Racial Differences in Pay Across Positions: Theory and Test*

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Abstract: The traditional Becker/Arrow style model of racial discrimination depicts white and nonwhite workers as perfectly substitutable inputs, implying that everyone has the same job assignment. The model is only appropriate for determining whether pay differences between whites and nonwhites doing job assignment A are attributable to prejudice ('within-assignment discrimination'); It is inappropriate, however, for determining whether pay differences between whites in job assignment A and nonwhites in job assignment B reflect discriminatory behaviour ('cross-assignment discrimination'). We extend the traditional theoretical and empirical models of discrimination to allow for the assessment of cross-assignment discrimination. A crucial issue in the measurement of cross-assignment discrimination is the structure of the production function. In the theory section of this paper, we first derive some counterintuitive implications from a generalized Leontief function when there is racial integration within job assignments and perfect competition. Becker's *Market Discrimination Coefficient* (MDC) is derived for the case of cross-assignment discrimination. We show that the MDC can vary in unexpected ways, depending upon the structure of the production function and racial group differences in productivity and labour supply. For example, race and productivity will interact. We then use a Cobb-Douglas function to derive predictions about the relationship between cross-assignment discrimination and labour market structure. Cross-assignment discrimination can vary in counterintuitive ways with monopsony power, e.g. it is possible for discrimination to rise as the labour market gets more competitive. Implications from both models are tested using data on Major League Baseball hitters and pitchers for four different seasons during the 1990s, a decade during which monopsony power fell. We find strong evidence of *ceteris paribus* racial pay differences between hitters and pitchers, as well as evidence that cross-assignment discrimination varies with labour market structure.

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I. Introduction

Discrimination is defined as the 'unequal treatment of equals'. Applied to the study of racial discrimination in the labour market, the word 'equals' implies that nonwhite workers have the same skills and qualifications as white workers. The words 'unequal treatment' imply that minority workers are valued differently by employers, co-workers or customers, compared to equally productive majority workers. In the theory of labour market discrimination, due originally to Becker (1971) and Arrow (1973), it is shown that prejudice can result in unequal labour market outcomes between equally productive racial groups. A considerable number of studies have been undertaken to test the Becker/Arrow model.[1]

In the context of production theory, 'equals' implies that white labour and nonwhite labour are perfect substitutes. Some researchers have suggested that perfect substitution may sometimes be an inappropriate approach to the analysis of discrimination. One reason is that white and nonwhite human capital endowments may differ. Welch (1967) argued that blacks and whites working in the same firm are unlikely to be perfect substitutes because, due to long term discrimination, blacks may have acquired less schooling or attended lower quality schools. He suggested that a racially integrated labour force could be an outcome of complementarity between blacks and whites.[2] Kahn (1991) presented a model of customer discrimination where whites and blacks are represented as different inputs in the production function. He models blacks and whites as distinct inputs because if customers are prejudiced, they will act as if the amount of black input is equal to just a fraction of the input of *otherwise identical* white workers. Bodvarsson and Partridge (2001) present a model of a professional sports team where white and nonwhite athletes are imperfect substitutes due to racial differences in prior training and experience. Borjas (2008) suggested that black and white workers may not be perfect substitutes when he states: "The two groups of workers might have different productivities because they might differ in the amount and quality of educational attainment, or

[1] This extensive literature is surveyed by Altonji and Blank (1999).

[2] Welch argued that if there is co-worker discrimination, integration creates inefficiencies that will cause joint product to be less than the sum of individual black and white worker marginal products. The firm will only integrate its labour force if there are sufficiently large complementarities to be exploited, i.e. if the gains from complementarity exceed the losses attributable to co-worker discrimination.

because they might have been employed in different occupations and hence are entering [a] firm with different types of job training." (page 128).

A number of empirical studies have confirmed that white and nonwhite labour groups are imperfect substitutes: Grant and Hamermesh (1981) found that black adults are imperfect substitutes for white men and complements to white women and youths; Borjas (1983) provided evidence indicating that black males are imperfect substitutes for white males, but Hispanics and white males are complementary; Borjas (1987) showed that black natives are imperfect substitutes for white natives; and Kahanec (2006) found that nonwhites are complementary to whites.

When different groups of workers perform different job assignments within a firm, they will also be imperfect substitutes because different job assignments typically require different types and levels of schooling, on-the-job training, talents, etc. This has a very important implication for the study of labour market discrimination. The traditional question posed in the discrimination literature has been: Are whites and nonwhites assigned to the same job paid differently, e.g. is there a *ceteris paribus* pay difference between white pilots (flight attendants) and non-white pilots (flight attendants)? In this paper, however, we ask a different type of question: Is there discrimination across job assignments? For example, are white flight attendants (pilots) *ceteris paribus* paid differently from nonwhite pilots (flight attendants); Do white salespersons in a store's sporting goods department *ceteris paribus* earn more than nonwhite salespersons in the clothing department; Are non-white medical doctors *ceteris paribus* paid differently from white nurses? These are examples of questions about 'cross-assignment' discrimination, a labour market outcome that the current model of discrimination is not equipped to measure.

Cross-assignment discrimination is an unexplored area in the theoretical and empirical literatures. Kahn (1991) and Bodvarsson and Partridge (2001) present the only theoretical models we know of where a racial wage differential is derived from a production function characterized by racial differences in productivity. These models have features that limit their applicabilities, however. In Kahn's model, whites and nonwhites are assigned the same job and would be perfect substitutes if customers were unprejudiced. Bodvarsson and Partridge's model imposes the restriction that the cross elasticity of demand for white labour with respect to nonwhite labour is negative. Furthermore, in testing for cross-assignment discrimination, the traditional empirical model is inappropriate because it is based on a theory where whites and nonwhites are perfect substitutes. While empirical researchers have usually controlled for job assignment differences with dummy variables, that approach has severe limitations because it fails to adequately control for the structure of the underlying production function. As Hashimoto and Kochin (1980) would argue, failure to account for *all* sources of productivity differences will lead to biased estimates of discrimination.

In this paper, we provide a theoretical model of cross-assignment discrimination and present evidence from tests of that model using a novel empirical strategy. The theoretical section is divided into two parts. In the first part, we present a relatively general model of cross-assignment discrimination where production is described by a generalized Leontief production function and the source of discrimination is prejudiced customers. We derive an extension of Becker's (1971) Market Discrimination Coefficient (MDC),[3] which, in the case developed here, measures the 'ceteris paribus' racial pay gap between job assignments. Discrimination across job assignments is found to vary in counterintuitive ways, depending upon the structures of the production function and labour market, as well as racial group differences in productivity and labour supply. In the second part, we examine how cross-assignment discrimination can be influenced by the structure of the labour market. It is well understood in the literature that when white and nonwhite workers are perfect substitutes, a reduction in monopsony power can reduce the amount of discrimination. We ask: Is the same true for cross-assignment discrimination? We address this question by use of a

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[3] Some early literature does provide hints on how the traditional model could be extended to account for discriminatory pay gaps across job categories. Becker (1971, pp. 59-62) briefly sketched an extension of his two-factor black/white worker model to a three-factor model. Two of the factors are perfectly substitutable blacks and whites that belong to a group that could be called 'Type 1 Labour.' Then, there is a third labour input, 'Type 2 Labour,' that discriminates against blacks and is complementary to or imperfectly substitutable for them. Type 2 workers could, for example, be managers. In this situation, Becker showed that there will be a *ceteris paribus* black/white wage gap within the Type 1 category. Arrow (1972) elaborated on this by showing that the black/white wage gap depends upon the sensitivity of Type 2 labour's reservation wage to the fraction of the firm's labour force that is black, as well as the importance of Type 2 labour as an input (importance is measured as the size of the payments to Type 2 labour relative to Type 1 labour). Neither Becker nor Arrow tested these propositions, nor did they investigate further the implications of complementarity in production for the black/white pay differential.

Cobb-Douglas production function, deriving some predictions with numerical simulations. We find that discrimination can vary in counterintuitive ways with labour market structure, e.g. it is possible for discrimination to rise when the labour market becomes more competitive. In the empirical section, we test implications from both theoretical models using data from the market for Major League Baseball (MLB) players. We find strong evidence of *ceteris paribus* racial wage differences between Major League hitters and pitchers.

II. A Theory of Cross-Assignment Discrimination

II.1 *The Problem Setting*

Suppose production requires two different groups of workers, each group performing a distinct job, function or task. We will distinguish between the two groups as the *Job 1 Group* and the *Job 2 Group.* The successful completion of Job 1 requires a different set of skills than what is required for the successful completion of Job 2. The firm assigns each worker to a particular group depending upon his/her observed skills and credentials. The degree of imperfect substitutability between the groups will depend upon many factors, especially the type of good or service being produced.

While both groups of workers are employed by the same firm and contribute to producing a common output, they may come from very different occupations and may have very distinct human capital endowments. The following examples illustrate this. A clinic employs physicians to diagnose and treat patients (Job 1) and nurses to assist physicians and perform minor diagnoses and treatments not requiring physician intervention (Job 2). Doctors require much more training than nurses and their services can either be substitutes to or complements for the services of nurses. An airline employs pilots to fly a plane (Job 1) and flight attendants to provide cabin service (Job 2). The skills required to be a pilot are very different from and complementary to the skills required to be a flight attendant. Salespersons at a local retail department store are typically assigned to different departments. While there are certain skills all salespersons must possess to be successful, clothing salespersons must know something about clothing and sporting goods salespersons must know something about sporting goods. In other words, a worker must always invest in some job-specific human capital. We contend that differences in the amount and type of job-specific human capital is an important reason for there being imperfect substitutability between Job 1 workers and Job 2 workers.[4]

Below we present several models of cross-assignment discrimination. In the first model, there is racial integration within job groups, imperfect substitutability across groups, and perfect competition. The advantage of this model is that it provides general and counterintuitive types of implications. The disadvantage is that we cannot obtain reduced form expressions for labour demand, wages, or the MDC. In the second model, we articulate a more specialized production function in which job assignment groups are complementary and there is complete racial segregation. The disadvantage of this model is that it depicts a more specialized situation, but the advantage is that one can obtain reduced form expressions and very specific, often detailed, counterintuitive implications. This second model is used to compare cross-assignment discrimination under perfect competition and pure monopsony. Comparative statics from the second model are obtained from simulations. For both models, it is assumed that the source of discrimination is always prejudiced customers and that firms must assign nonwhite workers to job assignments for which prejudiced customers must see them. One clear example is professional sports, the test case discussed later.

II.2 *A More General Model of Cross-Assignment Discrimination.*

The distinguishing features of the model below are that we: (i) endogenize racial integration within each job group; and (ii) there are racial differences in productivity not only across groups, but also within them. There are four different inputs– white workers doing job 1, white workers doing job 2, nonwhite workers doing job 1, and nonwhite workers doing job 2.

Assume that technology is characterized by the Generalized Leontief Production function [see Diewert (1971]:

[4] It is important to emphasize that within a job assignment, workers can be imperfect substitutes. For example, heart surgeons performing heart surgeries differ in their experience, ability, where they were trained, etc.

