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Race and Quarterback Survival in the National Football League

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Abstract

This study examines data from the 2001 to 2009 National Football League (NFL) seasons to determine whether Black quarterbacks face discrimination. When controlling for injury, age, experience, performance, team investment, backup quality, and bye weeks, Black quarterbacks are found to be 1.98–2.46 times more likely to be benched. Marginal evidence is also found that Black quarterbacks face less discrimination in areas with a larger percentage of Black residents. Additionally, it has been observed that when White quarterbacks are benched, the team improves by more than when Black quarterbacks are benched. This provides evidence that there is a cost to this discrimination.

Keywords

race, NFL, survival analysis, quarterback

Introduction

From 2001 to 2014, the number of Black opening day quarterbacks in the National Football League (NFL) has varied from as low as 5 to as high as 9. This represents only 16–28% of starting quarterbacks. These percentages are very surprising considering that Black athletes account for approximately 67% of the NFL. Black players also appear to dominate other offensive positions. For example, Black players

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represented 83% of running backs and 84% of receivers in 2013 (Lapchick, Donovan, Rogers, & Johnson, 2014). This discrepancy leads one to ask why there are not more Black starting quarterbacks in the NFL.

One possible explanation is that Black quarterbacks face some form of discrimination in the NFL labor market. One way to determine whether Black quarterbacks are facing discrimination is to analyze the hiring decisions of firms. However, this approach presents several practical difficulties. For example, it may be very difficult to identify the pool of all players who would like to be NFL quarterbacks. Additionally, the major qualification for NFL quarterbacking is experience in college football. Given the vast number of college football teams which compete in different leagues and at different levels, comparisons of college statistics between players would prove problematic at best.

An alternative approach is to consider whether the Black starting quarterbacks already in the league are treated differently than comparable White quarterbacks. One way to address this issue is to compare the salaries of White and Black players. This is the approach that most previous studies of discrimination against NFL players have taken. The earliest such studies, Mogull (1973, 1981), find no evidence of salary discrimination against Black players. Kahn (1992) examines salary data from the 1989 season and finds limited evidence of salary discrimination against Black players in metropolitan areas with relatively White populations. However, Kahn notes that the magnitude of this discrimination is less than 4% and insignificant in most equations. Based on salary data from the 1996 season, Gius and Johnson (2000) find evidence that Black players are actually paid 10% more than White players, suggesting reverse discrimination. Berri and Simmons (2009) also analyze player salaries, specifically looking at the quarterback position from 1995 to 2006. They find evidence of salary discrimination against Black quarterbacks in the upper half of the wage distribution. Additionally, they find that Black quarterbacks are more likely to run but do not appear to be rewarded for that skill. Most recently, Keefer (2013) finds evidence of salary discrimination against Black linebackers from 2001 to 2009.

Unlike most previous studies, the models presented here focus on survival rather than salaries. If Black players face employer or customer discrimination, it is likely that they will be treated differently in more than just compensation. Specifically, in the presence of discrimination, Black players may be shown less patience by the coaches and fans. This lack of patience may lead to young Black players being given less opportunity to develop and experienced Black players being benched more quickly than comparable White players. In other words, the presence of discrimination against Black players will make them less likely to survive from one season to the next and from one game to the next than comparable White players. Survival from season to season has previously been analyzed by Conlin and Emerson (2006). They examine the impact of race on whether drafted players remain under contract during their first three seasons. They find that non-White players are actually more likely to survive than observationally equivalent White players who were drafted in the same position. They interpret this finding as evidence that non-White players face discrimination in hiring but not retention. The analysis presented here further expands the literature on discrimination in professional football by considering survival from game to game rather than season to season.

The models presented here apply survival time analysis to data on starting quarterbacks during the 2001–2009 seasons to determine whether evidence exists that Black quarterbacks are being treated differently than comparable White quarterbacks. By focusing on survival rather than salaries, the analysis presented here approaches the issue of discrimination in a different manner than previous studies. While survival analysis has not been applied to NFL quarterbacks, it has been used previously to examine the role of race in sports. Volz (2009) uses survival analysis to evaluate the role of race in the survival of Major League Baseball managers. This article aims to contribute to the ongoing debate over the existence of discrimination in professional football by applying these survival analysis techniques to the NFL.

