Swinging for the Stars

Revisiting Racial Wage Discrimination in Major League Baseball

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Abstract

I do not find evidence of racial wage discrimination in Major League Baseball over the 2004-2019 seasons. Previous work has shown discrimination against black players in earlier years. Palmer and King (2006) and Holmes (2011) showed that on the low end of the salary distribution black players were paid up to 20% less than white and Latino players in the years 1998-2006. I introduce several new measures of marginal product that allow for more complete evaluation of player value. My results consistently indicate that there is not evidence of white players being paid more than black players in the years 2004-2019, and suggest a premium for Latino players. This premium exists for the subset of Latinos that are black as well. This premium is unexpected but could reflect fan preferences or issues with performance measures. Replication of older work on the years 2015-2019 supports a lack of discrimination against black players and does not support a Latino premium.

1 Introduction

The metrics used to evaluate baseball players have improved since earlier work found evidence of discrimination. This has driven change in the way teams are able to value players, and allows for better estimation by researchers. I use regression models that retain the structure of earlier work while introducing modern player performance measures. I conduct quantile regression in addition to least squares regression to parse out the effects at different points of the salary distribution. An observation is a player that was signed as a free agent in the seasons 2004-2019. Since salaries given to free agents are decided on an open market, they are the set of salaries that most closely match the true expected marginal product of a player. The dependent variable is the logarithm of first year salary in the new contract, since the first year is the again the most representative of expected player performance.

I fail to find evidence that black players are still underpaid at the low end of the salary distribution. There was no statistically significant evidence of differences between white and black player salaries at any level. There was some evidence for a systemic wage premium for Latino players at all salary levels over both white and black players.

1.1 Literature

Sports labor markets are conducive to examining discrimination since marginal product is relatively easy to measure. Without accurate measures of marginal product, discrimination can become indistinguishable from systemic differences in marginal product across groups. Since baseball began integrating in 1947, evidence of discrimination in Major League Baseball (MLB) has been found in several different aspects of the labor market. Pascal and Rapping (1972) found that white rookies got higher bonuses than similarly skilled black rookies throughout the 1950s. Scully (1974) argued that there was evidence that black players had a harder time remaining in the league than whites as their careers progressed. Jiobu (1988) found similar results for different years by analyzing career length. Bellmore (2001) found that the 60's and 70's saw black players promoted from the minors to the majors at a lower rate. While all these issues were evidence that forms of discrimination were happening in MLB, there was not clear evidence that white players were paid more than black players of similar skill. In two literature reviews on sports discrimination, Kahn (1991, 2000) found a lack of evidence that race was a determinant of salary in MLB.

More recent work has considered the possibility of differing effects across the salary distribution. Both Palmer and King (2006) and Holmes (2011) found that at lower salary levels, black hitters receive lower salaries than white hitters of similar skill levels but found conflicting results for Latino players. Palmer and King simply bucketed players in into low, medium, and high salary groups for the 2001 season and ran separate analyses for each group. For the low bucket, they found evidence of race as a determinant of lower salaries for black and Latino players. Holmes (2011) found similar results to Palmer and King, but used more stringent data selection criteria. Holmes considered only free agents over the years 1998-2006 and had rudimentary measures of defensive skill and player speed in the model. Using quantile regression he was able to show that both black and Latino players had incomes that were discounted by up to 20% from white salaries and that the effect persisted up to the fiftieth percentile of the salary distribution.

Baseball has always used statistics to evaluate players, and has seen evolution in its metrics over time. The movie *Moneyball* has entered the common lexicon in a way such that it tends to dominate the discussion around statistics in baseball. The reality is that growth in measuring the value of baseball players was happening before and after the events in 2002 that the movie covers. It was Bill James' work in the 1980s created some of the statistics used in Holmes' estimation. Serious changes in data collection and measurement have taken place since the years that Holmes and Palmer and King's work covers. As an example, ball tracking technology introduced in 2007 has reached the point that the velocities and trajectories of every movement of the ball on the field are recorded.[1] As this sort of data has accumulated, every action by a player can be compared to a set of historical situations and their relative skill can be measured. A defensive play that in the past would have been recorded simply as a catch now can be quantified in terms of probability of the ball being caught. The result is statistics that do not just count outcomes but instead weigh outcomes on their value to the team. Variants of this process underpin the construction of the defensive metrics I use: Ultimate Zone Rating and Defensive Runs Saved.

2 Theory

2.1 Theoretical treatment of discrimination

From Becker (2010) the traditional discrimination model offers three sources of wage discrimination: personal prejudice, statistical pre-judgement and non-competitive forces. Given the open nature of a player's performance, statistical pre-judgement does not have much basis as a source of discrimination in MLB. When considering free agents, there are no clear non-competitive forces. Discrimination arising in MLB is likely an expression of personal prejudice. When considering personal prejudice as a motive for discrimination, there are three parties that may be the discriminator: employees, employers, and consumers.