(1) $$Q=\sum_{j=1}^{2}\sum_{i=1}^{2}\gamma_{ij}[X_i^W(DX_j^{NW})]^{\frac{1}{2}} \qquad D<1$$

where Q is output, X_i^W is the quantity of white labour input i, X_j^{NW} is the quantity of nonwhite labour input j, and γ_{ij} is the technology coefficient. Using an approach similar to Kahn (1991), we include the parameter D above as a measure of the strength of customer prejudice against nonwhite workers. Customer prejudice may be viewed as a situation where customers discount the marginal revenue product (MRP) of nonwhite workers. The lower (higher) is D, the more (less) intense the prejudice and the lower (higher) is nonwhite MRP. If D equals 1, there is no prejudice. While it is traditional to think of customer discrimination as implying a price discount on the output of nonwhite workers, the approach above is equivalent. The parameter D reflects the idea that nonwhite input is valued less when customers are prejudiced. Note also that the above production function is constant returns to scale and imposes restrictions on the technology coefficients (the γ's) such that $\gamma_{ij}=\gamma_{ji}$. The sign of each technology coefficient indicates whether inputs i and j are substitutes ($\gamma_{ij}<0$) or complements ($\gamma_{ij}>0$).

We will assume that the product and labour markets are perfectly competitive and that product price is normalized at unity. Assume that r_i^W and r_j^{NW} are the market prices of white input i and nonwhite input j, respectively. The firm's profit function is thus:

(2) $$\pi=\sum_{j=1}^{2}\sum_{i=1}^{2}\gamma_{ij}[X_i^W(DX_j^{NW})]^{\frac{1}{2}}-\sum_{i=1}^{2}r_i^W X_i^W-\sum_{j=1}^{2}r_j^{NW}X_j^{NW}$$

If firms maximize profits and face constant input prices, the labour market will establish the following system of labour demand functions:

(3) $$r_1^W=\gamma_{11}+\gamma_{12}D^{\frac{1}{2}}(\frac{X_1^{NW}}{X_1^W})^{\frac{1}{2}}+\gamma_{13}(\frac{X_2^W}{X_1^W})^{\frac{1}{2}}+\gamma_{14}D^{\frac{1}{2}}(\frac{X_2^{NW}}{X_1^W})^{\frac{1}{2}}$$

(4) $$r_1^{NW} = \gamma_{22} D + \gamma_{12} D^{\frac{1}{2}} (\frac{X_1^W}{X_1^{NW}})^{\frac{1}{2}} + \gamma_{23} D^{\frac{1}{2}} (\frac{X_2^W}{X_1^{NW}})^{\frac{1}{2}} + \gamma_{24} D (\frac{X_2^{NW}}{X_1^{NW}})^{\frac{1}{2}}$$

(5) $$r_2^W = \gamma_{33} + \gamma_{13} (\frac{X_1^W}{X_2^W})^{\frac{1}{2}} + \gamma_{23} D^{\frac{1}{2}} (\frac{X_1^{NW}}{X_2^W})^{\frac{1}{2}} + \gamma_{34} D^{\frac{1}{2}} (\frac{X_2^{NW}}{X_2^W})^{\frac{1}{2}}$$

(6) $$r_2^{NW} = \gamma_{44} D + \gamma_{14} D^{\frac{1}{2}} (\frac{X_1^W}{X_2^{NW}})^{\frac{1}{2}} + \gamma_{24} D (\frac{X_1^{NW}}{X_2^{NW}})^{\frac{1}{2}} + \gamma_{34} D^{\frac{1}{2}} (\frac{X_2^W}{X_2^{NW}})^{\frac{1}{2}}$$

While equations (3) – (6) are not reduced form expressions, they provide some very useful implications. The wage paid to workers of a particular race who are assigned to a particular job depends upon four broad factors: (i) productivity; (ii) the strength of prejudice; (iii) the degrees of substitutability or complementarity between the various job/race subgroups; and (iv) the relative supplies of workers in the job/race subgroups. Consider, for example, the wage paid to nonwhites doing job 1 (equation (4)). That wage depends upon the group's productivity (reflected by γ_{22})[5], prejudice (D), the degrees of substitutability or complementarity between whites and nonwhites doing job 1 (γ_{12}), between nonwhites doing job 1 and whites doing job 2 (γ_{23}), between nonwhites doing job 1 and nonwhites doing job 2 (γ_{24}), the number of nonwhites doing job 1 per white doing job 1 $\left(X_1^{NW}/X_1^W\right)$, the number of whites doing job 2 per nonwhite doing job 1 $\left(X_2^W/X_1^{NW}\right)$, and the number of nonwhites doing job 2 per nonwhite doing job 1 $\left(X_2^{NW}/X_1^{NW}\right)$.

One particularly important insight from equations (3) through (6) is that the wage paid to workers of a particular race doing a particular job depends upon the amount of racial integration within and across groups. For example, according to equation (3), the wage paid to a white worker assigned to do job 1 is affected by the ratio of nonwhites to whites doing job 1, as well as the ratio of nonwhites doing job 2 to whites doing job 1. Furthermore, how whites doing job 1 are affected by an increase or a decrease in the number of nonwhites depends upon both the technology

[5] Note that γ_{22} is not equivalent to the marginal productivity of this job/race subgroup, but is correlated with it. If γ_{22} rises (falls), the marginal productivity curve will shift up (down). For example, an increase in γ_{22} could result from a technological advance, an increase in the average human capital endowment of each worker, or some other exogenous change.

coefficients and the degree of customer prejudice. If whites and nonwhites doing job 1 are substitutes (γ_{12} < 0), then if more nonwhites doing job 1 are hired the wage paid to whites doing job 1 will fall, all other things equal. However, the drop in that wage will be smaller (larger) the greater (lesser) is the degree of customer prejudice against nonwhites.[6] Thus, if whites and nonwhites are substitutes, prejudice attenuates the adverse effects experienced by whites when more nonwhites are hired and the degree of attenuation rises with the degree of prejudice. In contrast, suppose that whites doing job 1 are complementary to nonwhites doing job 2 (γ_{14} > 0). Then an increase in the supply of nonwhites doing job 2 will raise the wage paid to whites doing job 1, all other things equal. However, the increase in that wage will be smaller (larger) the greater (lesser) is the degree of prejudice.[7] Whites doing job 1 benefit from having more nonwhites doing job 2, but prejudice 'taxes' that benefit.

There are similar implications for nonwhite wages. Consider the wage paid to nonwhites doing job 1. If whites and nonwhites doing job 1 are substitutes, then greater employment of whites doing job 1 reduces the wage, but it falls less the *greater* is the amount of prejudice. In this seemingly odd way, nonwhites actually benefit from increased prejudice! In contrast, if nonwhites doing job 1 and whites doing job 2 are complements, then greater hiring of whites doing job 2 will raise the wage of nonwhites doing job 1, but the wage rises less the greater is prejudice. This is an indirect adverse effect of prejudice on nonwhites: Nonwhites are harmed directly because customers value their output less and indirectly because prejudice reduces the benefits enjoyed by nonwhites from having a complementary relationship in production with whites.

The next step in the analysis is to apply Becker's (1971) *Market Discrimination Coefficient* (MDC) to the case of discrimination across job groups. The MDC measures the *ceteris paribus* racial earnings gap, the percentage earnings premium paid to whites. Assume for the moment that

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[6] Note that $\partial^2 r_1^W / \partial\left(X_1^{NW}/X_1^W\right)\partial D < 0$, meaning that as D falls (customer prejudice is greater), the drop in the wage paid to whites in job assignment group 1 resulting from greater employment of nonwhites within that group will be less severe.

[7] Note that $\partial^2 r_1^W / \partial\left(X_2^{NW}/X_1^W\right)\partial D > 0$ > 0, meaning that as customer prejudice falls, the gain in the wage paid to whites in job assignment group 1 resulting from greater employment of nonwhites in job assignment group 2 will be larger.

'W' refers to the wage. According to Becker (1971, pg. 17), when there are productivity differences between whites and nonwhites, the MDC is:[8]

(7) $$MDC = \frac{W_{whites}(D<1)}{W_{nonwhites}(D<1)} - \frac{W_{whites}(D=1)}{W_{nonwhites}(D=1)}$$

The first term on the right-hand side of (7) is the wage ratio when there is prejudice, whereas the second term is the ratio in the absence of prejudice. The difference between the two ratios measures the *ceteris paribus* racial pay gap.

Applying equation (7), the *ceteris paribus* racial pay gap between whites doing job 1 and nonwhites doing job 2 is:

(8) $$MDC_{NW_2}^{W_1} = \frac{r_1^W(D<1)}{r_2^{NW}(D<1)} - \frac{r_1^W(D=1)}{r_2^{NW}(D=1)} =$$

$$\frac{\gamma_{11} + D^{\frac{1}{2}}[\gamma_{12}(\frac{X_1^{NW}}{X_1^W})^{\frac{1}{2}} + \gamma_{14}(\frac{X_2^{NW}}{X_1^W})^{\frac{1}{2}}] + \gamma_{13}(\frac{X_2^W}{X_1^W})^{\frac{1}{2}}}{D[\gamma_{44} + \gamma_{24}(\frac{X_1^{NW}}{X_2^{NW}})^{\frac{1}{2}}] + D^{\frac{1}{2}}[\gamma_{14}(\frac{X_1^W}{X_2^{NW}})^{\frac{1}{2}} + \gamma_{34}(\frac{X_2^W}{X_2^{NW}})^{\frac{1}{2}}]} - \frac{[\gamma_{11} + \gamma_{12}(\frac{X_1^{NW}}{X_1^W})^{\frac{1}{2}} + \gamma_{14}(\frac{X_2^{NW}}{X_1^W})^{\frac{1}{2}} + \gamma_{13}(\frac{X_2^W}{X_1^W})^{\frac{1}{2}}]}{[\gamma_{44} + \gamma_{24}(\frac{X_1^{NW}}{X_2^{NW}})^{\frac{1}{2}} + \gamma_{14}(\frac{X_1^W}{X_2^{NW}})^{\frac{1}{2}} + \gamma_{34}(\frac{X_2^W}{X_2^{NW}})^{\frac{1}{2}}]}$$

and the *ceteris paribus* racial pay gap between whites doing job 2 and nonwhites doing job 1 is

(9) $$MDC_{NW_1}^{W_2} = \frac{r_2^W(D<1)}{r_1^{NW}(D<1)} - \frac{r_2^W(D=1)}{r_1^{NW}(D=1)} =$$

$$\frac{\gamma_{33} + \gamma_{13}(\frac{X_1^W}{X_2^W})^{\frac{1}{2}} + D^{\frac{1}{2}}[\gamma_{23}(\frac{X_1^{NW}}{X_2^W})^{\frac{1}{2}} + \gamma_{34}(\frac{X_2^{NW}}{X_2^W})^{\frac{1}{2}}]}{D[\gamma_{22} + \gamma_{24}(\frac{X_2^{NW}}{X_1^{NW}})^{\frac{1}{2}}] + D^{\frac{1}{2}}[\gamma_{12}(\frac{X_1^W}{X_1^{NW}})^{\frac{1}{2}} + \gamma_{23}(\frac{X_2^W}{X_1^{NW}})^{\frac{1}{2}}]} - \frac{[\gamma_{33} + \gamma_{13}(\frac{X_1^W}{X_2^W})^{\frac{1}{2}} + \gamma_{23}(\frac{X_1^{NW}}{X_2^W})^{\frac{1}{2}} + \gamma_{34}(\frac{X_2^{NW}}{X_2^W})^{\frac{1}{2}}]}{[\gamma_{22} + \gamma_{24}(\frac{X_2^{NW}}{X_1^{NW}})^{\frac{1}{2}} + \gamma_{12}(\frac{X_1^W}{X_1^{NW}})^{\frac{1}{2}} + \gamma_{23}(\frac{X_2^W}{X_1^{NW}})^{\frac{1}{2}}]}$$

According to equations (8) and (9), racial discrimination across job assignments depends precisely upon the degree of prejudice, white/nonwhite productivity differences within and across job assignment groups, the degree of substitutability or complementarity between whites and nonwhites

[8] 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.

within and across job assignment groups, and on the relative supplies of white and nonwhite labour within and across groups.