Variable and Sample Selection

The goal of this analysis is to determine whether race has a significant impact on the probability of a starting quarterback surviving from one week to the next. Therefore, the sample consists of streaks of games started by quarterbacks. It is possible that a starting quarterback is not actually being considered for the starting job the following week. For example, a quarterback may be filling in for an injured player on a temporary basis. This is much less likely to be the case for a quarterback starting the first game of the season than a quarterback who begins their streak in the middle of the season. Therefore, for each season, a streak is constructed for each week one starting quarterback. The streak continues until that quarterback does not start the next week or reaches the end of the regular season. These streaks were constructed for the 2001-2009 seasons.[1] This results in 287 streaks comprised of 2,865 observations.[2]

The central interest of this analysis is the effect of being Black on the likelihood of survival. Therefore, a variable which is equal to 1 for Black quarterbacks and 0 otherwise is included as a covariate in the analysis. This results in 522 Black quarterback observation. One would expect that a Black quarterback is less likely to be discriminated against by a Black coach. In order to capture this effect, an interaction between the binary variables Black and Black Coach is included. Additionally, one would expect a Black quarterback to face less discrimination from Black fans. Therefore, an interaction between the binary variable Black and the percentage of Black residents in each team's metropolitan area is also included.[3]

In addition to race, there are several other variables, which are expected to influence quarterback survival. The most obvious reason a quarterback would not start the following week is if they are injured. Fortunately, NFL teams release injury reports each week which list all injured players that week along with their status for the upcoming game. While these reports are rather subjective, generally players listed as out or doubtful on the report do not play that week. Therefore, a variable equal to 1 for any player who is listed as out or doubtful and 0 otherwise is included in the analysis to control for injuries.[4]

As a quarterback ages, they may gain life experience and football-specific skills that make them a better starting quarterback. Therefore, older quarterbacks may be more likely to survive from one game to the next. However, teams may also have more patience with young quarterbacks who are still learning the game. Therefore, young quarterbacks may be more likely to survive from one game to the next. In order to control for these effects of age and to determine whether age increases or decreases survival, a variable equal to each players' age in years is included in the analysis. In many circumstances, age may have a diminishing effect. Therefore, the square of age is also included in the model.

It is also expected that experience as a starting quarterback will increase the likelihood of survival. As they play more games, quarterbacks should become more familiar with their team's plays and players. Experienced quarterbacks may also have more familiarity with their opponents which could translate into better decision making. More experience as a starting quarterback also translates into more experience dealing with the media. A quarterback who "says all the right things" may be able to survive a poor performance better than an inexperienced quarterback. Based on these ideas, a variable which is equal to the number of games a quarterback has started in their career is included in the analysis. Like age, the gains from experience may diminish over time, and therefore the square of games started is also included in the model.

In addition to his experience on and off the field, a quarterback's survival should depend on his level of performance on the field. Decisions on whether to bench a quarterback or not are made on a game-by-game basis, and therefore, it is expected that performance in the most recent game will have a significant impact on the likelihood of being benched. While recent performance is important, it is unlikely that a coach will make a decision based on one game alone. Therefore, a player's career statistics may also be important. In order to capture the impact of recent and past performance, a variety of performance statistics from recent performances and a player's career are included as covariates.

Most quarterbacks are valued on the field primarily for their ability to complete passes. Therefore, a measure of passing ability must be included as a covariate. The traditional measure of passing efficiency is the quarterback rating. This statistic combines information on completion percentage, yards gained per attempt, touchdown passes per attempt, and interceptions per attempt, into a single measure with a maximum value of 158.3. Quarterback ratings above 100 are considered exceptional performances. The primary advantage of this measure is that it compares quarterbacks to an ideal measure in each of the four categories so that no one category is weighted more heavily than another. The quarterback rating for each individual game and for the quarterback's career are calculated at the end of each game and included as covariates in determining the likelihood of surviving to the next game.

While passing is the traditional role of a quarterback, some quarterbacks are also valued for their ability to run the ball. Therefore, a measure of rushing performance must also be included as a covariate. Unfortunately, a widely accepted single measure of rushing ability does not exist. As a result, two rushing statistics are included in the analysis. These measures include yards per attempt and touchdowns per attempt. Per attempt measures are preferred to total yards or touchdowns, as some quarterbacks are asked to run more often than others. Therefore, having more total yards or touchdowns would not necessarily imply a better rushing performance.

While individual performance is important, it can be argued that the most important thing to fans and coaches is team performance. Therefore, whether the quarterback wins each week is also included as a covariate. Teams are likely more concerned about their league standing than whether they win or lose any one specific game. Therefore, a quarterback's record over the entire season may also be an important factor in his survival. In order to capture this effect, a variable equal to the quarterback's winning percentage up to that point in the season is included in the analysis. It is certainly possible that a team could lose, despite an exceptional performance by their quarterback. If the team loses, despite the offense scoring a large number of points, then teams may not blame the quarterback for the loss. Therefore, the number of points the offense scores each week is also included in the model.

