	1060.200	913.52	1016.772	880.39	1104.028	944.57
Slugging Average	0.407	0.06	0.404	0.06	0.410	0.07
Batting Average	0.267	0.03	0.264	0.02	0.269	0.02
Infielder	0.459	0.50	0.556	0.50	0.362	0.48
Outfielder	0.383	0.49	0.217	0.41	0.552	0.50
Catcher	0.116	0.32	0.189	0.39	0.042	0.20
Designated Hitter	0.059	0.24	0.046	0.21	0.072	0.26
Greater Metro Area Characteristics						
Percentage White	80.507	6.89	80.938	6.77	80.073	6.99
Percentage Black	13.273	6.58	12.959	6.60	13.589	6.56
Percentage Hispanic	10.621	10.65	10.719	10.80	10.522	10.50
Average Annual Income ($)	25562.99	3789.65	25508.57	3757.99	25617.90	3824.001
PopulationA[1]	5514009	4657988	5313189	4509095	5716676	4799205
PopulationB[2]	4250564	2347840	4164763	2343188	4337153	2351506
Year Dummies						
1992	0.250	0.43	0.255	0.44	0.244	0.43
1993	0.235	0.42	0.248	0.44	0.222	0.42
1997	0.260	0.44	0.248	0.43	0.272	0.45
1998	0.255	0.44	0.250	0.43	0.260	0.44

Notes: 1. Population A denotes the greater metro area population; 2. Population B records the greater metro population for all MSAs except Chicago, New York and San Francisco teams – these were divided by two.

Source: All variables except Race and Greater Metro Area Characteristics (GMAC) extracted from the Lahman Baseball Database (Version 5.0, Release Date: Dec. 15, 2002). Race is derived form observed Topps Baseball Cards, years 92, 93, 94, 97, 99 (only years available). GMAC derived from the Statistical Abstract 1997-1999, the BEA, CA1-3, and from Statistical Canada.

Table 7: Descriptive Statistics: Pitchers

Variable	*All (N =1204)* *Mean*	*Std. Dev*	*White (N =948)* *Mean*	*Std. Dev*	*Black (N = 256)* *Mean*	*Std. Dev*
Personal Characteristics						
Log Annual Salary	13.409	1.19	13.447	1.19	13.267	1.18
Age	29.815	4.09	30.214	4.05	28.336	3.90
White	0.787	0.41	-	-	-	-
Non-White	0.213	0.41	-	-	-	-
Professional Characteristics						
MLB Experience	5.988	4.2	6.153	4.30	5.375	4.16
MLB Experience-Squared	53.468	76.64	55.455	78.21	46.109	70.20
Tenure with Current Club	1.924	2.07	1.932	2.10	1.895	1.99
Free Agent	0.467	0.50	0.481	0.50	0.414	0.49
Eligible for Final Offer Arbitration	0.306	0.46	0.315	0.47	0.273	0.45
American League	0.513	0.50	0.519	0.50	0.492	0.50
National League	0.487	0.50	0.481	0.50	0.508	0.50
Canadian Team	0.069	0.25	0.062	0.24	0.094	0.29
Starter	0.442	0.50	0.438	0.50	0.457	0.50
Performance						
Wins	37.446	44.33	38.811	45.19	32.391	40.66
Losses	34.179	37.05	35.734	38.31	28.418	31.34
Games Started	74.12	105.53	77.276	108.36	62.43	93.54
Complete Games	10.15	22.24	10.911	23.28	7.328	17.65
Shutouts	2.875	6.08	3.045	6.31	2.242	5.105
Saves	19.488	51.87	20.831	52.78	14.516	48.145
Homeruns	56.517	62.57	58.573	64.35	48.906	54.919
Walks	225.779	249.73	230.824	257.16	207.098	219.491
Strikeouts	436.641	514.13	448.76	529.17	391.766	452.215
Innings Pitched	627.59	702.43	652.231	719.53	536.344	628.07
ERA	4.025	0.96	3.998	0.94	4.124	1.027
Strikeout Rate	0.078	0.02	0.078	0.02	0.080	0.019
Greater Metro Area Characteristics						
Percentage White	80.714	6.84	80.723	6.91	0.081	0.02
Percentage Black	13.038	6.46	12.936	6.50	80.68	6.56
Percentage Hispanic	10.975	10.77	10.853	10.59	13.416	6.327
Average Annual Income ($)	25488.2	3939.85	25499.05	3887.87	11.429	11.42
PopulationA[1]	5551948	4683875	5472495	4620212	5846175	4910606
PopulationB[2]	4230164	2347488	4183045	2305216	4404650	2494775
Year Dummies						
1992	0.221	0.42	0.24	0.424	0.17	0.38
1993	0.239	0.43	0.25	0.432	0.22	0.41
1997	0.264	0.44	0.26	0.436	0.30	0.46
1998	0.276	0.45	0.26	0.440	0.33	0.47

Notes: 1. Population A denotes the greater metro area population; 2. Population B records the greater metro population for all MSAs except Chicago, New York and San Francisco teams – these were divided by two.