Equations (8) and (9) imply a number of important predictions. First, we find that the *ceteris paribus* racial pay gap between white workers in one job assignment and nonwhite workers in another assignment is larger the greater is the degree of customer prejudice ($\partial MDC^{W_1}_{NW_2} \big/ \partial D < 0$ and $\partial MDC^{W_1}_{NW_2} \big/ \partial \gamma_{33} < 0$). This is similar to the prediction generated by the simpler Becker (1971) model where workers are perfect substitutes. However, there are other predictions, discussed below, which are less obvious:

(i) *If white workers in a job assignment group become more productive, then pay discrimination against nonwhite workers in the other job assignment group increases.*

This prediction is confirmed by:

(10) $$\frac{\partial MDC^{W_1}_{NW_2}}{\partial \gamma_{11}} = \frac{1}{D[\gamma_{44} + \gamma_{24}(\frac{X_1^{NW}}{X_2^{NW}})^{\frac{1}{2}}] + D^{\frac{1}{2}}[\gamma_{14}(\frac{X_1^{W}}{X_2^{NW}})^{\frac{1}{2}} + \gamma_{34}(\frac{X_2^{W}}{X_2^{NW}})^{\frac{1}{2}}]} - \frac{1}{[\gamma_{44} + \gamma_{24}(\frac{X_1^{NW}}{X_2^{NW}})^{\frac{1}{2}} + \gamma_{14}(\frac{X_1^{W}}{X_2^{NW}})^{\frac{1}{2}} + \gamma_{34}(\frac{X_2^{W}}{X_2^{NW}})^{\frac{1}{2}}]} > 0$$

(11) $$\frac{\partial MDC^{W_2}_{NW_1}}{\partial \gamma_{33}} = \frac{1}{D[\gamma_{22} + \gamma_{24}(\frac{X_2^{NW}}{X_1^{NW}})^{\frac{1}{2}}] + D^{\frac{1}{2}}[\gamma_{12}(\frac{X_1^{W}}{X_1^{NW}})^{\frac{1}{2}} + \gamma_{23}(\frac{X_2^{W}}{X_1^{NW}})^{\frac{1}{2}}]} - \frac{1}{[\gamma_{22} + \gamma_{24}(\frac{X_2^{NW}}{X_1^{NW}})^{\frac{1}{2}} + \gamma_{12}(\frac{X_1^{W}}{X_1^{NW}})^{\frac{1}{2}} + \gamma_{23}(\frac{X_2^{W}}{X_1^{NW}})^{\frac{1}{2}}]} > 0$$

If there is an exogenous increase in the productivity of whites doing job 1 (γ_{11} rises) or whites doing job 2 (γ_{33} rises), white wages rise. According to both equations (10) and (11), the white wage with prejudice (measured by the numerator in the left-hand ratio in equations (8) or (9)) will rise proportionately more than will the white wage in the absence of prejudice (measured by the numerator in the right-hand ratio in equations (8) and (9)). Regardless of the signs and magnitudes of the technology coefficients and the relative supplies of labour, cross-assignment discrimination rises. For example, a technological advance that makes whites doing one job assignment more efficient results in greater discrimination against nonwhites performing the other assignment;

(ii) *If nonwhite workers in a job assignment group become more productive, then they experience less discrimination .*

This prediction is confirmed by $\partial MDC_{NW_2}^{W_1} \big/ \partial \gamma_{44} < 0$ and $\partial MDC_{NW_1}^{W_2} \big/ \partial \gamma_{22} < 0$.[9] When nonwhites experience an increase in productivity, they benefit in two ways. First, their wage rises. Second, referring to equations (8) and (9), the productivity increase reduces the wage ratio with discrimination and without, but the left-hand wage ratio falls more than the right-hand ratio in either equation;

(iii) *Discrimination experienced by nonwhites in a job assignment group depends upon the racial compositions within and across both groups.*

As an example, consider equation (8). The *ceteris paribus* racial pay gap between whites in job assignment group 1 and nonwhites in job assignment group 2 depends upon the racial composition of group 1 $\left(X_1^{NW} \big/ X_1^{W}\right)$, the racial composition of group 2 $\left(X_2^{W} \big/ X_2^{NW}\right)$, the supply of nonwhites in group 2 relative to the supply of whites in group 1 $\left(X_2^{NW} \big/ X_1^{W}\right)$, the supply of whites in group 2 relative to the supply of whites in group 1 $\left(X_2^{W} \big/ X_1^{W}\right)$, the supply of nonwhites in group 1 relative to the supply of nonwhites in group 2 $\left(X_1^{NW} \big/ X_2^{NW}\right)$ and the supply of whites in group 1 relative to the supply of nonwhites in group 2 $\left(X_1^{W} \big/ X_2^{NW}\right)$. Compare these results with what would be predicted by the Becker (1971) model. In the Becker model, an increase in the relative supply of nonwhites results in a greater *ceteris paribus* pay differential between whites and nonwhites. This is the simple result for an economy where whites and nonwhites are identical in productivity and there is effectively just one job assignment. In our model, the relationship between discrimination and the

[9] These predictions were verified from simulations, available from the authors upon request.

relative supply of nonwhite labour is much more complicated. Not only does the amount of discrimination experienced by nonwhites in one group depend upon how many nonwhites there are in that group, but it also depends on how many nonwhites there are in other groups. Furthermore, how dominant whites and nonwhites are across groups, and how racially integrated one group is relative to another, will influence the level of discrimination experienced by nonwhites in one particular group. Note that we cannot sign the relationship between the MDC and any labour supply ratio without knowing the signs of the technology coefficients (γ_{ij}):

(iv) *Prejudice and productivity interact in the determination of racial pay differences across job assignment groups; the marginal effect of prejudice on pay depends upon whether whites and nonwhites are substitutes or complements and on the magnitudes of the elasticities of substitution.*

This implication is important because it suggests that in an empirical specification, interaction terms between race and productivity must be included in order to avoid estimation bias. As an example, note from equation (10) that the reduction in discrimination experienced by nonwhites in group 1 (relative to whites in group 2) resulting from a productivity increase will be lower the greater is the degree of customer prejudice $\left(\partial^2 MDC_{NW_2}^{W_1} / \partial\gamma_{11}\partial D < 0\right)$. Prejudice taxes the benefit nonwhites enjoy from being more productive and the tax is greater the greater is customer distaste for output made by nonwhite workers.

II.3 *How do changes in labour market structure influence cross-assignment discrimination?*

In this section, we analyze the relationship between cross-assignment discrimination and the degree of monopsony power in the labour market. Owing to its more general form, we found it extremely difficult to derive predictions about the effects of monopsony power using the Generalized Leontief function. Therefore, we chose a more specific form – Cobb-Douglas, which imposes the restriction of complementarity.[10]

Consider the following production function:

[10] It is easy to find examples of complementary job groups – pilots and flight attendants, doctors and nurses, workers on assembly lines, painters and drywall installers, secretaries and managers, teachers and administrators, and waiters and cooks. We suspect that in a typical firm, job assignments will have a much stronger tendency to be complementary.

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

where M is the number of workers in one particular job assignment and N is the number of workers in the other. Other inputs are fixed, so it is assumed that $\alpha + \beta < 1$. For simplicity, we assume there is complete segregation by race between job assignments and this segregation is exogenously determined. For example, suppose that only White workers are available to assemble the good, whilst only nonwhite workers are available to do the marketing. Think of M, therefore, as the quantity of *white* labour services and N as the quantity of *nonwhite* labour services used in production. This assumption is made so that we can obtain reduced form expressions.[11]

For analytical convenience, we incorporate prejudice somewhat differently: Before we used the D parameter to reduce the value of nonwhite output relative to white output by discounting the quantity of nonwhite input. We now reduce the value of nonwhite output by discounting the *productivity* of nonwhite labour. This is done by discounting the nonwhite share parameter in the production function by D:

(13) $Q = AM^{\alpha}N^{\beta D}$

The lower is D, the more intense the prejudice and the lower is nonwhite MRP. If D equals 1, the case of no prejudice, the production function reverts to equation (12). We will derive the MDC under both perfect competition and pure monopsony. Furthermore, in one version of the monopsony model, we allow for racial differences in the wage elasticity of supply.

II.3.1 *Perfect Competition*

Define W_M (W_N) as the market price of one unit of white (nonwhite) labour. With p as product price, the employer's profits π are now:

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

[11] We found it impossible to obtain reduced form expressions for the Cobb-Douglas function when we allowed for racial integration and racial productivity differences within each job assignment. We tried other functions such as the CES and encountered the same problem. By choosing the Cobb-Douglas form, we are trading away some generality in exchange for obtaining a number of novel implications that are likely to hold for more general cases.

First and second order conditions yield the following demand functions for white and nonwhite labour services, respectively:

$$(15) \qquad M = \left(\frac{\beta D}{W_N}\right)^{\frac{\beta D}{\gamma}} \left(\frac{\alpha}{W_M}\right)^{\frac{1-\beta D}{\gamma}} (pA)^{\frac{1}{\gamma}}$$

$$(16) \qquad N = \left(\frac{\beta D}{W_N}\right)^{\frac{1-\alpha}{\gamma}} \left(\frac{\alpha}{W_M}\right)^{\frac{\alpha}{\gamma}} (pA)^{\frac{1}{\gamma}}$$

where $\gamma = 1-\alpha-\beta D$. One implication of complementarity is that an increase in prejudice will result in lower hiring of workers in *both* job categories ($\partial M/\partial D$, $\partial N/\partial D > 0$). When customers become more prejudiced, this lowers the MRP of nonwhites and reduces its usage. Since both job assignments are complementary, less white labour is needed when the usage of nonwhite labour falls.