In addition to evaluating a player's performance, teams may also take into account how much they have invested in a specific player. For example, if a team is paying a quarterback a large salary, they may be less willing to bench that quarterback. This may be due to the fact that they would like to avoid the embarrassment of having made a wrong decision. The NFL also operates under a salary cap system. The more money a team pays to one quarterback, the less money they have available to pay another. Therefore, teams may be essentially stuck with a quarterback if they spent a large portion of the salary cap on that player. Additionally, previous research by Keefer (2015) finds evidence that an increase in a rookie's salary cap value increases their number of games started. Therefore, in order to control for the effect of a player's salary on their survival, the percentage of salary cap going toward each quarterback is calculated for each season and included as a covariate.[5]

As mentioned earlier, the quality of the backup quarterback may also influence a team's decision to bench their starting quarterback. In order to control for this effect, previous games started by the backup quarterback for each team are included as a covariate. Experience as a starting quarterback is chosen over performance measures, as many backup quarterbacks have very little playing experience. Therefore, their performance measures may be misleading. Switching from one quarterback to another may be a difficult process, especially if the backup quarterback does not have significant experience. Therefore, teams may be more likely to switch to the backup quarterback if they have extra time to prepare. This would be the case if the team has a bye week. Therefore, a variable equal to 1 if the team has a bye the following week and 0 otherwise is included in the analysis.

Similar to having money invested in a player, teams may also have a high draft pick invested in a player. Teams may be more patient with high draft picks, as they have higher expectations for them. Management may also want to avoid the embarrassment of having wasted a high draft pick on a player who is not playing. Therefore, each player's draft position is also included as a covariate.[6]

Taken together, these variables control for race, injury, age, experience, individual performance, team performance, team investment, backup quality, and bye weeks. Having compiled these statistics for each week one starting quarterback from 2001 to 2009, the resulting 287 streaks are analyzed using survival time analysis as described in the following section.

Methodology

The goal of this analysis is to determine whether race has a significant impact on the probability of a starting quarterback surviving from one week to the next. This can be analyzed using the technique of survival time analysis. The goal of survival analysis is to estimate a survival function which gives the probability of survival to a certain time period, given a set of covariates. Survival analysis can be conducted by making distributional assumptions about the survival function. Models that make such assumptions are referred to as parametric models. These models estimate the hazard rate as a function of the covariates. The hazard rate is simply the dropout rate in a given time period conditional on a set of covariates. This rate is always positive, so the model is assumed to be linear in the log of the hazard rate. Therefore, the model of interest is the following:

$$\log(h_i) = B_0 + B_1X_{i1} + B_2X_{i2} + \ldots + B_nX_{in}.$$

This model is independent of time and leads to a survival function of the following form:

$$S(t) = e^{-ht}.$$

This model, referred to as the exponential survival model, is the most simplistic of the parametric survival models because of its assumption of a constant hazard rate over time. While this model is valued for its simplicity, the assumption that the hazard rate is constant over time is often inappropriate, and therefore models which allow for the hazard rate to vary over time may be more appropriate. The most common of these parametric models are the Weibull and Gompertz models. These models assume that there is some underlying hazard rate which varies with time. It is also assumed that there is no interaction between time and the covariates. The covariates effect the hazard rate by proportionally changing the underlying rate for a given time period. This is why these models are referred to as parametric proportional hazards models. Specifically, the hazard rate is modeled as follows:

$$h(t) = h_0(t)\exp(B_0 + B_1X_{i1} + B_2X_{i2} + \ldots + B_nX_{in}).$$

Different functional forms of $h_0(t)$ will lead to different survival functions. The underlying hazard rate is commonly assumed to have a Weibull distribution. This leads to the following survival function:

$$S(t) = e^{-(ht)p}.$$

This survival function is useful as the hazard rate will be either increasing or decreasing monotonically with time depending on the value of the estimated parameter p. If p is greater than 1, the hazard rate is increasing over time. If p is less than 1, the hazard rate is decreasing over time. If p is equal to 1, this implies the hazard rate is independent of time and leads to the exponential model previously presented.