Source: All variables except Race and Greater Metro Area Characteristics (GMAC) extracted from the Lahman Baseball Database (Version 5.0, Release Date: Dec. 15, 2002). Race is derived form observed Topps Baseball Cards, years 92, 93, 94, 97, 99 (only years available). GMAC derived from the Statistical Abstract 1997-1999, the BEA, CA1-3, and from Statistical Canada.

Table 8: Log Annual Salary – Hitters

	(1) All		*(2) White*		*(3) Non-White*		*(4) Early Period*		*(5) Latter Period*		*Compt. (6)*		*Non-Compt (7)*	
	Coef	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*
Personal Characteristics														
Age	-0.048	-4.13	-0.065	-3.77	-0.027	-1.69	-0.021	-1.19	-0.064	-4.19	-0.049	-3.70	-0.019	-1.30
Non-White	-0.003	-0.06	-	-	-	-	0.068	1.15	-0.082	-1.49	0.011	0.25	0.030	0.55
Professional Characteristics														
MLB Experience	0.320	8.99	0.355	7.26	0.298	5.63	0.206	3.92	0.433	8.86	0.409	15.33	-	-
MLB Experience-Squared	-0.021	-13.93	-0.021	-9.99	-0.023	-9.74	-0.017	-8.07	-0.027	-11.82	-0.025	-20.44	0.017	0.66
Tenure with Current Club	0.043	6.53	0.034	3.81	0.049	4.58	0.042	4.58	0.046	4.84	0.044	6.42	-0.011	-0.23
Free Agent	0.632	4.72	0.458	2.41	0.741	3.90	0.855	4.42	0.320	1.73	-	-	-	-
Eligible for Final Offer Arbitration	0.365	4.30	0.338	2.74	0.374	3.18	0.521	4.26	0.148	1.27	-	-	-	-
American League	-0.061	-1.53	-0.130	-2.29	-0.025	-0.45	-0.009	-0.15	-0.0589	-1.08	-0.098	-2.24	0.034	0.64
Canadian Team	-0.065	-0.46	-0.219	-1.10	0.066	0.32	-0.315	-1.50	-0.151	-0.59	0.003	0.02	-0.733	-3.90
Career Characteristics														
At Bats	2.00-4	2.65	0.000	1.04	2.00-4	2.43	0.000	1.97	0.000	3.13	0.000	3.15	-0.002	-2.93
Stolen Bases	0.001	4.26	0.001	2.25	0.001	3.30	0.001	1.84	0.002	4.72	0.001	4.04	0.001	0.59
Bases on Balls	0.000	0.69	0.000	-0.09	0.000	1.79	0.000	0.86	-0.000	-0.08	0.000	0.73	0.001	0.74
Total Bases	0.000	1.44	0.000	1.36	0.000	0.80	0.000	0.86	-0.000	-0.12	0.000	0.48	0.008	4.01
Slugging Average	4.215	7.36	4.429	5.07	3.836	5.01	4.028	5.02	5.155	6.21	5.042	7.58	-2.174	-2.01
Batting Average	3.435	3.27	0.910	0.62	5.979	3.87	4.095	2.79	2.235	1.50	3.135	2.65	2.573	2.06
Infielder	0.027	0.17	-0.256	-0.94	0.072	0.36	0.270	1.09	-0.526	-1.27	0.010	0.06	0.058	0.99
Outfielder	-0.113	-0.71	-0.385	-1.39	-0.088	-0.44	0.166	0.67	-0.685	-1.65	-0.147	-0.88	-	-
Catcher	0.305	1.83	-0.026	-0.09	0.509	2.17	0.613	2.38	-0.300	-0.72	0.315	1.78	-.0125	0.12
Designated Hitter	0.047	0.35	-0.198	-0.77	0.157	0.98	0.117	0.78	-0.476	-1.15	0.052	0.36	-0.293	-0.99
Greater Metro Area Characteristics														
Percentage White	0.004	0.79	0.002	0.27	0.003	0.43	-0.016	-1.51	0.006	0.81	0.005	0.87	-0.003	-0.46
Percentage Black	0.008	1.47	0.009	1.08	0.007	0.93	-0.014	-1.29	0.008	1.08	0.009	1.53	-0.013	-1.56
Percentage Hispanic	0.002	1.02	0.005	1.43	-0.001	-0.43	-0.008	-2.07	0.007	2.29	0.003	0.99	-0.001	-0.43
Average Income	0.000	0.87	0.000	0.50	0.000	0.97	-0.000	-1.57	0.000	0.43	0.000	1.09	-0.000	-1.87
Population	0.000	-0.32	0.000	-0.39	0.000	-0.03	0.000	1.32	0.000	0.26	0.000	-0.24	0.000	1.31
Year Dummies														
1993	0.068	1.31	0.047	0.64	0.089	1.21	0.119	2.09	-	-	0.080	1.41	0.040	2.54
1997	0.129	1.89	0.185	1.87	0.054	0.57	-	-	-	-	0.128	1.69	-0.007	1.91
1998	0.208	2.69	0.209	1.83	0.176	1.66	-	-	0.088	1.71	0.197	2.31	0.198	3.85
Constant	9.556	12.23	11.038	9.38	8.461	8.03	11.735	7.41	10.237	8.93	9.269	10.44	11.370	13.50
Adjusted R-Squared	0.7317		0.7128		0.7567		0.6938		0.7722		0.6589		0.6925	
F-Statistic	111.30 (27, 1065)		53.32 (26, 552)		65.95 (26, 517)		48.94 (25, 504)		77.22 (25, 537)		76.56 (25, 953)		12.06 (23, 90)	
Root Mean Squared Error	0.58448		0.58932		0.57075		0.58681		0.55981		0.60836		0.2428	
Observations	1093		549		544		530		563		979		114	