We now develop the supply side of the labour market. The labour supply curve equations are:

$$(17) \qquad W_M = \varepsilon\theta_M$$

$$(18) \qquad W_N = \lambda\theta_N$$

where θ_M and θ_N are the supplies of white and nonwhite workers, respectively, with ε and $\lambda > 0$. These supply functions are first used to obtain partial equilibrium wages. Assume F employers. When the white worker market is in equilibrium, $FM = \theta_M$, and when the nonwhite worker market is in equilibrium, $FN = \theta_N$. We note from equation (17) that:

$$(19) \qquad \theta_M = \frac{W_M}{\varepsilon}$$

Now multiply equation (14) by F, set this equal to equation (19) and solve for the white wage:

$$(20) \qquad W_M = \left[\varepsilon F \left(\frac{\beta D}{W_N}\right)^{\frac{\beta D}{\gamma}} (pA)^{\frac{1}{\gamma}} (\alpha)^{\frac{1-\beta D}{\gamma}}\right]^{\frac{1}{1+\frac{1-\beta D}{\gamma}}}$$

From equation (18):

(21) $$\theta_N = \frac{W_N}{\lambda}$$

Multiply equation (16) by F, set equal to equation (21) and solve for the nonwhite wage:

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

To obtain the general equilibrium white wage, we substitute expression (22) for W_N in expression (20) and solve again for the white wage:

(23) $$W_M = \left(\frac{Z}{\alpha^{\theta}} \right)^{\frac{1}{1-\theta}}$$

where:

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

and:

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

To obtain the general equilibrium nonwhite wage, substitute expression (20) for W_M in expression (22) and solve again for the nonwhite wage:

(26) $$W_N = \left[\frac{X}{(\beta D)^{\theta}} \right]^{\frac{1}{1-\theta}}$$

where:

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

In general equilibrium, wages depend upon the strength of customer demand for the product, the size of the industry, prejudice, the wage elasticities of labour supply, the quantity of other input services used (reflected in A), and the productivities of the labour inputs (reflected in α and β, respectively).

The MDC is obtained by inserting equations (23) and (26) into (7):

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

Comparative statics were obtained using simulations in Excel, available from the authors, and which are discussed below:

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

Starting from the bottom of Table 1, notice that as D falls, the MDC rises at an increasing rate;

(ii) *The magnitude of discrimination across job assignments depends upon how productive nonwhites are relative to whites ($\partial MDC/\partial \beta$, $\partial MDC/\partial \alpha \neq 0$).*

This finding confirms the more general finding obtained from the analysis of the Generalized Leontief function. As the second and third columns of Table 1 show, when the nonwhite share parameter rises from 0.4 to 0.5, the MDC falls at any level of prejudice. This implies that nonwhites can overcome the adverse effects of customer prejudice by becoming more productive. The reason is that when the nonwhite occupation share parameter rises, the white wage falls and the nonwhite wage rises, which will reduce MDC. In another example, as the fourth and fifth columns of Table 1 show, when the white share parameter rises from 0.4 to 0.5, MDC rises at any level of prejudice.

(iii) *When the nonwhite reservation wage rises (falls), wage discrimination against those workers falls (rises);* $\partial MDC/\partial \lambda < 0$. *When the white reservation wage rises (falls) wage discrimination against nonwhite workers rises (falls);* $\partial MDC/\partial \varepsilon > 0$.

These predictions illustrate the effects that labour supply differences have on discrimination across job assignments. When nonwhite opportunity costs rise, that group's labour supply curve becomes steeper, raising the group's wage and resulting in lower employment. White labour usage falls, depressing the white wage. This reduces the MDC. The opposite is true if the white group's opportunity costs rise.

We also find that changes in industry size, product price and the capital stock do not influence the MDC. For example, at each level of prejudice, a doubling of price raises both groups' wages, but they rise in the same proportion, causing the MDC to be unchanged.

II.3.2 *Monopsony*

Suppose the firm is a pure monopsony and faces these labour supply curves,

(29) $W_M = M^{\varepsilon ø}$

(30) $W_N = N^{\lambda ø}$

where εø is the inverse of the wage elasticity of supply for whites and λø is the inverse of the wage elasticity of supply for nonwhites. Note that we assume a constant wage elasticity of supply within each labour category.[12] The firm's profits π are:

(31) $p = pAM^{\alpha}N^{\beta D} - M^{\varepsilon ø+1} - N^{\lambda ø+1}$

First and second order conditions yield these labour demand equations:

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

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

$$(33)\qquad M = \left[\left(\frac{\alpha pA}{\varepsilon\phi + 1} \right) \left[\left[\frac{\beta DpA}{(\lambda\phi + 1)} \left(\frac{\alpha pA}{\varepsilon\phi + 1} \right)^{\frac{\alpha}{\varepsilon\phi - (\alpha - 1)}} \right]^{\frac{1}{\lambda\phi - \frac{\beta D\alpha}{\lambda\phi - (\alpha - 1)} - (\beta D - 1)}} \right]^{\beta D} \right]^{\frac{1}{\varepsilon\phi - (\alpha - 1)}}$$

The firm will pay $W_M = M^{\varepsilon ø}$ for white labour and $W_N = N^{\lambda ø}$ for nonwhite labour. Inserting expressions (32) and (33) into expressions (29) and (30), the MDC is now:

$$(34)\quad MDC = \frac{\left[\left(\frac{\varepsilon\alpha pA}{\varepsilon\phi + 1} \right) \left[\left[\frac{\beta DpA}{(\lambda\phi + 1)} \left(\frac{\alpha pA}{\varepsilon\phi + 1} \right)^{\frac{\alpha}{\varepsilon\phi - (\alpha - 1)}} \right]^{\frac{1}{\lambda\phi - \frac{\beta D\alpha}{\lambda\phi - (\alpha - 1)} (\beta D - 1)}} \right]^{\beta D} \right]^{\frac{\varepsilon\phi}{\varepsilon\phi - (\alpha - 1)}}}{\left[\frac{\beta DpA}{(\lambda\phi + 1)} \left(\frac{\alpha pA}{\varepsilon\phi + 1} \right)^{\frac{\alpha}{\varepsilon\phi - (\alpha - 1)}} \right]^{\frac{\phi}{\lambda\phi - \frac{\beta D\alpha}{\lambda\phi - (\alpha - 1)} (\beta D - 1)}}} -$$

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

According to equation (34), discrimination also depends upon the amount of monopsony power ($\varepsilon ø$ and $\lambda ø$, respectively). Recall from the Becker model (1971) that a reduction in market power will reduce the amount of employer discrimination, but not customer discrimination. In contrast, our model demonstrates that when there are racial productivity differences, more competition will reduce *customer* discrimination.

Comparative statics were again obtained from Excel simulations. In tables 2-4 we assume that the wage elasticity of supply is unity, hence no monopsonistic wage discrimination. In table 5, however, we allow for different elasticities in order to see how racial discrimination and monopsonistic wage discrimination jointly influence pay. Below is a summary of key findings:

(i) *An increase in customer prejudice will reduce employment and wages in both job assignments, but will heighten the amount of cross-assignment discrimination.*

Table 2 shows calculations of employment levels and wages for alternative values of *D*. These calculations are done for three different sets of share parameters, assuming A = 5, p = 2 and a wage elasticity (1/ø) equalling 1. Note that, given the labour 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 labour, but raises the amount of racial discrimination. The reason is that the nonwhite wage falls faster than the white wage, causing *MDC* to rise;

(ii) *The amount of discrimination across job assignments depends on productivity differences between job assignment groups.*

Relative productivity of nonwhite labour will rise if the nonwhite partial elasticity of output rises relative to the white partial elasticity. Table 3 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, ø = 1, A = 5 and p =2. At the same level of prejudice, *MDC* declines as the nonwhite elasticity rises and/or the white elasticity falls;

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

Table 4 shows calculations of *MDC* for values of the wage elasticity ranging from 0.001 (near 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 white share parameter is relatively large; and (c) the nonwhite share parameter is relatively large. As Table 4 shows, for cases (a) and (b) an increase in monopsony power unambiguously bolsters 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 nonwhite share parameter is sufficiently large. When monopsony power rises, marginal and average costs of labour rise, inducing the firm to employ less labour services from each job assignment (note that Excel calculations confirm that $\partial M/\partial ø$ and $\partial N/\partial ø < 0$) and pay lower wages. Common to the three cases above is that wages in both jobs with and without prejudice will decline when monopsony power rises. However, the 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;[13]

(iv) *Racial discrimination will be lower when there are greater opportunities for the employer to practice monopsonistic wage discrimination.*

Table 5 shows three sets of calculations of *MDC* for a range of values for the wage elasticity of supply for nonwhite labour ($\lambda ø$), assuming that the wage elasticity for white labour is fixed at unity. For all three sets, the MDC is found to fall when the wage elasticity for nonwhite labour gets lower. While not shown in the table, the nonwhite/white wage ratio falls when nonwhite labour supply becomes less elastic, implying that an employer with monopsony power will substitute the practice of monopsonistic wage discrimination for the practice of racial discrimination. When nonwhite labour supply becomes less elastic, it becomes more efficient for the employer to *substitute*

[13] 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 nonwhite workers is so large relative to white workers, the nonwhite wage exceeds the white wage. However, according to equation (33), the wage ratio attributable solely to prejudice is in favour of white 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 labour market in which firms can indulge prejudicial tastes only by adjusting the nonwhite 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 labour 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. Our analysis has two novel implications. First, as case (c) shows, competition in the labour market is not guaranteed to alleviate discrimination ($\partial MDC/\partial ø$ is not always positive). In fact, it is possible that under certain conditions, a more competitive labour 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), Becker (1971) and Arrow (1972), 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 nonwhite workers are in production. For cases (a) and (b), for example, as nonwhite workers become more important in production, the marginal effect of an increase in monopsony power on wage discrimination will lessen ($\partial^2 MDC/\partial\beta\partial ø < 0$).

monopsonistic wage discrimination for racial wage discrimination. This is true even when whites and nonwhites have equal productivity, as the third column from the right in table 5 shows.

III. A Test Case: Major League Baseball

III.1 *Description of the Test Case*

In this section, we test a number of the implications of the models presented above. We chose an industry where: (a) there are accurate data on salaries and productivity for individual workers across distinct job assignments and these data are available for different firms; (b) the productivities of job assignment groups within the firm are interrelated; (c) there is racial integration; (d) the pay of some workers is competitively determined, whilst the pay of others is determined under conditions resembling monopsony; (e) there is potential for customer discrimination; and (f) there have been changes in the number of employers in the industry over time.

One industry satisfying all these criteria is Major League Baseball (MLB) in the USA.[14] In MLB, each team requires two distinctly complementary types of player skill - hitting (an offensive skill) and pitching (a defensive skill) - in the production of baseball entertainment.[15] 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

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

[15] Woolway (1997) and Zech (1981) argue that the Cobb-Douglas function is a particularly appropriate description of an MLB team's production situation. They both estimated Cobb-Douglas functions where the dependent variable is team winning percentage and the independent variables are player and team career statistics.

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.

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 empirically disentangle one player's revenue contribution from another. We thus proxy MRP by the player's years of MLB experience, tenure with his current team, 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*.[16] 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.[17] 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.*[18]

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[16] 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 hitting power, which is total bases divided by at bats.

[17] 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 the strengths and weaknesses of the batter.

[18] 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

III. 2 *Empirical Analysis*

Our empirical analysis is set out in Tables 6-10d. Tables 6 and 7 present descriptive statistics for hitters and pitchers, respectively. Our full sample comprises 1093 hitters (549 white, 367 black and 177 Hispanic) and 1204 pitchers (942 white, 127 black and 135 Hispanic). Salary, experience, performance and position data were drawn from the *Lahman Baseball Database* (see: 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 (see: www.bea.gov). For the Canadian teams, similar data were obtained from the Statistics Canada website (see: www.statcan.ca). Per-capita income data for the Canadian cities were converted to U.S. dollars.