Employee discrimination in MLB would lead to a group requiring higher wages to play on a team with high numbers of a group they are prejudiced against. The plausibility of employee discrimination affecting

[1] https://tht.fangraphs.com/how-will-ball-tracking-analysis-change-the-game/

salary is low. No team in MLB is racially homogeneous, and players who sign as free agents are usually not able to observe the racial breakdown of a team when they sign. Players and teams prefer to sign free agents prior to the period of pre-season practices known as Spring Training, and it is only after Spring Training that the team is decided upon. Even after Spring Training, trades, injuries, and player promotions can change the composition of a team at any time.

Employer discrimination is defined by a preference on the part of employers to employ certain groups. Consider the case of an employer who prefers white laborers to minority laborers. As a result of this preference, they will discount the marginal revenue productivity of minority workers when offering salaries. In a market where only some firms discriminate, those firms will be less profitable than the nondiscriminatory firms. In the long run in competitive markets, discriminatory firms will lose market share or be bought out by owners that can increase profitability by halting discrimination. If there are barriers to competition, different results may occur. Baseball is a market where employers could take lower profits indefinitely and maintain their rights to a geographic region and to revenue sharing within the league. If all or many employers in MLB prefer a group of players, a wage gap based on employer preference could emerge.

Customer prejudice is another possible source of discrimination. It may be that consumers prefer a certain group of workers to serve them or interact with them. For example, a predominantly white consumer base may prefer white performers to minority performers. In this scenario, the value of a minority worker to an employer is diminished because of the prejudice of the customer. Firms will now maximize profits through discrimination instead of through fair treatment, and unlike employer prejudice, market forces will not end the discrimination. A wage gap again is expected to emerge for minority workers. In particular, employers will seek to hire primarily white workers in roles that are more visible to consumers.

In the case of employer or consumer discrimination it is possible that a wage premium may emerge for the preferred group of employees. It is also possible that in MLB employer or consumer discrimination may create a wage premium only at the low end of the salary distribution. A baseball team has 25 players on the roster, but of that roster, about 12 to 14 players will take the majority of playing time since teams typically have a consistent set of 8 starting fielders and 4 to 6 starting pitchers. This set of players determines most of the performance of the team, so the quality of these players matters much more than the rest of the team. Employers and consumers care about team performance, so discrimination is more costly among this set of players. This cost may push employers or consumers to set aside their tastes in favor of team success. It is possible that either consumer or employer prejudice underpinned earlier salary discrimination.

2.2 The Labor Market in MLB

In many markets, data on worker production is obscure and must be proxied. MLB offers very publicly available and comprehensive metrics for measuring production. The primary unit of measure of a baseball player's production is the outcome of a plate appearance. A player can have one of three roles in a plate appearance: the batter, pitcher, or a defensive player. I do not consider pitchers in this analysis. The performance of a player in the role of batter is discretely determined by his plate appearances and is almost exclusively determined by the actions of the himself, the player pitching to him and the defender who attempts to field his hits. Measurement of the velocity and trajectory of the ball at all stages of this three-way interaction can explain how well the batter and defensive player have performed relative to historical data. Over the course of a season, a starting player can have over 400 plate appearances in over 120 games and a coinciding amount of time playing defense, creating a large enough sample to iron out random variation. For these reasons, MLB has been and will continue to be an ideal market to investigate wage discrimination.

While the recent literature finds that discrimination exists at low wage levels, new data will allow for much more thorough models. Earlier models did not include thorough treatments of defense or player fame when estimating salary. Advanced defensive metrics constructed with data from new ball tracking technology have made rigorous quantification of defensive value possible. Statistics like Defensive Runs Saved and Ultimate Zone Rating are built on massive databases that have been compiled only since the 90s. These statistics do not exist in a vacuum, but rather compare a players' success rate to decades of other players' success in identical situations to determine the value added.

Since fame and rigorous measures of defense have not been in earlier models, some justification for their inclusion is in order, as well as description of expected effects. Fame can be considered the effect a player has on fan propensity to consume the team's product. The source of fame does not affect the model but may come from past performance, current performance, or actions taken outside of MLB. Consider a simple model of an MLB team as a profit maximizing firm with three revenue streams: TV advertisements, ticket sales, and merchandise sales. In a year, some consumers will watch games, attend games, and buy merchandise regardless of team performance or player fame. Many other consumers will consume in proportion to the level of interest in a team. Two primary factors that drive interest in a team are team success and the level of interest in individual players. A firm with some controversial or highly skilled players can draw additional revenue on the strength of consumer interest in those players. Similarly, a team that wins many games can draw interest. With more consumers interested in a team, ticket prices, TV revenue and merchandise sales rise. For this reason, wins and player fame are the main drivers of team revenue that can be affected through player selection.

This model of the firm leads to a clear justification of including defense in a model of player salary. Since better defense contributes to wins and team success, it will drive higher revenues. Particularly in modern MLB, the proliferation of statistics which quantify a player's defensive performance in terms of wins leads to the expectation that teams will offer higher salaries for superior defenders, ceteris paribus.

Since more famous players drive fan consumption, fame similarly will contribute to higher revenues for a firm. The source of a player's fame does not need to be known or consistent across more famous players, just observable and clearly beneficial to a firm. There are ways that a team may be able to see directly the value a high-profile player offers. Firms can observe the differences in merchandise sales among players, and see less obvious indicators of fan interest like spikes in season ticket sales after signing a player. Rational teams with access to this information will be willing to pay more for famous players to get access to these revenue benefits.