Notes: 1. *Early* (*Latter*) *Period* denotes 1992 and 1993 (1997 and 1998); 2. (*Non-*) *Compt* refers to Hitters who are (neither) *Free Agents* or (nor) *Eligible for Final Offer Arbitration*

Table 9:Log Annual Salary – Pitchers

	(1) All		*(2) White*		*(3) Non-Whites*		*(4) Early Period*		*(5) Latter Period*		*(6) Compt.*		*(7) Non-Compt.*	
	Coef	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*
Personal Characteristics														
Age	0.003	0.28	0.014	1.32	-0.052	-2.37	-0.011	-0.76	0.007	0.60	-0.0229	-1.99	0.025	2.59
Non-White	0.011	0.26	-	-	-	-	-0.155	-2.28	0.073	1.34	-0.073	-1.33	0.119	3.05
Professional Characteristics														
MLB Experience	0.152	5.20	0.179	5.64	0.154	2.01	0.216	4.83	0.154	3.59	0.275	11.61	0.000	0.00
MLB Experience-Squared	-0.014	-12.30	-0.014	-11.58	-0.021	-6.34	-0.015	-8.63	-0.016	-9.00	-0.017	-17.54	-0.0135	-0.87
Tenure with Current Club	0.068	7.86	0.064	6.78	0.066	3.22	0.069	5.39	0.064	5.38	0.063	6.67	-0.013	-0.42
Free Agent	0.748	6.60	0.753	6.09	0.481	1.71	0.760	4.42	0.574	3.61	-	-	-	-
Eligible for Final Offer Arbitration	0.427	6.44	0.463	6.31	0.18	1.20	0.442	4.33	0.318	3.46	-	-	-	-
American League	0.009	0.24	0.024	0.62	0.027	0.32	-0.018	-0.33	-0.001	-0.01	-0.033	-0.76	0.047	1.22
Canadian Team	0.027	0.21	0.017	0.12	-0.154	-0.58	-0.146	-0.80	0.004	0.02	-0.078	-0.47	-0.022	-0.18
Career Characteristics														
Starter	0.385	8.31	0.386	7.49	0.426	4.34	0.387	5.83	0.370	5.66	0.485	8.09	0.107	1.74
Wins	0.009	2.60	0.006	1.58	0.039	4.59	0.010	2.08	0.012	2.43	0.009	2.33	0.016	2.01
Losses	0.005	1.43	0.004	0.97	0.012	1.57	0.007	1.47	0.003	0.51	0.007	1.94	-0.010	-1.16
Games Started	-0.003	-2.70	0.001	-0.82	-0.012	-4.54	-0.003	-2.06	-0.003	-1.76	-0.003	-1.96	-0.012	-2.57
Complete Games	0.001	0.42	0.002	0.53	-0.019	-1.93	0.006	1.66	-0.008	-1.43	0.005	1.40	0.020	0.83
Shutouts	-0.047	-4.48	-0.057	-5.05	0.005	0.20	-0.049	-3.42	-0.040	-2.53	-0.047	-4.16	-0.014	-0.35
Saves	0.003	4.63	0.003	4.81	0.000	0.34	0.001	1.32	0.004	5.31	0.002	3.62	0.010	2.36