Another commonly used distributional assumption is the Gompertz distribution. If the underlying hazard is assumed to follow a Gompertz distribution, the resulting survival function is of the following form:

$$S(t) = \exp[(h/r)(1 - e^{rt})].$$

Under this assumption, the hazard rate will either increase or decrease at an exponential rate depending on the value of the estimated parameter r. Taken as a group, these three distributional assumptions can be used to estimate a hazard rate which is constant over time, increasing over time, or increasing exponentially over time. These three parametric models are estimated using maximum likelihood. The results are presented in Tables 1, 2, and 3 and are discussed in the next section.

An alternative approach to these parametric models is to estimate a Cox proportional hazards model. To estimate this model, the ratio of hazards for two observations is taken as follows:

$$h_i(t)/h_j(t) = h_0(t)\exp(B_0 + B_1X_{i1} + \ldots + B_nX_{in}) \\ /h_0(t)\exp(B_0 + B_1X_{j1} + \ldots + B_nX_{jn}).$$

Because of the fact that the baseline hazards are independent of the covariates, the baseline hazards cancel leaving the following hazard ratio which is independent of time:

$$h_i(t)/h_j(t) = \exp(B_0 + B_1X_{i1} + \ldots + B_nX_{in}+)/\exp(B_0 + B_1X_{j1} + \ldots + B_nX_{jn}).$$

Despite the fact that the underlying hazard function is not defined, the model can still be estimated by the method of partial likelihood. This partial likelihood method is presented by Cox in the 1972 article in which he first introduces the Cox model (Cox, 1972). Although these models are not as efficient as a correctly specified parametric model, they do not depend on distributional assumptions. This avoids the risk of obtaining misleading results because of an incorrectly specified parametric model. A Cox proportional hazards model is also estimated with the results presented in Table 4 and discussed in the next section.

The advantage of the Cox model is that it does not rely on distributional assumptions about the survival function. However, the model is only appropriate if the assumption of

Table 1. Exponential Model.

Covariate	All Variables Included		Significant Variables	
	Hazard Ratio	P-Value	Hazard Ratio	P-Value
Black	2.20	.057*	1.42	.041**
Black × Metro % Black	0.98	.196	—	
Black × Black Coach	0.84	.720	—	
Injury List	15.95	.000***	16.45	.000***
Age	1.15	.607	1.03	.026**
Age^2	1.00	.699	—	
Career Starts	1.00	.925	—	
Career Starts^2	1.00	.811	—	
Salary Cap %	0.00	.007***	0.00	.000***
Draft Pick	1.00	.556	—	
Bye Next Week	0.58	.072*	0.62	.076*
Backup QB Experience	1.00	.024**	1.00	.015**
Win	0.70	.115	0.70	.087*
Winning Percentage	0.41	.003***	0.38	.001***
Offensive Points	0.98	.025**	0.97	.003***
Passer Rating	1.00	.552	—	
Rush Yards/Attempt	0.99	.460	—	
Rush TD/Attempt	1.28	.685	—	
Career Passer Rating	0.99	.281	—	
Career Rush Yards/Attempt	1.03	.624	—	
Career Rush TD/Attempt	1.34	.854	—	

Note. Streaks = 287, n = 2,865, TD = Touchdowns, Wald test of coefficients equal to 0: p = .0000.
*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

proportional hazards is satisfied. The proportional hazards assumption can be tested by running a generalized linear regression of the scaled Schoenfeld residuals on time. A significant coefficient on time would provide evidence that the proportional hazards assumption is violated. A global test for the time covariates fails to reject the null hypothesis of zero slope for all models estimated. Therefore, the Cox proportional hazards model is appropriate to use in this analysis. Wald tests of whether the coefficients are equal to 0 are also rejected with p-values of .0000 for all models estimated.

Results

Tables 1–3 present the estimated hazard ratios from the three parametric survival models. Table 4 presents the results from the Cox Proportional Hazards model. A hazard ratio greater than 1 implies that the covariate decreases the likelihood of survival, while a hazard ratio less than 1 implies that the covariate increases the

Table 2. Weibull Model.

	All Variables Included		Significant Variables	
Covariate	Hazard Ratio	P-Value	Hazard Ratio	P-Value
Black	2.76	.025**	2.59	.014**
Black × Metro % Black	0.97	.119	0.97	.102
Black × Black Coach	0.97	.956	—	
Injury List	15.98	.000***	16.34	.000***
Age	1.22	.508	1.03	.037**
Age^2	1.00	.650	—	
Career Starts	1.00	.455	—	
Career Starts^2	1.00	.706	—	
Salary Cap %	0.00	.033**	0.00	.000***
Draft Pick	1.00	.738	—	
Bye Next Week	0.58	.071*	0.60	.074*
Backup QB Experience	1.01	.028**	1.00	.031**
Win	0.77	.205	—	
Winning Percentage	0.23	.000***	0.19	.000***
Offensive Points	0.98	.017**	0.97	.000***
Passer Rating	1.00	.667	—	
Rush Yards/Attempt	0.98	.346	—	
Rush TD/Attempt	1.43	.531	—	
Career Passer Rating	0.99	.171	—	
Career Rush Yards/Attempt	1.02	.803	—	
Career Rush TD/Attempt	0.64	.818	—	
p	1.37		1.35	