3 Empirical Model of Discrimination

I carry out two main model specifications, one that is based around a performance statistic known as Wins Above Replacement (WAR) and covers the years 2004-2019 and another that is a modified version of Holmes' model on the years 2015-2019. These two categories will be referred to as the WAR model and Holmes model. Data availability determine the years chosen for both models, as some variables are unavailable before 2004, and speed data restricting the Holmes model to 2015-2019. In all iterations, players that appear more than once are weighted such that the contribution of each incidence is the inverse of their frequency.

The regression model will take a log linear form, estimating salary with player and team demographics, player performance, year and race:

$$\ln(\text{SALARY}_{t,j,i}) = \beta_0 + \beta_1 Demographics_{t-1,j,i} + \beta_2 PERFORMANCE_{t-1,i} + \beta_3 YEAR_t + \beta_4 RACE_i + \epsilon$$

Player and team demographics include player age, position played, team revenue and population of the metropolitan statistical area of the team. Performance measures vary across models. Theory also suggests that a measure of fame belongs in the model, but I lack a suitable empirical measure for fame as is discussed in the next section.

3.1 Data

An observation is a player that is signed by a team out of free agency in a particular season. I do not include pitchers since a model of their value requires different performance metrics. I maintain catchers and designated hitters despite their omission in earlier literature since the differences in their value to a team is

Variable	Description
3-Year OBP	On Base Percentage for 3 seasons before free agency (measure of ability to avoid getting out)
3-Year SLG	Slugging percentage for 3 seasons before free agency (measure of ability to hit for power)
Diff OBP	On Base Percentage in season prior to free agency minus the 3-year OBP
Diff SLG	Slugging percentage in season prior to free agency minus the 3-year SLG
RBIs	Runs batted in the season before free agency
Sprint Speed	Fasted speed per foot a player reaches in a season
Position	Primary defensive location played in the season prior to free agency
Gold Gloves	Number of Gold Glove awards won over career
Age	Player age in year of free agency
Revenue	Team revenue in millions in year of free agency
Population	Population of Metropolitan Statistical Area of the team player signs with
Race	Race of the player with black as the base category
Adjusted WAR	Expected wins added by a player per at bat relative to a replacement level player

Table 1: List of independent variables

accounted for in modern defensive value metrics and position dummy variables. Players are excluded if they had less than 100 plate appearances in the prior season to ensure sufficient sample size. Asian players were eliminated for small sample size with only 9 observations.

The full data set covers 655 free agents in the years 2004-2019. Of this sample, 99 were black, 208 were Latino and 348 were white. Of the Latino players, 42 received an additional designation of being within the subgroup of black Latinos. Racial designations were inferred from a player's country of origin, photos found online, and parentage. Latino players were designated as those from Latin countries or the descendants of people from Latin countries. Some of these Latino players are partly or primarily of African heritage, and therefore could be considered black by a discriminator. These Afro-Latinos received a designation of being a black Latino in addition to being Latino. Having designated Latino players, white and black designations were given out with players of mixed heritage marked as black.

As noted, I restrict the data to contracts that were signed by free agents. Players may sign contracts under several circumstances that restrict their ability to get their open market value. A single team nearly always has exclusive rights to be negotiating with a player about their salary. Players that have been drafted or are currently under contract with a team are not able to negotiate or discuss contracts with other teams. It is only once a player has entered free agency that they will get access to the whole market. Contracts signed in free agency closely represent the value MLB assigns to a player, whereas other contracts do not since they are subject to restrictions.

The dependent variable is defined as the first year salary of a free agent's contract because it is the best representation of team's valuation of a player. The first year is the only year where the players' salary is directly based on the prior year's performance. Modeling the salary in later years of a contract means using data that the team did not have access to when they wrote the contract years before. The error this introduces to the model is unnecessary and could hide the true way teams value players. Salary data was primarily drawn from Baseball Prospectus[2] with some gaps filled from Sean Lahman's Baseball Archive.[3] I subject salary to a logarithmic transformation because of the skewed nature of the data. Since salary is the dependent variable the models will be log-linear in form.

Independent variable data covers the seasons 2001-2018 since salary is predicted using the prior year or average of the prior three years. Player performance and demographics were drawn from several places. Sean Lahmnan's Baseball Archive was the source of basic offensive and defensive statistics. Defensive Runs Saved (DRS), Ultimate Zone Rating (UZR) and Wins Above Replacement data came from FanGraphs[4] and speed from Baseball Savant.[5] Free agency status was determined using Retrosheet's transaction data.[6] Chadwick Bureau's[7] ID database was used to accurately merge sources. Revenue data was drawn from Forbes[8], with some gaps filled by estimation. The years 2004, '10, '11, '16, and '17 did not have figures available so the data was filled in by averaging the adjacent years. Since the Montreal Expos moved to Washington DC prior to the 2005 season, I plug 2004 revenue for Washington with the true value for Washington from 2005. The revenue from Montreal in 2004 would not be representative since the Expos were a failing franchise that moved because of revenue troubles, and their revenue nearly doubled by moving to DC. Population data is based on metropolitan statistical area populations from the 2000, 2010 US Censuses and the 2001, 2006 and 2011 Canadian Censuses. For the US, the years 2011-2018 have yearly estimates from the Census Bureau, so these are utilized instead of using 2010 data for all the years.