Homeruns	-0.005	-4.64	-0.006	-4.72	-0.005	-1.41	-0.007	-3.89	-0.003	-1.74	-0.003	-2.61	-0.002	-0.55
Walks	-0.000	-1.15	-0.001	-1.90	0.000	0.09	-0.001	-1.47	-0.001	-1.29	0.000	0.00	-0.001	-0.86
Strikeouts	0.001	2.75	0.001	4.29	-0.002	-3.23	0.001	2.77	0.000	0.06	0.001	2.78	0.002	1.35
Innings Pitched	0.001	3.30	0.001	2.56	0.002	2.16	0.001	1.70	0.002	2.79	0.001	1.21	0.004	2.40
ERA	-0.133	-6.11	-0.146	-5.93	-0.037	-0.82	-0.150	-4.13	-0.121	-4.33	-0.329	-8.72	0.018	1.09
Strikeout Rate	5.562	4.59	5.749	4.19	8.624	3.30	6.663	3.17	5.644	3.57	3.970	2.37	1.564	1.13
Greater Metro Area Characteristics														
Percentage White	0.001	0.22	0.002	0.37	-0.002	-0.18	-0.010	-1.08	0.004	0.62	0.000	0.03	-0.005	-0.97
Percentage Black	0.004	0.84	0.005	0.95	0.006	0.56	-0.002	-0.23	0.003	0.45	0.004	0.67	-0.001	-0.18
Percentage Hispanic	0.005	2.60	0.005	2.16	0.007	1.50	0.003	0.98	0.006	2.16	0.003	1.28	0.004	1.89
Average Income	0.000	0.52	0.000	0.48	0.000	0.45	0.000	-0.37	0.000	0.24	0.000	0.90	0.000	-0.73
Population	0.000	0.67	0.000	0.89	-0.000	-0.34	0.000	-0.28	0.000	1.30	0.000	0.07	0.000	0.34
Year Dummies														
1993	0.011	0.22	0.034	0.78	0.112	0.97	0.0232	0.48	-	-	0.028	0.48	-0.012	-0.23
1997	0.140	2.17	0.121	1.69	0.091	0.63	-	-	-	-	0.173	2.16	0.206	3.05
1998	0.267	3.75	0.202	2.54	0.305	1.91	-	-	0.126	2.73	0.283	3.16	0.417	5.81
Constant	11.314	16.90	11.505	15.41	9.412	6.45	12.779	9.28	10.922	10.59	12.894	15.14	11.252	16.54
Adjusted R-Squared	0.7787		0.7906		0.7790		0.7873		0.7832		0.6953		0.6146	
F-Statistic	141.99 $_{(30, 1172)}$		124.15 $_{(29, 917)}$		31.99 $_{(29, 226)}$		73.96 $_{(28, 524)}$		84.74 $_{(28, 621)}$		76.78 $_{(28, 902)}$		41 78 $_{(27, 244)}$	
Root Mean Squared Error	0.56095		0.54624		0.55437		0.55815		0. 54845		59851		0.27321	
Observations	1203		947		256		553		650		931		272	

Notes: 1. *Early* (*Latter*) *Period* denotes 1992 and 1993 (1997 and 1998); 2. (*Non-*) *Compt* refers to Hitters who are (neither) *Free Agents* or (nor) *Eligible for Final Offer Arbitration*