Note. Streaks = 287, n = 2,865, TD = Touchdowns, Wald test of coefficients equal to 0: p = .0000. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

likelihood of survival. In addition to the model with all variables included, each table also presents a model with only statistically significant variables included. These models were selected by eliminating one at a time the least significant variables until all variables were significant at the 10% level. The only variable which goes from highly insignificant to significant when other variables are eliminated is age. This is likely due to the correlation between Age and Age^2. None of the other covariates' p-values change meaningfully with the elimination of other variables. In addition to showing that the results are robust to variable selection, this provides some evidence that multicollinearity is not a problem in this model.

The variable of interest in this analysis is Black. As can be seen in Tables 1–4, the hazard ratio for Black is greater than 1 for all model specifications. This result is statistically significant with p-values ranging from .005 to .057 depending on the model. A statistically significant hazard ratio which is greater than 1 implies that Black quarterbacks are less likely to survive to the next week than observationally equivalent White quarterbacks. Additionally, the hazard ratio for Black × Metro

Table 3. Gompertz Model.

	All Variables Included		Significant Variables	
Covariate	Hazard Ratio	P-Value	Hazard Ratio	P-Value
Black	2.56	.032**	1.43	.044**
Black × Metro % Black	0.97	.131	—	
Black × Black Coach	0.91	.855	—	
Injury List	16.62	.000***	16.72	.000***
Age	1.21	.504	1.03	.034**
Age^2	1.00	.641	—	
Career Starts	1.00	.562	—	
Career Starts^2	1.00	.820	—	
Salary Cap %	0.00	.023**	0.00	.000***
Draft Pick	1.00	.700	—	
Bye Next Week	0.62	.116	—	
Backup QB Experience	1.01	.021**	1.01	.016**
Win	0.73	.142	0.71	.092*
Winning Percentage	0.29	.000***	0.28	.000***
Offensive Points	0.98	.018**	0.97	.003***
Passer Rating	1.00	.695	—	
Rush Yards/Attempt	0.98	.377	—	
Rush TD/Attempt	1.41	.557	—	
Career Passer Rating	0.99	.188	—	
Career Rush Yards/Attempt	1.03	.647	—	
Career Rush TD/Attempt	0.92	.963	—	
r	0.06		0.06	

Note. Streaks = 287, *n* = 2865, TD = Touchdowns, Wald test of coefficients equal to 0: p = .0000.
*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

% Black is less than 1 and statistically significant at the 10% level for the Cox model. This provides limited evidence that Black quarterbacks face less discrimination in areas with a higher percentage of Black residents. It should be noted, however, that the overall marginal effect of being Black remains negative for all teams. The hazard ratio for Black × Black Coach is found to be statistically insignificant for all model specifications. This implies that Black quarterbacks with Black coaches are not treated differently than those with White coaches. However, it should be noted that there is a very small number of instances where a Black quarterback played for a Black coach in this sample. Therefore, this insignificant result may simply reflect a lack of variation in the data.

Figure 1 presents predicted survival functions for each model specification with all variables included. The predicted survival functions for a White quarterback versus a Black quarterback are plotted with all other covariates evaluated at their means. As is evidenced by the lower curves for Black quarterbacks, Black quarterbacks have a lower probability of survival each week. Specifically, Black quarterbacks are

Table 4. Cox Proportional Hazards Model.

Covariate	All Variables Included		Significant Variables	
	Hazard Ratio	P-Value	Hazard Ratio	P-Value
Black	2.82	.018**	2.88	.005***
Black × Metro % Black	0.97	.098*	0.97	.068*
Black × Black Coach	1.07	.858	—	
Injury List	16.20	.000***	16.71	.000***
Age	1.24	.442	1.04	.017**
Age^2	1.00	.532	—	
Career Starts	1.00	.947	—	
Career Starts^2	1.00	.975	—	
Salary Cap %	0.00	.010***	0.00	.000***
Draft Pick	1.00	.562	—	
Bye Next Week	0.62	.112	—	
Backup QB Experience	1.01	.002***	1.01	.001***
Win	0.70	.100*	0.69	.070*
Winning Percentage	0.37	.004***	0.37	.003***
Offensive Points	0.98	.021**	0.97	.001***
Passer Rating	1.00	.447	—	
Rush Yards/Attempt	0.99	.534	—	
Rush TD/Attempt	1.34	.636	—	
Career Passer Rating	0.99	.116	—	
Career Rush Yards/Attempt	1.02	.737	—	
Career Rush TD/Attempt	1.34	.862	—	