It would appear from Table 6 that there are no major differences between the personal and professional characteristics of white hitters, black hitters and Hispanic hitters, nor in the characteristics of the greater metropolitan area in which they play. In terms of career characteristics, however, black hitters record significantly more *At Bats*, *Stolen Bases, Bases on Balls* and *Total Basses* than either white hitters or Hispanic hitters. They are also less likely to play as an infielder

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.

or catcher, but more likely to play as an outfielder or designated hitter. Compared to Hispanic hitters, white hitters record significantly more *At Bats*, *Bases on Balls* and *Total Bases*, but significantly fewer *Stolen Bases*. They are also more likely to play as a catcher, but less likely to play as an outfielder or designated hitter.

In Table 7, the domination of white pitchers is immediately apparent. White pitchers are on average older than both black and (especially) Hispanic pitchers. 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 either blacks or Hispanic pitchers, with Hispanic pitchers recording generally lower figures than black pitchers.

To ascertain the level of discrimination across player positions, we need to control for position-specific productivity. In one sense this is straightforward because some measures of off-field productivity (MLB experience and tenure with current team, for example) are common across pitchers and hitters. On-field measures of productivity, however, vary across hitters and pitchers; e.g. runs for hitters and strike-outs for pitchers. Given our objective of ascertaining the extent of racial discrimination *across* job assignments, we need a standardized productivity measure. We thus adopt the following two-stage approach. We first assume that wages reflect productivity as follows:

(35) $$\ln w^j = \mathbf{X}_0^j \mathbf{B}_0^j + \mathbf{X}_1 \mathbf{B}_1^j$$

$\ln w^j$, $j = (H, P)$, denotes the log wages of hitters and pitchers respectively, $\mathbf{X}_0^j$ is a vector of 'position-specific' productivity measures (e.g. runs, strike–outs, etc.), $\mathbf{X}_1$ is a vector of 'common' (off-field) productivity measures and other career characteristics, and the **B**'s denote parameter vectors. Our aim is to derive an estimating equation of the form:

(36) $$\ln w^j = \mathbf{X}_0 \mathbf{B}_0^j + \mathbf{X}_1 \mathbf{B}_1^j$$

where $\mathbf{X}_0$ denotes some standardized (imputed) measure of productivity related to on-field performance. We therefore estimate the following 'first-stage' regressions:

(37) $\ln w^j = \mathbf{X}_0^j \mathbf{A}_0^j$

That is, we estimate separate wage regressions for hitters and pitchers on only their respective position specific variables vis. Pitchers - *Starter*; *Wins*; *Losses*; *Games Started*; *Complete Games*; *Shutouts*; *Saves*; *Homeruns*; *Walks*; *Strikeouts*; *Innings Pitched*; *ERA*; and *Strikeout Rate*; Hitters – *At Bat*; *Stolen Bases*; *Bases on Balls*; *Total Bases*; *Slugging Average*; *Batting Average*; *Infielder*; *Outfielder*; *Catcher*; and *Designated Hitter*. We then use the predicted values from these regressions, $\hat{w} = \left(\hat{w}^h, \hat{w}^p\right)$, as our standardized on-field measure of productivity in a second-stage regression:

(38) $\ln w^j = \hat{w}\mathbf{B}_0^j + \mathbf{X}_1\mathbf{B}_1^j$

Table 8 reports six second-stage regressions with white pitchers, black pitchers, Hispanic pitchers, white hitters, black hitters, and Hispanic hitters being defined as the default race-position category respectively.

The results in Table 8 show strong evidence of cross-, as well as within-, assignment discrimination in MLB. Our estimated coefficients suggest that even after controlling for both on- and off-field productivity, white pitchers earn: (i) 16.4 percent more than black pitchers; (ii) 10.6 per cent more than black hitters; and (iii) 9.2 per cent (but only at the 90 per cent level of confidence) more than Hispanic hitters. Hispanic pitchers earn: (i) 17.0 per cent more than black pitchers; (ii) 17.6 per cent more than white hitters; and (iii) 11.2 per cent (but only at the 90 per cent level of confidence) more than black hitters.

We estimated a number of variants of the Table 8 regressions to test our theoretical priors that discrimination increases with heightened customer prejudice, but can decline as labour markets become less competitive. Specifically, we re-estimated the Table 8 regressions for the 'competitive' and ‘non-competitive’ MLB markets separately, where the latter is defined as those players subject to the reserve clause or eligible for final offer arbitration. We also estimated separate Table 8 regressions for the ‘early’ (i.e. 1992 and 1993) and ‘latter’ (i.e. 1997 and 1998) periods of our data, both for the overall MLB market, and then for the competitive and non-competitive markets separately. Our objective here was to pick up the effects of the expansion in the size of the league, and the subsequent decline in monopsony power, during the 1990’s. Finally, we tested for customer discrimination generally, and the predictions from our theoretical and numerical analysis particularly (that within a competitive labour market, an increase in customer prejudice will heighten the amount of wage discrimination across job assignments), by estimating separate Table 8 regressions for all players, ‘competitive’ players, and ‘non-competitive’ players, playing for teams located in greater metropolitan areas with above and below average nonwhite populations.

The results of these various regressions (over 80 in total) are available on request. For brevity we report the salient details only. We find discrimination to be generally more evident in the competitive MLB market than in the non-competitive MLB market, and also more evident in the ‘latter’ (i.e. post-expansion) period of our data than in the ‘early’ (i.e. ‘pre-expansion’) period. Breaking the analysis down further, discrimination appears to be more prevalent in the competitive MLB market in the latter period than it is in either the competitive market in the early period or the non-competitive market in the latter period, both of which exhibit more discrimination than the non-competitive market in the early period. In terms of customer discrimination, we find substantial evidence of discrimination in greater metropolitan areas with below average nonwhite populations, but less compelling evidence in those with above average non-white population. And finally, in terms of the former areas, discrimination appears to be more widespread in the competitive rather than in the non-competitive MLB market. While the standard prediction regarding the relationship between discrimination and monopsony power is that of a positive relationship, our results appear to indicate a generally *negative* relationship. While this may seem counterintuitive, it is certainly consistent with our theoretical model, which is capable of predicting a negative relationship assuming certain parameter restrictions are in place.

In Table 9a and Table 9b we explore our theoretical prior that wage discrimination across player job assignments interacts with productivity differences between white, black and Hispanic hitters and pitchers. We test this prediction by creating a *Relative Productivity* variable that equals the difference between a player's individual productivity and the mean productivity of players in the other racial/position group multiplied by the player's individual productivity. Thus, in Column (1) of Table 9a, where we focus on white pitchers relative to black hitters, our *Relative Productivity* (*White Pitcher:Black Hitter*) variable is defined as: *Individual White Pitcher Productivity* x (*Individual White Pitcher Productivity* - *Mean Black Hitter Productivity*), where productivity is estimated according to the two-stage process outlined in equations (35)-(38).

There is some tentative evidence from Tables 9a and 9b that relative productivity does affect *ceteris paribus* race-position salary differentials. Whilst white pitcher / black hitter, Hispanic pitcher / black hitter and Hispanic pitcher / white hitter differentials are unaffected by relative productivity, the differential of white pitchers over Hispanic hitters declines, in accordance with our theoretical prior, as the relative productivity of Hispanic hitters rises. Our results for black pitchers are, however, somewhat puzzling. Whilst there are no differences between the salaries of black pitchers and white hitters and black pitchers and Hispanic hitters *ceteris paribus*, the earnings of black pitchers relative to these two groups declines as the relative productivity of black pitchers increases and the relative productivities of Hispanic hitters and white hitters decrease accordingly.

III. 3 *Decomposition Analysis*

In this section, we attempt to identify cross-assignment discrimination using another empirical approach. The fact that players of a particular race in a particular position enjoy a wage differential over players of another race in another position could be a reflection of the former group's greater endowment of 'earning characteristics'. White pitchers may, for example, be more productive or have more experience on average than nonwhite (i.e. black or Hispanic) hitters. Alternatively, white pitchers may be better rewarded for the characteristics they do possess, suggesting some form of positive (negative) discrimination from employers towards white pitchers (nonwhite hitters). To address this issue we perform a Blinder-Oaxaca *decomposition* to separate the earnings differential into an 'endowment component', to account for differences in endowments between individuals, and a 'price component', which is usually associated with discrimination.[19]

Recalling equation (35), we write the earnings function of players of race *j* in position *i* as:

(39) $\ln w^{ij} = \mathbf{X}^{ij}\mathbf{B}^{ij} + \varepsilon^{ij}$

where $i = (W, NW)$ and $j = (H, P)$ denote white and nonwhite and pitchers and hitters respectively, and where $NW = (B, H)$ denotes black and Hispanic respectively. $\mathbf{X}^{ij} = (\mathbf{X}_0^{ij}, \mathbf{X}_1^{ij})$ denotes our vectors of position-specific and common productivity characteristics, $\mathbf{B}^{ij} = (\mathbf{B}_0^{ij}, \mathbf{B}_1^{ij})$ the corresponding coefficient vectors to be estimated, and ε^{ij} some well-behaved error term. Thus, the earnings functions of white pitchers, nonwhite pitchers, white hitters and nonwhite hitters may be denoted:

(40) $\ln w^{WP} = \mathbf{X}^{WP}\mathbf{B}^{WP} + \varepsilon^{WP}$

(41) $\ln w^{NWP} = \mathbf{X}^{NWP}\mathbf{B}^{NWP} + \varepsilon^{NWP}$

(42) $\ln w^{WH} = \mathbf{X}^{WH}\mathbf{B}^{WH} + \varepsilon^{WH}$

(43) $\ln w^{NWH} = \mathbf{X}^{NWH}\mathbf{B}^{NWH} + \varepsilon^{NWH}$

The Blinder-Oaxaca decomposition divides wage differentials into a part that is 'explained' by group differences in productivity and a residual part that cannot be accounted for by such differences in wage determinants. This latter 'unexplained' component is often used as a measure for discrimination. For example, the predicted average white pitcher/nonwhite hitter (WP-NWH) differential may be represented as:

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[19] This method of decomposition, initially proposed by Oaxaca (1973) and Blinder (1973), and later generalized by Oaxaca and Ransom (1994), has been applied extensively to discrimination on the basis of gender, race, caste and religion.

$$\Delta \ln w^{WP-NWH} = \ln w^{WP} - \ln w^{NWH} = \bar{\mathbf{X}}^{WP}\hat{\mathbf{B}}^{WP} - \bar{\mathbf{X}}^{NWH}\hat{\mathbf{B}}^{NWH}$$

(44) $\Rightarrow$

$$\Delta \ln w^{WP-NWH} = \hat{\mathbf{B}}^{NWH}\left(\bar{\mathbf{X}}^{WP} - \bar{\mathbf{X}}^{NWH}\right) + \bar{\mathbf{X}}^{WP}\left(\hat{\mathbf{B}}^{WP} - \hat{\mathbf{B}}^{NWH}\right)$$

The first term, $\hat{\mathbf{B}}^{NWH}\left(\bar{\mathbf{X}}^{WP} - \bar{\mathbf{X}}^{NWH}\right)$, represents differences in endowments between members of the two groups whilst the second term, $\bar{\mathbf{X}}^{WP}\left(\hat{\mathbf{B}}^{WP} - \hat{\mathbf{B}}^{NWH}\right)$, represents differences in rewards. Note that if the overall differential is negative (i.e. $\Delta \ln w^{WP-NWH} < 0$) but the second term is positive [i.e. $\bar{\mathbf{X}}^{WP}\left(\hat{\mathbf{B}}^{WP} - \hat{\mathbf{B}}^{NWH}\right) > 0$], then it would suggest that nonwhite hitters are discriminated against despite earning, on average, more than white hitters - i.e. nonwhite hitters would do even better with the earnings generating function of white pitchers than with their own.