3.1.1 Fame

A theoretical model of player salary includes fame, but no empirical models covered in this paper include it because of a lack of suitable data. Fame may be able to be estimated from player branded merchandise sales or internet activity. Complete data on player jersey and merchandise sales are not made publicly available. MLB releases the top twenty selling jerseys each year, but only a few of these players enter free agency every year so there are not enough points to add meaningfully to the data set. Potential online sources such as social media followings tend to be unreliable. For example, Twitter followers seems like a reasonable measure of fan interest in a player, but it conflates player interest in Twitter and fan interest in players. Looking at the list of top twenty jersey sellers in 2019 on Twitter, some players do not even have verified accounts (Paul Goldschmidt) while other players tweet multiple times a day (Aaron Judge).

[2]https://www.baseballprospectus.com/
[3]http://www.seanlahman.com/
[4]https://www.fangraphs.com/
[5]https://baseballsavant.mlb.com/
[6]https://www.retrosheet.org/
[7]https://github.com/chadwickbureau
[8]https://www.forbes.com/

Variable	Mean	Median	Standard Error	Maximum	Minimum
Salary (in millions)	3.8	2	4.42	28	0.1
WAR	1.07	0.7	1.64	9.7	-2.3
WAR lag 1	1.23	0.9	1.58	7.3	-2.2
WAR lag 2	1.54	1.3	1.76	9.5	-2.4
Population (in millions)	6.1	4.45	4.86	20.0	1.50
Revenue (in millions)	209	190	77.0	668	81
Age	33.8	34	3.43	49	26

Table 2: Summary of independent variables for WAR model

The most promising measure of fan interest in players I considered was Google search activity. Google allows for the comparison of up to five search terms' relative frequency over periods of time on Google Trends. The output from a query on Trends is cardinal but measured out of 100, with the peak point in any query's result being normalized to 100. I compiled and normalized a novel data set of Google Trends search frequency for all free agents in the seasons 2012-2016. An observation was the average weekly search volume of a player in the 52 weeks prior to the start of free agency. All players were normalized against one base player in each year and then normalized across years. The years 2012-2016 were selected since they were recent and relatively clean. In the years after 2016, as search volume rises, variance in player search volume rises meaning many players have insufficient searches to distinguish their search volume from zero. The data turned out to be indistinguishable from noise. Simple regressions trying to predict fame using race and performance did not have predictive power. Fame was not different by race given performance and was not even increasing as performance increased. Fame was also roughly consistently distributed across the salary distribution. Empirically, it did not improve the models when added and only restricted the dataset. For this reason, my measure of fame was discarded. Future work should seek a robust measure of player fame to more accurately model player value.

3.2 WAR Model

The first measure of player performance I will use is WAR, or Wins Above Replacement. The introduction of WAR as a measure of player performance is novel but prudent. Earlier work has struggled to precisely quantify the value of a player's performance because simple statistics do not capture all the value added by a player. WAR was created in order to aggregate the offensive, defensive, and baserunning value of a player in one number. The basic premise of WAR is that the true value added to a team by a player is equal to the number of expected wins that would be lost if he were removed from the team. If he were removed, the team would be forced to employ a replacement level player: a player who could be added at little cost, like a free agent or a minor league promotion. From this basis, it is straightforward to compare players across teams, positions, and seasons in terms of their pure value in wins. Studies have found that 83% of variation

Variable	Model 1	Model 2
Intercept	14.1***	14.1***
	(.936)	(.933)
White	-.086	-.086
	(.109)	(.11)
Latino	.283**	
	(.113)	
Latino (not black)		.26**
		(.118)
Latino (black)		.354**
		(.151)
Adjusted WAR	122.3***	122.8***
	(11.3)	(11.5)
Adjusted WAR lag 1	52.6***	52.5***
	(12.6)	(12.7)
Adjusted WAR lag 2	52.5***	52.1***
	(12.6)	(10.7)
ln(Population)	-.032	-.031
	(.061)	(.061)
Revenue	.001	.000
	(.001)	(.000)
Age	-.009	-.009
	(.01)	(.01)
Standard Errors in parenthesis		
*** significant at 1% level		
** significant at 5% level		
* significant at 10% level		

Table 3: Estimated coefficient values for WAR weighted least squares regression; dependent variable is logarithm of salary

in team wins is explained by WAR.[9] Since WAR is a cumulative metric, for use in the model I will normalize it to WAR per at bat. To measure performance in this section, I use WAR per at bat for the three seasons prior to free agency. Earlier work often used the average of a performance metric over the prior three seasons or only the prior season. It stands to reason that more recent performance is more representative of future performance and of salary, therefore I do not average over the three seasons. Similarly, if the most recent year for a player is an outlier due to injury or random factors, it will fail to be representative of their value in the way that considering each of the prior three seasons does.