Note. Streaks = 287, *n* = 2865, TD = Touchdowns, Wald test of coefficients equal to 0: p = .0000.
*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

1.98 to 2.46 times more likely to be benched than an observationally equivalent White quarterback depending on the model and week chosen. The predicted probabilities of being benched for the Cox model are presented in Table 5. For example, in Week 8 of the season, the Cox model predicts that an average White quarterback has a 4% chance of being benched, while an average Black quarterback has a 9.7% chance of being benched. As can be seen in Table 5, the model estimates that Black quarterbacks are more than twice as likely to be benched as White quarterbacks for each week. This provides evidence that Black quarterbacks may face some form of discrimination in the National Football League. This evidence appears robust to model specification and variable selection.

According to Becker (1957) discrimination may be based on the preferences of employees, customers, or employers. An implication of Becker's model of employee discrimination is that in the presence of such discrimination we should see segregated work forces. Given that the NFL is far from segregated, it is unlikely that any discrimination against Black quarterbacks comes from fellow players. This seems especially unlikely considering that the vast majority of the receivers quarterbacks throw to are Black.

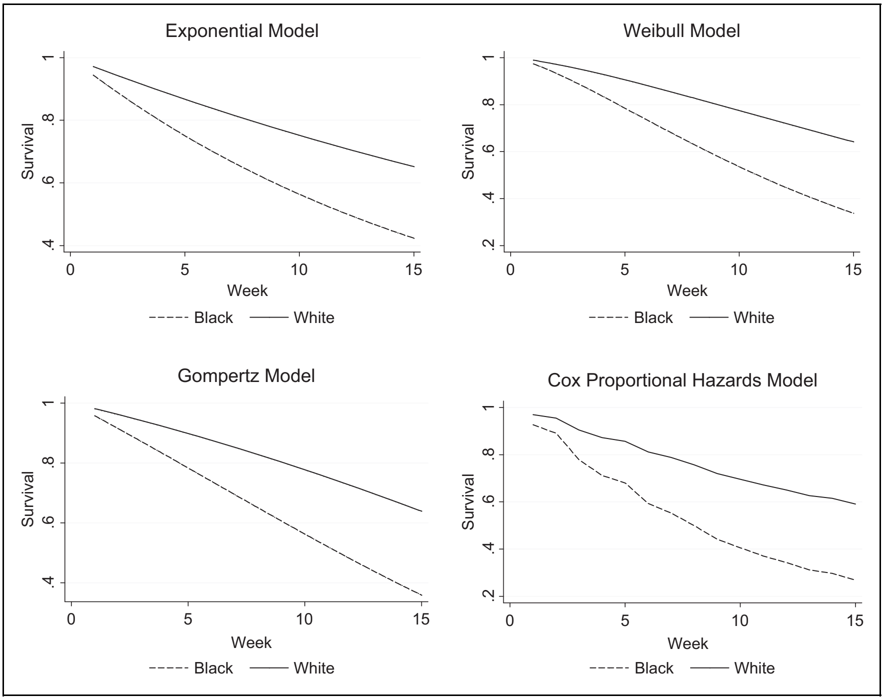

Figure 1. Estimated survival functions by race.

Table 5. Predicted Probability of Being Benched.

Cox Model Including All Variables		
Week	White	Black
1	0.030	0.074
2	0.016	0.038
3	0.053	0.127
4	0.035	0.086
5	0.018	0.044
6	0.054	0.128
7	0.028	0.068
8	0.040	0.097
9	0.048	0.115
10	0.034	0.082
11	0.035	0.086
12	0.031	0.074
13	0.038	0.092
14	0.019	0.047
15	0.039	0.095

Table 6. Difference in PPG Between Replacement and QB.

QBs not Appearing on Injury Report 2001–2009			
	Mean	*N*	Standard deviation
White	1.756	235	9.027
Black	−0.755	56	9.559

Note. Test of Black–White <0: p = .038. PPG = Points Per Game, QB = Quarterback.