Specification (44) presumes that the nonwhite hitter wage structure prevails in the absence of discrimination. But this is a matter of debate. Assuming away any feelings of malevolence or benevolence from one group towards the other, then it is equally valid to presume that the white pitcher wage structure prevails, thereby requiring (44) to be re-specified as:

(45) $$\Delta \ln w^{WP-NWH} = \hat{\mathbf{B}}^{WP}\left(\bar{\mathbf{X}}^{WP} - \bar{\mathbf{X}}^{NWH}\right) + \bar{\mathbf{X}}^{NWH}\left(\hat{\mathbf{B}}^{WP} - \hat{\mathbf{B}}^{NWH}\right)$$

The first and second terms on the right hand side of (45) still represent differences in endowments and rewards respectively, but they will generally differ from those derived from equation (44).[20] Many authors concede this ambiguity by simply reporting both decompositions. Some, however, have attempted to confront the issue head-on by hypothesizing the non-discriminatory parameter vector, $\bar{\mathbf{B}}$, directly.[21] Reimers (1983), for example, proposes using the average coefficients over both groups as an estimate of $\bar{\mathbf{B}}$. Neumark (1988) advocates using the coefficients from a pooled regression over both groups as an estimate of $\bar{\mathbf{B}}$. In what follows, we follow the 'hybrid' decomposition technique popularized by Cotton (1988) in which the prevailing non-discriminatory

[20] The point that an undervaluation of one group implies an overvaluation of the other is neatly summarized by Cotton (1988, p. 238): '… not only is the group discriminated against undervalued, but the preferred group is overvalued, and the undervaluation of the one subsidizes the overvaluation of the other.'

[21] Oaxaca and Ransom (1994) provide an integrative treatment of the various methods.

wage structure is assumed to be a weighted average of the wage structures of the two groups under consideration:

$$\text{(46)} \quad \Delta \ln w^{WP-NWH} = \bar{X}^{WP}\left(\hat{B}^{WP} - \bar{B}\right) + \bar{X}^{NWH}\left(\bar{B} - \hat{B}^{NWH}\right) + \bar{B}\left(\bar{X}^{WP} - \bar{X}^{NWH}\right)$$

where $\bar{B} = \Omega\hat{B}^{WP} + (1-\Omega)\hat{B}^{NWH}$ represents the estimated non-discriminatory parameter vector, with Ω denoting the proportion of the sample comprised by white pitchers. The first right-hand term in the decomposition is the overpayment enjoyed by white pitchers, the second term is the underpayment suffered by nonwhite hitters, and the third term is the portion of the wage differential that is explained by differences in endowments. We perform the above three decompositions for the white pitcher/nonwhite hitter and white hitter/nonwhite pitcher differentials, and our results, based on the regressions set out in Table 8, are collected in Tables 10a-10d.

Considering Table 10a, our regression model implies a positive salary premium for black hitters over white pitchers *ceteris paribus*. The first decomposition, which follows specification (44) in presuming the black hitter wage structure would prevail in the absence of any discrimination, suggests that this premium would be even greater in the absence of discrimination, with discrimination *against* black hitters alleviating the potential differential by some 33 per cent. The second decomposition, which follows specification (45) in presuming that the white pitcher wage structure would prevail in the absence of discrimination, suggests that discrimination against black hitters alleviates the overall potential differential by a somewhat less, but still considerable, 22 percent. The hybrid decomposition, derived from specification (46), echoes the finding that discrimination assuages the potential black hitter wage premium with white pitcher overpayment and black hitter underpayment reducing the potential premium by approximately 9 per cent and 15 percent respectively.

Table 10b focuses on the white pitcher / Hispanic hitter differential. Our results here imply a positive salary premium for Hispanic hitters over white pitchers *ceteris paribus*. The decomposition of this differential suggests even larger discrimination than that evident in the white pitcher / black hitter differential. Decomposition based on the white pitcher wage structure suggests that discrimination against Hispanic hitters reduces the potential Hispanic hitter premium by over 45 per cent, whilst decomposition based on the Hispanic hitter wage structure puts the figure at 23 per cent. The hybrid decomposition suggests that white pitcher overpayment and Hispanic hitter underpayment offset the potential Hispanic hitter wage premium by approximately 7 per cent and 19 percent respectively.

Tables 10c and 10d focus on the white hitter / black pitcher and white hitter / Hispanic pitcher decomposition. Both decompositions imply a positive salary premium for white hitters. Table 10c suggests that discrimination plays a relative minor role in the white hitter / black pitcher differential, discrimination *against* white hitters reducing the potential white hitter premium by just over 5 per cent according to the black pitcher wage structure, and just under 2 per cent according to the white hitter wage structure. The hybrid decomposition implies white hitter overpayment and black pitcher underpayment reduce the differential by 1 per cent and 1.5 per cent respectively.

It would appear that discrimination plays a much more significant role in the white hitter / Hispanic pitcher differential. According to Table 10d, discrimination *against* white hitters reduces the potential differential by 46 per cent according to the Hispanic pitcher wage structure and by 30 per cent according to the white hitter wage structure. The hybrid decomposition suggests that white hitter overpayment and Hispanic pitcher underpayment reduces the potential white hitter premium by 9 per cent and 24 per cent respectively.

IV. Concluding Remarks

In this study, we address a previously un-researched problem in the literature on taste discrimination in pay: Ascertaining the extent to which racial or gender differences in pay across job assignments are attributable to prejudice. Nearly all wage discrimination studies have focused on discrimination within the same job assignment, thus treating whites and nonwhites (or males and females) as perfect substitutes. We extend the theory to the case of discrimination across job assignments where assignments are viewed as distinct inputs. Our theoretical findings underscore the importance of carefully considering the production function when there are productivity differences between majority and minority workers. An important finding from our theoretical analysis is that the magnitude of white/nonwhite productivity differences influences the amount of discrimination. Furthermore, when whites and nonwhites are interrelated in production, race and productivity will interact. This is an important implication, for it means that *whenever* white and nonwhite workers have productivity differences, the researcher should include productivity x race interactions in any empirical specification.

We tested our model using data from Major League Baseball, an industry characterized by complementary job assignments, a history of racial integration and discrimination, and a dual labour market structure. We found convincing evidence of racial differences in pay across player job assignments, even after controlling for a wide array of demographic variables and position-specific productivity. Moreover, we find strong evidence of our theoretical prior that racial pay differentials across assignments are affected by changes in relative productivities.

This study can be seen as making three contributions. First, it extends the traditional theory of 'within-job assignment/occupation' discrimination to the case of discrimination across job assignments/occupations. It was found that when the traditional discrimination model was extended in this manner, novel predictions were obtained. Second, the study extends our understanding of the effects of labour market structure on pay discrimination. Third, we provide several novel empirical methodologies appropriate for the study of cross-assignment discrimination. One potentially fruitful theoretical extension of this work would be a general equilibrium approach in which occupational segregation and wage discrimination are both endogenous. Our theory and empirical strategies are sufficiently general that they can be applied to a wide variety of industries and data sets.

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Table 1: The Effects of Prejudice on Discrimination under Perfect Competition

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	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note:[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 2: The Effects of Prejudice on Employment, Wages and Discrimination

pA	*f*	*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 3: The Effects of White / Nonwhite Productivity Differences on Employment, Wages and Discrimination

pA	*f*	*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 4: Wage Discrimination When Monopsony Power Varies

D	*pA*	*1/f*	*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 5: Taste Discrimination When There is Monopsonistic Wage Discrimination

D	εf	λf	*MDC* $\alpha = \beta = 0.4$	*MDC* $\alpha = 0.7$, $\beta = 0.1$	*MDC* $\alpha = 0.1$, $\beta = 0.7$
0.8	1	0.5	0.1429	0.3695	0.0588
0.8	1	1	0.1180	0.3123	0.0446
0.8	1	2	0.0888	0.2286	0.0306
0.8	1	3	0.0723	0.1769	0.0249
0.8	1	4	0.0614	0.1432	0.0216
0.8	1	5	0.0536	0.1199	0.0193
0.8	1	10	0.0333	0.0654	0.0131
0.8	1	20	0.0197	0.0341	0.0084
0.8	1	50	0.009	0.0141	0.0043
0.8	1	100	0.005	0.0073	0.0025

Note:[i] All calculations assume values of A = 5 and p =2

Table 6: Descriptive Statistics: Hitters

	All		*White*		*Black*		*Hispanic*	
Variable	*Mean*	*Std. Dev*	*Mean*	*Std. Dev*	*Mean*	*Std. Dev*	*Mean*	*Std. Dev*
Personal Characteristics								
Log Annual Salary	13.890	1.13	13.865	1.10	13.938	1.13	13.866	1.22
Age	30.304	3.70	30.596	3.49	30.488	3.95	29.023	3.55
White	0.502	0.500	-	-	-	-	-	-
Black	0.336	0.472	-	-	-	-	-	-
Hispanic	0.162	0.369	-	-	-	-	-	-
Professional Characteristics								
MLB Experience	7.061	3.89	7.062	3.87	7.223	4.07	6.723	3.55
MLB Experience-Squared	64.957	69.31	64.785	70.06	68.684	74.23	57.763	54.59
Tenure with Current Club	2.672	3.00	3.062	3.38	2.305	2.62	2.226	2.24
Free Agent	0.600	0.49	0.598	0.49	0.605	0.49	0.599	0.49
Eligible for Final Offer Arbitration	0.296	0.46	0.304	0.46	0.294	0.46	0.271	0.45
American League	0.514	0.50	0.521	0.50	0.469	0.50	0.588	0.49
National League	0.486	0.50	0.479	0.50	0.057	0.23	0.124	0.33
Canadian Team	0.073	0.26	0.067	0.25	7.223	4.07	6.723	3.55
Performance								
At Bats	2506.414	2001.58	2419.738	1940.51	2699.202	2198.95	2375.525	1720.23
Stolen Bases	69.746	112.52	44.800	72.35	111.055	157.89	61.480	69.63
Bases on Balls	254.275	247.74	253.131	233.32	285.349	293.87	193.39	161.14
Total Bases	1060.200	913.52	1016.772	880.39	1162.845	1013.19	982.073	771.85
Slugging Average	0.407	0.06	0.404	0.06	0.416	0.06	0.397	0.07
Batting Average	0.267	0.03	0.264	0.02	0.271	0.02	0.266	0.02
Infielder	0.459	0.50	0.556	0.50	0.281	0.45	0.531	0.50
Outfielder	0.383	0.49	0.217	0.41	0.657	0.48	0.333	0.47
Catcher	0.116	0.32	0.189	0.39	0.016	0.13	0.096	0.30
Designated Hitter	0.059	0.24	0.046	0.21	0.079	0.27	0.056	0.23
Greater Metro Area Characteristics								
Percentage White	80.507	6.89	80.938	6.77	80.683	6.72	78.808	7.39
Percentage Black	13.273	6.58	12.959	6.60	13.676	6.62	13.409	6.44
Percentage Hispanic	10.621	10.65	10.719	10.80	10.331	10.58	10.918	10.36
Average Annual Income ($)	25562.990	3789.65	25508.570	3757.99	25551.300	3731.59	25756.00	4016.17
Population[1]	5514009	4657988	5313189	4509095	5513759	4729589	6137413	4927354
Year Dummies								
1992	0.250	0.43	0.255	0.44	0.243	0.43	0.249	0.43
1993	0.235	0.42	0.248	0.44	0.237	0.43	0.192	0.40
1997	0.260	0.44	0.248	0.43	0.270	0.44	0.277	0.45
1998	0.255	0.44	0.250	0.43	0.251	0.43	0.282	0.45
Sample Size	1093		549		367		177	