I first use weighted least squares regression to observe the effect of race on salary, then quantile regression to observe the effects at different salary levels. Quantile regression uses the same model specification as least squares, but instead of estimating the conditional mean, it estimates the conditional median or conditional quantile. In this way, differential effects of race across the range of salaries can be estimated. In earlier work, discrimination was only shown at lower salary levels, and linear regression could obscure the conditional effect of race.

[9] https://tht.fangraphs.com/what-is-war-good-for/

Model 1 (Column 1 of Table 3) maintains the demographic variables seen in prior models, but replaces all player performance with the WAR per at bat for the player for each of the last three years. In Model 2 (Column 2 of Table 3) black Latinos are evaluated as their own group. If discrimination happens on the basis of appearance, then this group of Latinos should be seeing lower salaries than the rest of Latinos. In both Model 1 and 2, there is no evidence that white players receive higher salaries than black players, with white carrying a negative, though insignificant, coefficient. Latino players have statistically significantly higher salaries than both white and black players. Table 3 shows a .283 coefficient for Latino, and running the model with white omitted for race yields a coefficient for Latino of .354, and is significant at the .001 level. These coefficients translate to implied premiums of 32.7% and 42.4% respectively. This is a surprisingly high result, as it is larger than any premium found by Holmes. Model 2 shows that Latinos who are black have a coefficient that is slightly higher than non-black Latinos. In sum, within both the Latino and non-Latino groups, there is no evidence of discrimination against black players, although there is a gap between the Latino and non-Latino salaries.

The race coefficients were estimated with quantile regression at all deciles of the salary distribution, and can be seen in Figures 1 and 2 in the Appendix. The clear premium that Latino players hold over non-Latino players is notable for being roughly consistent across the distribution (Figure 1, Appendix). Visually there seems to be a dip in the premium for the 80th and 90th percentiles, but there is not a pattern of differential effects at low salary levels as seen in earlier work. Though there is evidence of Latino players being paid more than black players, since they also are paid more than white players it does not appear to be evidence of discrimination against black players. The source of this apparent Latino premium will be covered further in the discussion.

3.3 Holmes Model

I replicate Holmes' model on the years 2015-2019 in order to check the robustness of my results. Holmes used a statistic called Zone Rating and the number of Gold Gloves won to measure defensive value. Zone Rating is the percentage of balls hit into a fielder's area of the field that are fielded successfully. Zone Rating is a crude enough measure that it is no longer tracked or compiled for usage, but it has been replaced by more rigorous metrics. Gold Gloves are an award given to the player voted best at fielding at his position by coaches and managers in the league. Gold Gloves similarly are a crude measure as the second-best fielder at a position every year gets the same amount of credit as the worst: none. The specification in Column 1 of Table 5 is the same as Holmes, but without zone rating. The next two iterations (Columns 2 and 3 of Table 5) replace Zone Rating and Gold Gloves with two modern statistics. The first is Ultimate Zone Rating

Variable	Mean	Median	Standard Error	Maximum	Minimum
Salary (in millions)	7.04	5	6.45	28	0.508
3 year OBP	0.331	0.33	0.027	0.412	0.277
3 year SLG	0.425	0.421	0.060	0.598	0.294
Diff OBP	-0.005	-0.004	0.024	0.059	-0.061
Diff SLG	-0.01	-0.009	0.042	0.134	-0.114
RBI	53.2	50	30.5	156	7
Sprint speed	26.7	26.7	1.31	30	22.6
Population (in millions)	6.33	4.73	4.89	20.0	1.56
Revenue (in millions)	283.7	263.3	86.7	668	155
3 year DRS	-0.001	-0.006	0.022	0.067	-0.0397
3 year UZR150	0.571	-2.2	22.4	71	-48.6
Age	33.8	34	3.43	49	26

Table 4: Summary of independent variables for Holmes regression

150 (UZR), which measures the fielding performance of a fielder relative to the average performance at his position. The second is Defensive Runs Saved (DRS) which similarly measures the number of runs saved or lost by a player relative to the average. The data covers the years 2015-2019, and contains 198 observations with 32 black, 62 Latino and 104 white. DRS and UZR were averaged over the three seasons prior to free agency as there is high variation year to year, and averages are more representative of performance.

In all three specifications, the white and Latino terms are negative, offering no evidence of discrimination against black players. In fact, the first specification suggests that white players are paid less at a 5% significance level, but this model lacks advanced measures of defense. It is noteworthy that including defense decreases the implied discount for white players, which implies an absence of accurate defensive measures could lead to an undervaluation of black players. The white and Latino terms are not significant for the model with DRS (Column 2) or with UZR (Column 3) so there is not evidence that black players receive a premium.

Quantile regression tells the same story with no quantile showing black players below white or Latino (see Figures 3-5, appendix). In the quantile regression charts, we also see slopes that invert the pattern seen in earlier work. At salary quantiles below the median, the coefficients for white and Latino players are generally lower than those above the median. It was below the median that discrimination against black players was previously shown, but the indication here is that black players may be paid the most at low salary levels.