Table 10: Log Annual Salary – Combined

	(1) White		(2) Non White		(3) Early Period		(4) Latter Period		(5) Compt.		(6) Non-Compt	
	Coef	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*
Personal Characteristics												
Age	-0.071	-6.23	-0.044	-2.58	-0.061	-4.38	-0.059	-4.63	-0.076	-6.74	-0.006	-0.52
Non-White	-	-	-	-	0.028	0.52	-0.002	-0.03	-0.004	-0.09	0.118	2.77
Pitcher	-0.041	-0.96	-0.219	-3.39	-0.018	-0.35	-0.177	-3.59	-0.098	-2.35	-0.115	-2.55
Professional Characteristics												
MLB Experience	0.363	11.27	0.362	6.49	0.283	7.46	0.426	10.33	0.499	23.58	0.000	0.00
MLB Experience-Squared	-0.012	-9.38	-0.014	-5.71	-0.009	-6.37	-0.015	-8.62	-0.017	-18.44	0.054	3.32
Tenure with Current Club	0.096	12.24	0.116	9.34	0.085	9.46	0.119	12.08	0.101	13.96	0.101	3.00
Free Agent	0.763	5.63	0.705	3.29	1.113	7.08	0.436	2.65	-	-	-	-
Eligible for Final Offer Arbitration	0.405	4.89	0.186	1.48	0.613	6.35	0.116	1.18	-	-	-	-
American League	-0.031	-0.73	0.071	1.15	-0.021	-0.41	0.038	0.76	-0.025	-0.60	0.077	1.85
Canadian Team	-0.259	-1.64	0.213	0.95	-0.311	-1.74	-0.181	-0.73	-0.172	-1.09	-0.053	-0.39
Greater Metro Area Characteristics												
Percentage White	-0.009	-1.57	0.004	0.55	-0.019	-2.12	-0.003	-0.47	-0.007	-1.23	0.001	0.19
Percentage Black	-0.002	-0.33	0.002	0.20	-0.019	-1.99	0.002	0.21	-0.003	-0.42	0.001	0.10
Percentage Hispanic	0.004	1.64	0.006	1.75	-0.003	-0.86	0.007	2.43	0.004	1.64	0.004	1.67
Average Income	0.000	-0.27	0.000	1.18	-0.000	-0.99	-0.000	-0.03	0.000	0.29	0.000	0.47
PopulationA	0.000	0.86	0.000	0.82	0.000	1.52	0.000	1.38	0.000	1.40	0.000	0.09
Year Dummies												
1993	0.122	2.14	0.059	0.68	0.100	2.10	-	-	0.119	2.11	0.027	0.48
1997	0.195	2.58	0.047	0.43	-	-	-	-	0.154	2.10	0.149	2.08
1998	0.295	3.45	0.249	2.08	-	-	0.155	3.21	0.276	3.33	0.346	4.38
Constant	14.023	17.39	11.694	10.62	15.346	11.81	13.198	13.08	13.829	17.70	11.648	15.64
Adjusted R-Squared	0.5665		0.5541		0.5607		0.5749		0.3804		0.2405	
F-Statistic	119.51 $_{(17, 1478)}$		59.41 $_{(17, 782)}$		87.32 $_{(16, 1066)}$		103.44 $_{(16, 1196)}$		74.25 $_{(16, 1893)}$		9.13 $_{(15, 370)}$	
Root Mean Squared Error	0.5740		0.80272		0.7637		0.79085		0.84389		0.37698	
Observations	1496		800		1083		1213		1910		386	

Notes: 1. *Early* (*Latter*) *Period* denotes 1992 and 1993 (1997 and 1998); 2. (*Non-*) *Compt* refers to Hitters who are (neither) *Free Agents* nor *Eligible for Final Offer Arbitration*

Table 11: Log Annual Salary (Combined) – Estimates of Interoccupational Pay Discrimination