Note: 1. Population denotes the greater metro area population.
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

	All		*White*		*Black*		*Hispanic*	
Variable	*Mean*	*Std. Dev*	*Mean*	*Std. Dev*	*Mean*	*Std. Dev*	*Mean*	*Std. Dev*
Personal Characteristics								
Log Annual Salary	13.409	1.19	13.451	1.20	13.238	1.16	13.276	1.18
Age	29.815	4.09	30.190	4.02	29.016	4.00	27.948	4.03
White	0.782	0.41	-	-	-	-	-	-
Black	0.105	0.31	-	-	-	-	-	-
Hispanic	0.162	0.37	-	-	-	-	-	-
Professional Characteristics								
MLB Experience	5.988	4.20	6.158	4.20	5.772	4.49	5.000	3.75
MLB Experience-Squared	53.468	76.64	55.562	78.38	53.331	75.31	38.985	63.34
Tenure with Current Club	1.924	2.07	1.935	2.10	1.843	1.97	1.926	1.99
Free Agent	0.467	0.50	0.482	0.50	0.441	0.50	0.385	0.49
Eligible for Final Offer Arbitration	0.306	0.46	0.314	0.46	0.236	0.43	0.319	0.47
American League	0.513	0.50	0.518	0.50	0.543	0.50	0.452	0.50
National League	0.487	0.50	0.475	0.50	0.528	0.50	0.556	0.50
Canadian Team	0.069	0.25	0.063	0.24	0.055	0.23	0.126	0.33
Performance								
Starter	0.442	0.50	0.441	0.50	0.402	0.49	0.489	0.50
Wins	37.446	44.33	39.007	45.27	34.386	42.41	29.430	38.34
Losses	34.179	37.05	35.904	38.37	29.236	30.11	26.785	32.12
Games Started	74.12	105.53	77.769	108.53	59.646	92.16	62.274	93.98
Complete Games	10.15	22.24	10.981	23.33	6.433	14.87	7.844	19.65
Shutouts	2.875	6.08	3.065	6.32	1.984	4.74	2.385	5.35
Saves	19.488	51.87	20.941	52.93	19.362	62.60	9.474	26.16
Homeruns	56.517	62.57	58.842	64.46	50.409	52.94	46.044	56.11
Walks	225.779	249.73	231.782	257.66	224.095	217.58	185.474	217.41
Strikeouts	436.641	514.13	450.726	530.21	436.047	490.18	338.919	402.35
Innings Pitched	627.59	702.43	655.160	720.78	558.969	620.14	499.785	627.21
ERA	4.025	0.96	3.995	0.94	4.175	1.11	4.094	0.97
Strikeout Rate	0.078	0.02	0.078	0.02	0.083	0.02	0.079	0.02
Greater Metro Area Characteristics								
Percentage White	80.714	6.84	80.695	6.91	80.335	6.56	81.201	6.59
Percentage Black	13.038	6.46	12.946	6.49	14.026	6.46	12.750	6.19
Percentage Hispanic	10.975	10.77	10.899	10.61	10.909	10.40	11.573	12.20
Average Annual Income ($)	25488.2	3939.85	25491.51	3895.30	25852.23	3898.44	25122.19	4271.98
Population[1]	5551948	4683875	5481401	4631793	6035905	4915887	5588930	4829139
Year Dummies								
1992	0.221	0.42	0.236	0.42	0.189	0.39	0.148	0.36
1993	0.239	0.43	.248	0.43	0.244	0.43	0.170	0.38
1997	0.264	0.44	.256	0.44	0.276	0.45	0.311	0.46
1998	0.276	0.45	.260	0.44	0.291	0.46	0.370	0.48
Sample Size	1204		942		127		135	

Note: 1. Population denotes the greater metro area population.

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: Discrimination Controlling for Position Specific Productivity
Dependent Variable: Log Annual Salary

	(1) All Default – White Pitcher		(2) All Default - Black Pitcher		(3) All Default – Hispanic Pitcher		(4) All Default – White Hitter		(5) All Default - Black Hitter		(6) All Default - Hispanic Hitter	
	Coef	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*
Imputed Productivity	0.863	34.05	0.863	34.05	0.863	34.05	0.863	34.05	0.863	34.05	34.05	34.05
Race Dummies												
White Pitcher	**-**	**-**	**0.164**	**2.69**	**-0.005**	**-0.09**			**0.106**	**2.60**	**0.092**	**1.79**
Black Pitcher	**-0.164**	**-2.69**	**-**	**-**	**-0.170**	**-2.15**	**0.006**	**0.09**			**-0.072**	**-0.98**
Hispanic Pitcher	**0.005**	**0.09**	**0.170**	**2.15**	**-**	**-**	**0.176**	**2.81**	**0.112**	**1.70**		
White Hitter			**-0.006**	**-0.09**	**-0.176**	**-2.81**	**-**	**-**	**-0.064**	**-1.52**	**-0.078**	**-1.46**
Black Hitter	**-0.106**	**-2.70**			**-0.112**	**-1.70**	**0.064**	**1.52**	**-**	**-**	**-0.014**	**-0.25**
Hispanic Hitter	**-0.092**	**-1.79**	**0.072**	**0.98**			**0.078**	**1.46**	**0.014**	**0.25**	**-**	**-**
Professional Characteristics												
Age	-0.024	-3.27	-0.024	-3.27	-0.024	-3.27	-0.024	-3.27	-0.024	-3.27	-0.024	-3.27
MLB Experience	0.152	3.45	0.152	3.45	0.152	3.45	0.152	3.45	0.152	3.45	0.152	3.45
MLB Experience-Squared	-0.010	-4.79	-0.010	-4.79	-0.010	-4.79	-0.010	-4.79	-0.010	-4.79	-0.010	-4.79
Tenure	0.056	10.00	0.056	10.00	0.056	10.00	0.056	10.00	0.056	10.00	0.056	10.00
Free Agent	0.879	6.14	0.879	6.14	0.879	6.14	0.879	6.14	0.879	6.14	0.879	6.14
Final Offer Arbitration	0.471	5.94	0.471	5.94	0.471	5.94	0.471	5.94	0.471	5.94	0.471	5.94
American League	-0.006	-0.23	-0.006	-0.23	-0.006	-0.23	-0.006	-0.23	-0.006	-0.23	-0.006	-0.23
Canadian	-0.022	-0.21	-0.022	-0.21	-0.022	-0.21	-0.022	-0.21	-0.022	-0.21	-0.022	-0.21
Greater Metro Area Characteristics												
Percent White	0.001	0.34	0.001	0.34	0.001	0.34	0.001	0.34	0.001	0.34	0.001	0.34
Percent Black	0.005	1.24	0.005	1.24	0.005	1.24	0.005	1.24	0.005	1.24	0.005	1.24
Percent Hispanic	0.005	3.39	0.005	3.39	0.005	3.39	0.005	3.39	0.005	3.39	0.005	3.39
Average Annual Income	0.000	1.45	0.000	1.45	0.000	1.45	0.000	1.45	0.000	1.45	0.000	1.45
Population	0.000	0.11	0.000	0.11	0.000	0.11	0.000	0.11	0.000	0.11	0.000	0.11
Year Dummies												
1993	0.051	1.31	0.051	1.31	0.051	1.31	0.051	1.31	0.051	1.31	0.051	1.31
1997	0.046	0.97	0.046	0.97	0.046	0.97	0.046	0.97	0.046	0.97	0.046	0.97
1998	0.130	2.44	0.130	2.44	0.130	2.44	0.130	2.44	0.130	2.44	0.130	2.44
Constant	0.994	1.63	0.830	1.37	0.100	1.65	0.824	1.34	0.888	1.44	0.902	1.48
R-Squared	0.7360		0.7360		0.7360		0.7360		0.7360		0.7360	
F-Statistic	$422.35_{22, 2274}$		$422.35_{22, 2274}$		$422.35_{22, 2274}$		$422.35_{22, 2274}$		$422.35_{22, 2274}$		$422.35_{22, 2274}$	
Root Mean Squared Error	0.61289		0.61289		0.61289		0.61289		0.61289		0.61289	
Observations	2297		2297		2297		2297		2297		2297	

Table 9a: Discrimination Controlling for Position Specific Productivity and Relative Productivity (Pitchers – Hitters)
Dependent Variable: Log Annual Salary

	(1) White Pitchers / Black Hitters		(2) White Pitchers / Hispanic Hitters		(3) Black Pitchers / White Hitters		(4) Black Pitchers / Hispanic Hitters		(5) Hispanic Pitchers / White Hitters		(6) Hispanic Pitchers / Black Hitters	
	Coef	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*
Imputed Productivity	0.894	18.94	0.998	18.13	0.882	17.03	0.974	13.87	0.874	17.32	0.960	16.49
Race Dummies												
White Pitcher	0.108	2.63	0.102	1.90	-	-	-	-	-	-	-	-
Black Pitcher	-	-	-	-	-0.061	-0.92	-0.125	-1.68	-	-	-	-
Hispanic Pitcher	-	-	-	-	-	-	-	-	0.240	2.60	0.201	1.98
Relative Productivity												
White Pitcher: Black Hitter	-0.003	-0.90	-	-	-	-	-	-	-	-	-	-
White Pitcher: Hispanic Hitter	-	-	-0.013	-2.99	-	-	-	-	-	-	-	-
Black Pitcher: White Hitter	-	-	-	-	-0.018	-3.85	-	-	-	-	-	-
Black Pitcher: Hispanic Hitter	-	-	-	-	-	-	-0.018	-3.49	-	-	-	-
Hispanic Pitcher: White Hitter	-	-	-	-	-	-	-	-	0.007	0.95		
Hispanic Pitcher: Black Hitter	-	-	-	-	-	-	-	-	-	-	0.003	0.50
Constant	0.808	-0.85	-0.783	-0.79	0.047	0.04	-3.335	2.03	0.596	0.53	-1.285	-0.96
R-Squared	0.7483		0.7632		0.7194		0.7837		0.7203		0.7346	
F-Statistic	$323.49_{19, 1289}$		$315.75_{19, 1099}$		$127.73_{19, 656}$		$99.30_{19, 284}$		$132.23_{19, 664}$		$105.17_{19, 482}$	
Root Mean Squared Error	0.60484		0.59354		0.61113		0.59296		0.61166		0.61851	
Observations	1309		1119		676		304		684		502	

Notes: 1. Other explanatory regressors were those set out in Table 8; 2. 'Relative Productivity' is defined as, e.g., 'White Pitcher: Black Hitter' = Individual White Pitcher Productivity x (Individual White Pitcher Productivity - Mean Black Hitter Productivity).