4 Discussion

The evidence is against non-white players being paid less than white players. White salaries were consistently lower than black salaries though the difference was generally insignificant. Relative to black players,

Variable	Model 1	Model 2	Model 3
Intercept	9.31***	7.79***	7.73***
	(2.22)	(2.55)	(2.49)
Latino	-.213	-.148	-.161
	(.185)	(.199)	(.203)
White	-.381**	-.23	-.249
	(.165)	(.161)	(.164)
3-Year OBP	10.1***	9.93***	9.81***
	(2.63)	(3.50)	(3.46)
3-Year SLG	3.25*	5.4**	4.71**
	(1.72)	(2.06)	(1.96)
Diff OBP	5.47*	3.06	3.81
	(2.86)	(3.19)	(3.15)
Diff SLG	.628	1.84	1.18
	(1.64)	(2.02)	(2.042)
RBIs	.013***	.011***	.013***
	(.003)	(.004)	(.004)
Sprint Speed	.034	.047	.059
	(.058)	(.063)	(.061)
Gold Gloves	.02		
	(.053)		
Age	-.023	-.021	-.017
	(.022)	(.023)	(.024)
Revenue			.001
	(.001)	(.001)	(.001)
Population	.000	.000	.000
	(.000)	(.000)	(.000)
DRS		6.07**	
		(2.39)	
UZR 150			.006**
			(.002)

Standard Errors in parenthesis
*** significant at 1% level
** significant at 5% level
* significant at 10% level

Table 5: Estimated coefficient values for Holmes weighted least squares regression; dependent variable is logarithm of salary

the smallest suggested discount for white players was still 8.9%. Though insignificant, these types of differences point in the opposite direction of discrimination against black players. A safe conclusion is that MLB does not show evidence of discrimination against black players. This result is not surprising as the combination of incentives to win and more accurate modern measures of player value may well have eliminated earlier discrimination. The evidence that black and white players are paid less than Latino players offered in the models utilizing WAR does not fit with expectations. A simple explanation is that WAR is systemically biased against Latino players and they are worth higher WAR than they are credited with. Why this would be the case is not clear. The formula for WAR is not public knowledge, so the possibility of bias in WAR could not be investigated further.

Consumer preferences could also drive a Latino premium, but there is little reason to expect fans to prefer Latino players. Nielsen viewer data from 2013 indicates 83% of MLB viewers are white, so the basic expectation is that these white, primarily American viewers would be inclined to favor white American players.[10] Other work on consumer tastes in MLB with respect to race mostly supports this assumption, and at the least does not support a hypothesis of fan preferences for Latinos. Nardenelli and Simon (1990) and Fort and Gill (2000) find that the prices of baseball cards in 1989 indicate that consumers would pay more for white cards. Hanssen and Anderson (1999) looked at fan All Star game voting and found black players received less votes in the 70s but not in the 80s or 90s. Jewell et. al. (2002) similarly found that it was players that were on the verge of being elected to the hall of fame that saw race affect their chances. Depkin and Ford (2006) looked at All Star voting again and argued that the 90s showed a slight favoritism to Latino and black players over white players. Given this literature, there is reason to no group faced significant consumer discrimination or favoritism in the years covered in this paper. Further, a pair of recent analyses similarly suggests that there is not a basis for fame driving the Latino premium seen in the WAR based models. Watanabe et. al. (2017) study Twitter activity and conclude that Latino players receive less interest than white, Asian or black players. Two writers for the Atlantic watched 200 consecutive MLB games from the 2011 season and coded every comment made by the commentators on players. [11] They found that Latino players received more negative feedback than black and white players. Considering the Homles model did not show indications of a Latino premium, and the lack of a theoretical basis for it, I do not claim to have found strong evidence of a premium for Latino players.

[10] shorturl.at/FKWY6

[11] https://www.theatlantic.com/entertainment/archive/2012/08/how-mlb-announcers-favor-american-players-over-foreign-ones/261265/

5 Conclusion

Since the results show a lack of evidence for discrimination instead of positive evidence that salary discrimination against black players does not exist, I cannot reject the possibility of discrimination. Still, it is reasonable to propose that wage discrimination against black players is no longer present in MLB. Advances in measuring player value since the period where Palmer and King and subsequently Holmes found evidence of discrimination have improved the ability of teams to accurately value players. The ambiguity in player value that may have helped discrimination to persist no longer exists. My analysis was limited to free agents in MLB, and therefore it is possible that discrimination persists in other areas of baseball. In the market for free agents, I do not find evidence for lower wages for black players in Major League Baseball in the years 2004-2019. All model specifications yielded coefficients that indicated white players were paid less than black players, though these coefficients were mostly insignificant. I do find mixed evidence for a premium for Latino players, but the theoretical basis for it is not clear.