Alternatively quarterbacks may be facing customer discrimination. A major implication of the customer discrimination model is that firms may attempt to hide minority labor from their customers. On most NFL teams, the quarterback is the most visible player both on and off the field. It is possible that teams may be responding to customer preferences by avoiding Black quarterbacks and attempting to hide Black labor at less visible positions.

It is also possible that Black quarterbacks are facing employer discrimination. In his analysis of employer discrimination, Becker argues that discriminating employers or firms should be driven from a competitive labor market by firms which are willing to take advantage of minority labor. However, with only 32 teams and very limited entry of new teams, it can be argued that the NFL is not a competitive market. Therefore, it may be possible for discriminating employers to operate in the NFL without being driven from the market.

If this is the case, one would expect to see evidence of the costs of discrimination in terms of team performance. In theory, a team should only be willing to replace their starting quarterback if there is some expected gain to doing so. This will only be the case when the expected points with the backup are greater than the expected points with the starter. However, if the team exercises taste discrimination as described in Becker (1957) or has asymmetric beliefs about Black and White quarterbacks as presented in Arrow (1973), they may act as if a Black quarterback has lower expected points than they actually do. This may cause them to bench a Black starter when the expected points for the backup are equal to or even less than that of the starter. If teams are making decisions in this manner then on average the payoff when replacing a Black quarterback will be less than the payoff when replacing a White quarterback. In other words, the presence of a Black starting quarterback will cause teams to make worse decisions.

In order to test whether this is the case, the average points per game are calculated for each starting quarterback and his replacement for all quarterbacks who were benched during the sample period. The original quarterback's points per game are then compared to the average points per game achieved by the quarterback replacing them. The average differences between the starting quarterback and replacement quarterback by race are presented in Table 6. In order to avoid replacements due to injury, only those quarterbacks who were not listed on the injury report when benched are included. As can be seen in Table 6, on average, when a White quarterback is replaced the team scores 1.76 points more per game under the new quarterback. However, on average, when a Black quarterback is replaced, the team scores .75 points less per game under the new quarterback. This provides evidence that teams do indeed make worse decisions when replacing Black quarterbacks. This difference of 2.5 points per game is statistically significant with a p-value of .038. During the 2014 NFL season, 9% of games were decided by two points or less and 20% of games were decided by three points or less. Therefore, it is likely that over a 16-game season discriminating teams may lose an additional game or two because of their poor decision making. This provides evidence that discriminating against Black quarterbacks does have a meaningful cost. However, whether teams are willing to bear this cost based on their own tastes, as a result of asymmetric beliefs, or in response to the preferences of their customers remains unclear.

When considering performance measures, it appears that team performance is more important than individual performance. This is evidenced by a statistically significant hazard ratio of less than 1 for Winning Percentage for all model specifications. This ratio implies that having a high winning percentage in the current season increases a quarterback's likelihood of starting the next game. This is not surprising as winning games should be the focus of every football coach when making personnel decisions. The hazard ratio on Win is only marginally significant in some model specifications. These two observations combined imply that teams are more concerned with their overall league standing than what has happened in the most recent game. This makes sense as it is the overall win percentage that determines whether a team makes the playoffs, not what has happened in the most recent game. Additionally, Offensive Points is statistically significant in all models with a hazard ratio less than 1. This implies that the more points a team scores the less likely the quarterback is to be benched independent of how those points are scored. This implies that a poor performance by a quarterback may be overlooked if the offense is still able to score an appropriate level of points.

Unlike team performance, it appears that individual performance measures do not have a statistically significant impact on quarterback survival. The hazard ratios on all passing and rushing measures are statistically insignificant for all model specifications.[7] This combined with the significant results for team performance measures implies that quarterbacks are judged based on the performance of the team and offense as a whole. It appears that quarterbacks are held responsible for poor team or offensive performance independent of their own performance statistics.

If Black quarterbacks are being discriminated against, it may not only be the case that they have a lower overall probability of survival but also that their performances are evaluated differently than those of White quarterbacks. In order to test whether individual and team performances have a different impact on survival for Black quarterbacks, interaction terms between Black and the performance variables were also added to the models. None of these interaction terms were significant at conventional levels. This implies that individual or team performance does not marginally impact Black quarterbacks any differently than White quarterbacks.

The Age and Age^2 variables are individually and jointly insignificant for the models which include both variables. However, Age becomes significant when Age^2 is eliminated from the model. A significant hazard ratio greater than 1 for Age implies that younger quarterbacks are more likely to survive than older quarterbacks. This may reflect the idea that teams have more patience with young quarterbacks who are learning than they do with older quarterbacks.