Table 9b: Discrimination Controlling for Position Specific Productivity and Relative Productivity (Hitters – Pitchers)
Dependent Variable: Log Annual Salary

	(1) White Hitters / Black Pitchers		(2) White Hitters / Hispanic Pitchers		(3) Black Hitters / White Pitchers		(4) Black Hitters / Hispanic Pitchers		(5) Hispanic Hitters / White Pitchers		(6) Hispanic Hitters / Black Pitchers	
	Coef	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*	*Coef*	*T-Stat*
Imputed Productivity	0.635	10.38	0.950	10.27	0.862	23.55	1.012	10.48	0.838	22.05	0.730	10.17
Race Dummies												
White Hitters	-0.030	-0.47	-0.189	-2.75	-	-	-	-	-	-	-	-
Black Hitters	-	-	-	-	-0.109	-2.57	-0.168	-2.24	-	-	-	-
Hispanic Hitters	-	-	-	-	-	-	-	-	-0.137	-2.42	0.052	0.70
Relative Productivity												
White Hitter: Black Pitcher	0.018	4.12	-	-	-	-	-	-	-	-	-	-
White Hitter: Hispanic Pitcher	-	-	-0.005	-0.84	-	-	-	-	-	-	-	-
Black Hitter: White Pitcher	-	-	-	-	-0.000	-0.11	-	-	-	-	-	-
Black Hitter: Hispanic Pitcher	-	-	-	-	-	-	-0.004	-0.65	-	-	-	-
Hispanic Hitter: White Pitcher	-	-	-	-	-	-	-	-	0.007	1.90		
Hispanic Hitter: Black Pitcher	-	-	-	-	-	-	-	-	-	-	0.018	3.65
Constant	3.386	2.60	-0.211	-0.13	1.346	1.67	-1.800	-1.05	1.511	1.82	-0.096	-0.06
R-Squared	0.7200		0.7727		0.7481		0.7347		0.7620		0.7840	
F-Statistic	$132.29_{19, 656}$		$132.82_{19, 664}$		$321.88_{19, 1289}$		$104.98_{19, 482}$		$309.12_{19, 1099}$		$101.52_{19, 284}$	
Root Mean Squared Error	0.61053		0.61184		0.60507		0.61840		0.59513		0.59260	
Observations	676		684		1309		502		1119		304	

Notes: 1. Other explanatory regressors were those set out in Table 8; 2. 'Relative Productivity' is defined as, e.g., 'White Hitter: Black Pitcher = Individual White Hitter Productivity x (Individual White Hitter Productivity - Mean Black Pitcher Productivity).

Table 10a: Oaxaca-Cotton Decompositions: White Pitcher / Black Hitter

$\Delta \ln w^{WP-BH} = \ln w^{WP} - \ln w^{BH}$

		Coef.	*%*
Black Hitter Wage Structure			
Endowment Effect:	$\hat{B}^{BH}\left(\bar{X}^{WP}-\bar{X}^{BH}\right)$	-0.649	*133.29*
Price Effect:	$\bar{X}^{WP}\left(\hat{B}^{WP}-\hat{B}^{BH}\right)$	0.162	*-33.29*
Total Differential:	$\hat{B}^{BH}\left(\bar{X}^{WP}-\bar{X}^{BH}\right)+\bar{X}^{WP}\left(\hat{B}^{WP}-\hat{B}^{BH}\right)$	-0.487	*100.00*
White Pitcher Wage Structure			
Endowment Effect:	$\hat{B}^{WP}\left(\bar{X}^{WP}-\bar{X}^{BH}\right)$	-0.591	*121.49*
Price Effect:	$\bar{X}^{BH}\left(\hat{B}^{WP}-\hat{B}^{BH}\right)$	0.104	*-21.49*
Total Differential:	$\hat{B}^{WP}\left(\bar{X}^{WP}-\bar{X}^{BH}\right)+\bar{X}^{BH}\left(\hat{B}^{WP}-\hat{B}^{BH}\right)$	-0.487	*100.00*
Hybrid Wage Structure			
White Pitcher Overpayment:	$\bar{X}^{WP}\left(\hat{B}^{WP}-\bar{B}\right)$	0.045	*-9.33*
Black Hitter Underpayment:	$\bar{X}^{BH}\left(\bar{B}-\hat{B}^{BH}\right)$	0.075	*-15.47*
Endowment Effect:	$\bar{B}\left(\bar{X}^{WP}-\bar{X}^{BH}\right)$	-0.607	*124.80*
Total Differential:	$\bar{X}^{WP}\left(\hat{B}^{WP}-\bar{B}\right)+\bar{X}^{BH}\left(\bar{B}-\hat{B}^{BH}\right)+\bar{B}\left(\bar{X}^{WP}-\bar{X}^{BH}\right)$	-0.487	*100.00*

Table 10b: Oaxaca-Cotton Decompositions: White Pitcher / Hispanic Hitter

$\Delta \ln w^{WP-HH} = \ln w^{WP} - \ln w^{HH}$

		Coef.	*%*
Hispanic Hitter Wage Structure			
Endowment Effect:	$\hat{B}^{HH}\left(\bar{X}^{WP}-\bar{X}^{HH}\right)$	-0.604	*145.33*
Price Effect:	$\bar{X}^{WP}\left(\hat{B}^{WP}-\hat{B}^{HH}\right)$	0.189	*-45.33*
Total Differential:	$\hat{B}^{HH}\left(\bar{X}^{WP}-\bar{X}^{HH}\right)+\bar{X}^{WP}\left(\hat{B}^{WP}-\hat{B}^{HH}\right)$	-0.416	*100.00*
White Pitcher Wage Structure			
Endowment Effect:	$\hat{B}^{WP}\left(\bar{X}^{WP}-\bar{X}^{HH}\right)$	-0.512	*123.12*
Price Effect:	$\bar{X}^{HH}\left(\hat{B}^{WP}-\hat{B}^{HH}\right)$	0.096	*-23.12*
Total Differential:	$\hat{B}^{WP}\left(\bar{X}^{WP}-\bar{X}^{HH}\right)+\bar{X}^{HH}\left(\hat{B}^{WP}-\hat{B}^{HH}\right)$	-0.416	*100.00*
Hybrid Wage Structure			
White Pitcher Overpayment:	$\bar{X}^{WP}\left(\hat{B}^{WP}-\bar{B}\right)$	0.030	*-7.17*
Hispanic Hitter Underpayment:	$\bar{X}^{HH}\left(\bar{B}-\hat{B}^{HH}\right)$	0.081	*-19.46*
Endowment Effect:	$\bar{B}\left(\bar{X}^{WP}-\bar{X}^{HH}\right)$	-0.527	*126.63*
Total Differential:	$\bar{X}^{WP}\left(\hat{B}^{WP}-\bar{B}\right)+\bar{X}^{HH}\left(\bar{B}-\hat{B}^{HH}\right)+\bar{B}\left(\bar{X}^{WP}-\bar{X}^{HH}\right)$	-0.416	*100.00*

Table 10c: Oaxaca-Cotton Decompositions: White Hitter / Black Pitcher

$\Delta \ln w^{WH-BP} = \ln w^{WH} - \ln w^{BP}$

		Coef.	%
Black Pitcher Wage Structure			
Endowment Effect:	$\hat{B}^{BP}\left(\bar{X}^{WH} - \bar{X}^{BP}\right)$	0.660	*105.27*
Price Effect:	$\bar{X}^{WH}\left(\hat{B}^{WH} - \hat{B}^{BP}\right)$	-0.033	*-5.27*
Total Differential:	$\hat{B}^{BP}\left(\bar{X}^{WH} - \bar{X}^{BP}\right) + \bar{X}^{WH}\left(\hat{B}^{WH} - \hat{B}^{BP}\right)$	0.627	*100.00*
White Hitter Wage Structure			
Endowment Effect:	$\hat{B}^{WH}\left(\bar{X}^{WH} - \bar{X}^{BP}\right)$	0.639	*101.89*
Price Effect:	$\bar{X}^{BP}\left(\hat{B}^{WH} - \hat{B}^{BP}\right)$	-0.012	*-1.89*
Total Differential:	$\hat{B}^{WH}\left(\bar{X}^{WH} - \bar{X}^{BP}\right) + \bar{X}^{BP}\left(\hat{B}^{WH} - \hat{B}^{BP}\right)$	0.627	*100.00*
Hybrid Wage Structure			
White Hitter Overpayment:	$\bar{X}^{WH}\left(\hat{B}^{WH} - \bar{B}\right)$	-0.006	*-0.99*
Black Pitcher Underpayment:	$\bar{X}^{BP}\left(\bar{B} - \hat{B}^{BP}\right)$	-0.010	*-1.53*
Endowment Effect:	$\bar{B}\left(\bar{X}^{WH} - \bar{X}^{BP}\right)$	0.643	*102.52*
Total Differential:	$\bar{X}^{WH}\left(\hat{B}^{WH} - \bar{B}\right) + \bar{X}^{BP}\left(\bar{B} - \hat{B}^{BP}\right) + \bar{B}\left(\bar{X}^{WH} - \bar{X}^{BP}\right)$	0.627	*100.00*

Table 10d: Oaxaca-Cotton Decompositions: White Hitter / Hispanic Pitcher

$\Delta \ln w^{WH-HP} = \ln w^{WH} - \ln w^{HP}$

		Coef.	%
Hispanic Pitcher Wage Structure			
Endowment Effect:	$\hat{B}^{HP}\left(\bar{X}^{WH} - \bar{X}^{HP}\right)$	0.859	*145.76*
Price Effect:	$\bar{X}^{WH}\left(\hat{B}^{WH} - \hat{B}^{HP}\right)$	-0.270	*-45.76*
Total Differential:	$\hat{B}^{HP}\left(\bar{X}^{WH} - \bar{X}^{HP}\right) + \bar{X}^{WH}\left(\hat{B}^{WH} - \hat{B}^{HP}\right)$	0.589	*100.00*
White Hitter Wage Structure			
Endowment Effect:	$\hat{B}^{WH}\left(\bar{X}^{WH} - \bar{X}^{HP}\right)$	0.765	*129.86*
Price Effect:	$\bar{X}^{HP}\left(\hat{B}^{WH} - \hat{B}^{HP}\right)$	-0.176	*-29.86*
Total Differential:	$\hat{B}^{WH}\left(\bar{X}^{WH} - \bar{X}^{HP}\right) + \bar{X}^{HP}\left(\hat{B}^{WH} - \hat{B}^{HP}\right)$	0.589	*100.00*
Hybrid Wage Structure			
White Hitter Overpayment:	$\bar{X}^{WH}\left(\hat{B}^{WH} - \bar{B}\right)$	-0.053	*-9.03*
Hispanic Pitcher Underpayment:	$\bar{X}^{HP}\left(\bar{B} - \hat{B}^{HP}\right)$	-0.141	*-23.96*
Endowment Effect:	$\bar{B}\left(\bar{X}^{WH} - \bar{X}^{HP}\right)$	0.784	*132.99*
Total Differential:	$\bar{X}^{WH}\left(\hat{B}^{WH} - \bar{B}\right) + \bar{X}^{HP}\left(\bar{B} - \hat{B}^{HP}\right) + \bar{B}\left(\bar{X}^{WH} - \bar{X}^{HP}\right)$	0.589	*100.00*