Appendices

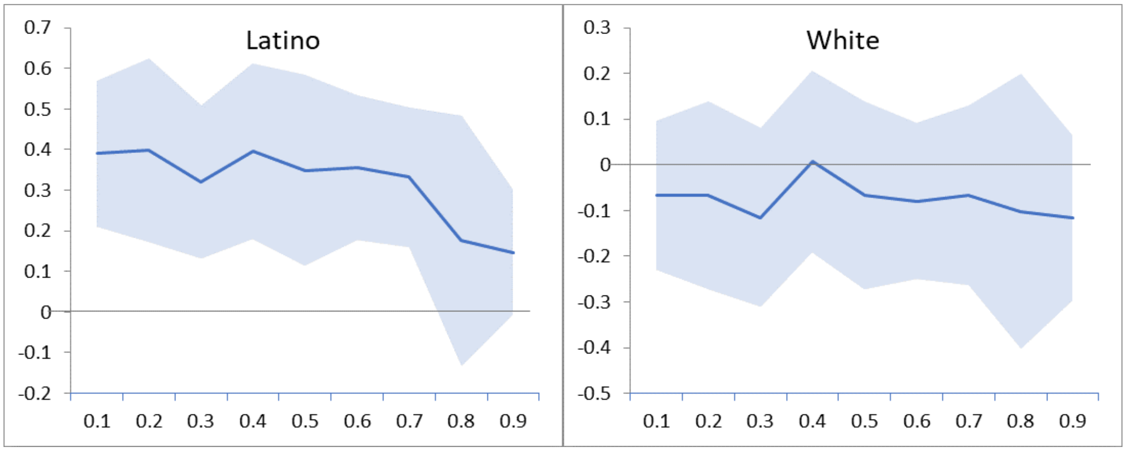

Figure 1: Quantile regression race coefficients for WAR model 1. The shaded area represents a 95% confidence bound

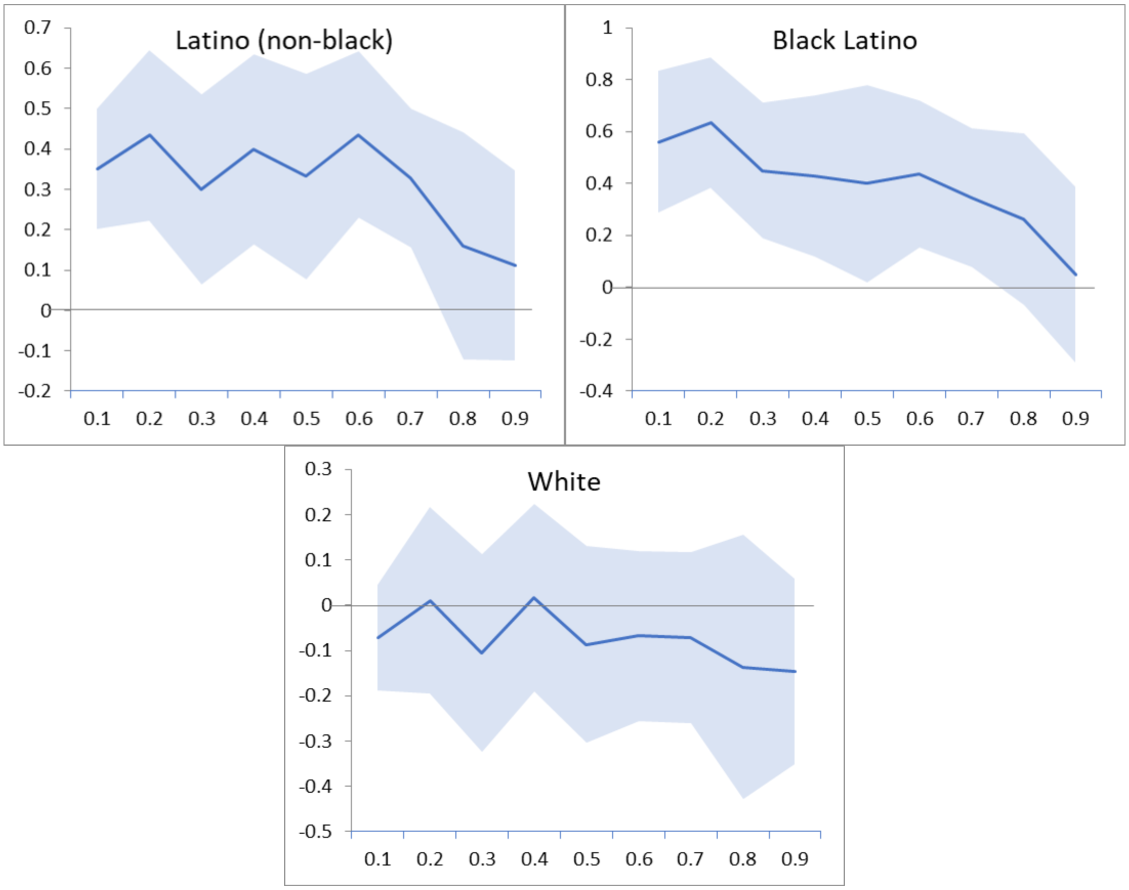

Figure 2: Quantile regression race coefficients for WAR model 2. The shaded area represents a 95% confidence bound