It appears that higher paid starting quarterbacks are more likely to survive from one week to the next. This is evidenced by the hazard ratios being less than 1 and statistically significant for the Salary variable under all models and samples. This implies that teams may be less willing to bench a quarterback in whom they have a large financial investment. Unlike their salary, it appears that a player's draft pick does not influence his likelihood of survival. The variable Draft Pick is insignificant for all models and samples.

Conclusion

This analysis has shown that when controlling for injury, age, experience, individual performance, team performance, team investment, backup quality, and bye weeks Black starting quarterbacks are 1.98 to 2.46 times more likely to be benched the next game than observationally equivalent White quarterbacks. This result is statistically significant and appears robust to model and variable selection. This implies that Black quarterbacks may face some level of discrimination in the NFL. Limited evidence is found that Black quarterbacks face less discrimination in areas with a larger percentage of Black residents. This implies that at least some of this discrimination may be attributable to the customers. Additionally, it has been observed that when White quarterbacks are replaced, the team improves by more than when Black quarterbacks are replaced. This provides evidence that there is a cost to this discrimination. Given that the NFL is not a perfectly competitive market it is possible that discriminating employers are not being driven out of the market as economic theory would predict. However, it is also possible that owners are simply responding to the desires of their customers. Future research should seek to better analyze the sources of this discrimination by identifying situations where employer or customer preferences can be observed independently.

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Notes

1. The 2010 National Football League (NFL) season was played without a salary cap. Therefore, the chosen sample ends in 2009 to avoid including a year with an inconsistent salary measure.
2. Team performance and individual performance and characteristics are based on publicly available data from http://www.pro-football-reference.com.
3. These data were taken from the 2009 Census Bureau State and Metropolitan Area Data Book, table B-3.
4. Models were also estimated using separate binary variables for each possible listing on the injury report. The results from these models did not meaningfully differ from those presented here.
5. Player salary cap values are based on the USA Today NFL Salary Database available at http://content.usatoday.com/sportsdata/football/nfl/salaries/team.
6. Players who were not drafted are treated as being drafted after the last pick.
7. It should be noted that individual performance statistics are likely correlated with team performance statistics. In the presence of such multicollinearity, variables which are significant may appear insignificant. In order to test for this multicollinearity, models were also run excluding Win, Winning Percentage, Offensive Points, and Salary Cap Percentage. Even when excluding those measures from the model individual performance statistics are found to be insignificant.

References

Arrow, K. J. (1973). The theory of discrimination. In O. Ashenfelter & A. Rees (Eds.), *Discrimination in labor markets* (pp. 3–33). Princeton, NJ: Princeton University Press.

Becker, G. S. (1957). *The economics of discrimination* (2nd ed., 1971). Chicago, IL: University of Chicago Press.

Berri, D. J., & Simmons, R. (2009). Race and the evaluation of signal callers in the National Football League. *Journal of Sports Economics*, *10*, 23–43.

Conlin, M., & Emerson, P. M. (2006). Discrimination in hiring versus retention and promotion: An empirical analysis of within-firm treatment of players in the NFL. *The Journal of Law, Economics, & Organization*, *22*, 115–135.

Cox, D. R. (1972). Regression models and life tables (with discussion). *Journal of the Royal Statistical Society, Series B*, *34*, 187–220.

Gius, M., & Johnson, D. (2000). Race and compensation in professional football. *Applied Economics Letters*, *7*, 73–75.

Kahn, L. M. (1992). The effects of race on professional football players' compensation. *Industrial and Labor Relations Review*, *45*, 295–310.

Keefer, Q. A. W. (2013). Compensation discrimination for defensive players applying quantile regression to the National Football League Market for linebackers. *Journal of Sports Economics*, *14*, 23–44.

Keefer, Q. A. W. (2015). The sunk-cost fallacy in the National Football League: Salary cap value and playing time. *Journal of Sports Economics*. doi:10.1177/1527002515574515

Lapchick, R., Donovan, D., Rogers, S., & Johnson, A. (2014). The 2014 racial and gender report card: National Football League. *UCF Institute for Diversity and Ethics in Sport*. Retrieved from http://www.tidesport.org/The%202014%20NFL%20Racial%20and%20Gender%20Report%20Card.pdf

Mogull, R. G. (1973). Salaries and race: Some empirical evidence. *Industrial Relations*, *12*, 109–112.

Mogull, R. G. (1981). Salary discrimination in professional sports. *Atlantic Economic Journal*, *9*, 106–110.

Volz, B. D. (2009). Minority status and managerial survival in major league baseball. *Journal of Sports Economics*, *10*, 522–542.

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