	(1) All		*(2) All Default – White Hitter*		*(3) All Default – Non-White Hitter*		*(4) All Default – White Pitcher*		*(5) All Default – Non White Pitcher*	
	Coef	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*
Personal Characteristics										
Age	-0.061	-6.53	-0.063	-6.69	-0.063	-6.69	-0.063	-6.69	-0.063	-6.69
Non-White	0.017	0.45	-	-	-	-	-	-	-	-
Pitcher	-0.097	-2.73	-	-	-	-	-	-	-	-
White Hitter	-	-	**-**	**-**	**-0.091**	**-1.89**	**0.038**	**0.87**	**0.125**	**2.04**
Non White Hitter	-	-	**0.091**	**1.89**	**-**	**-**	**0.128**	**2.96**	**0.216**	**3.57**
White Pitcher	-	-	**-0.038**	**-0.87**	**-0.128**	**-2.96**	**-**	**-**	**0.088**	**1.54**
Non White Pitcher	-	-	**-0.125**	**-2.04**	**-0.216**	**-3.57**	**-0.088**	**-1.54**	**-**	**-**
Professional Characteristics										
MLB Experience	0.356	12.85	0.356	12.87	0.356	12.87	0.356	12.87	0.356	12.87
MLB Experience-Squared	-0.012	-10.91	-0.012	-10.88	-0.012	-10.88	-0.012	-10.88	-0.012	-10.88
Tenure with Current Club	0.101	15.27	0.102	15.43	0.102	15.43	0.102	15.43	0.102	15.43
Free Agent	0.770	6.78	0.767	6.77	0.767	6.77	0.767	6.77	0.767	6.77
Eligible for Final Offer Arbitration	0.351	5.10	0.346	5.04	0.346	5.04	0.346	5.04	0.346	5.04
American League	-0.001	-0.02	0.001	0.02	0.001	0.02	0.001	0.02	0.001	0.02
Canadian Team	-0.121	-0.93	-0.110	-0.85	-0.110	-0.85	-0.110	-0.85	-0.110	-0.85
Greater Metro Area Characteristics										
Percentage White	-0.005	-1.10	-0.005	-0.98	-0.005	-0.98	-0.005	-0.98	-0.005	-0.98
Percentage Black	-0.001	-0.29	-0.001	-0.20	-0.001	-0.20	-0.001	-0.20	-0.001	-0.20
Percentage Hispanic	0.004	2.14	0.005	2.25	0.005	2.25	0.005	2.25	0.005	2.25
Average Income	0.000	0.40	0.000	0.38	0.000	0.38	0.000	0.38	0.000	0.38
PopulationA	0.000	1.26	0.000	1.30	0.000	1.30	0.000	1.30	0.000	1.30
Year Dummies										
1993	0.099	2.07	0.101	2.12	0.101	2.12	0.101	2.12	0.101	2.12
1997	0.147	2.38	0.152	2.46	0.152	2.46	0.152	2.46	0.152	2.46
1998	0.283	4.09	0.290	4.19	0.290	4.19	0.290	4.19	0.290	4.19
Constant	13.313	20.48	**13.263**	**20.41**	**13.354**	**20.67**	**13.226**	**20.44**	**13.138**	**20.36**
Adjusted R-Squared	0.5656		0.5665		0.5665		0.5665		0.5665	
F-Statistic	167.02 (18, 2277)		158.88 (19, 2276)		158.88 (19, 2276)		158.88 (19, 2276)		158.88 (19, 2276)	
Root Mean Squared Error	0.78204		0.7812		0.7812		0.7812		0.7812	
Observations	2296		2296		2296		2296		2296	

Notes: 1. *Early* (*Latter*) *Period* denotes 1992 and 1993 (1997 and 1998); 2. (*Non-*) *Compt* refers to Hitters who are (neither) *Free Agents* nor *Eligible for Final Offer Arbitration*

Table 12:Log Annual Salary – Discrimination Across Time

	Hitters								*Pitchers*							
	(1)Non White Early Period		*(2) Non White Latter Period*		*(3) White Early Period*		*(4) White Latter Period*		*(5) Non White Early Period*		*(6) Non White Latter Period*		*(7) White Early Period*		*(8) White Latter Period*	
	Coef	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*
Greater Metro Area Characteristics																
Percentage White	-0.023	-1.59	-0.002	0.890	-0.009	-0.58	0.008	0.82	-0.054	-2.04	0.002	0.12	-0.006	-0.61	0.008	1.01
Percentage Black	-0.028	-1.88	0.007	0.551	-0.002	-0.12	0.010	0.99	-0.030	-1.17	0.008	0.53	0.003	0.28	0.005	0.69
Percentage Hispanic	-0.020	-3.62	0.005	0.329	-0.001	-0.12	0.009	2.21	-0.006	-0.63	0.009	1.29	0.003	0.91	0.006	2.01
Adjusted R-Squared	0.7436		0.7753		0.6478		0.7894		0.8458		0.7372		0.7883		0.8047	
F-Statistic	31.57 $_{(24, 229)}$		42.54 $_{(24, 265)}$		22.08 $_{(24, 251)}$		43.48 $_{(24, 248)}$		20.31 $_{(27, 68)}$		17.52 $_{(27, 132)}$		63.89 $_{(27, 429)}$		75.60 $_{(27, 462)}$	
Root Mean Squared Error	0.54098		0.57967		0 .62436		0.51385		0.46942		0.59806		0.55572		0.52221	
Observations	254		290		276		273		96		160		457		490	

Note: Other explanatory regressors were those set out in Tables 8 and 9 accordingly.