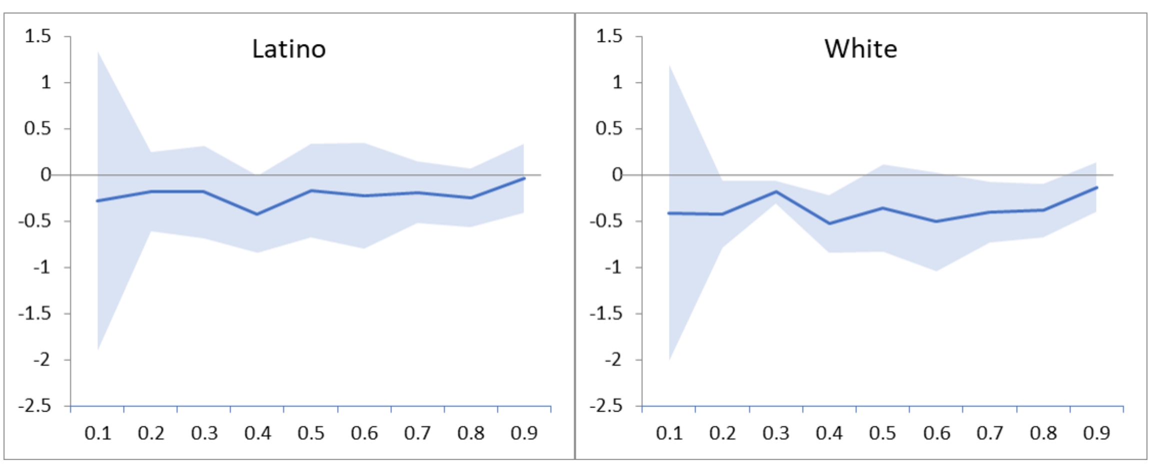

Figure 3: Quantile regression race coefficients for Holmes model 1. The shaded area represents a 95% confidence bound

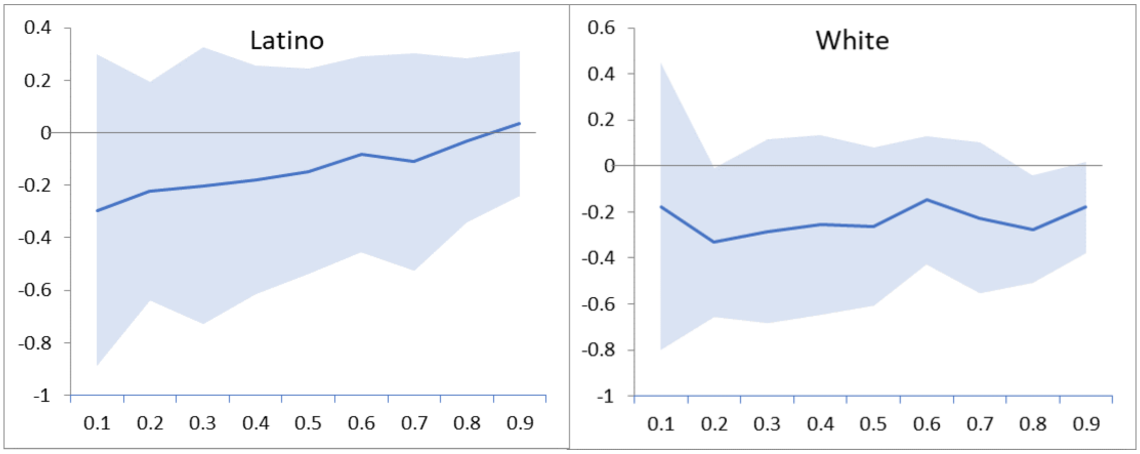

Figure 4: Quantile regression race coefficients for Holmes model 2. The shaded area represents a 95% confidence bound

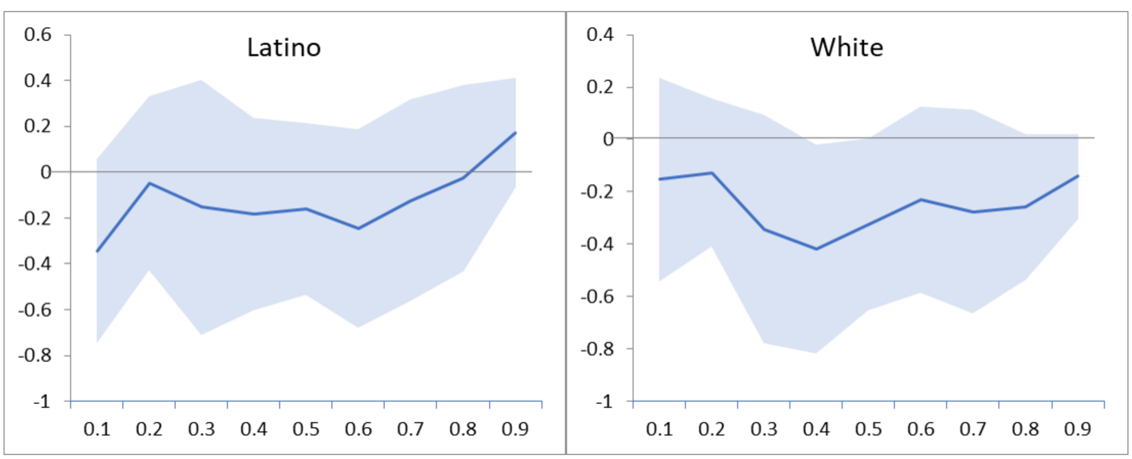

Figure 5: Quantile regression race coefficients for Holmes model 3. The shaded area represents a 95% confidence bound

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