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Letian Zhang

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Who Loses When a Team Wins? Better Performance Increases Racial Bias

Letian Zhang^a

^aHarvard Business School, Boston, Massachusetts 02163

Contact: letian.lt.zhang@gmail.com,  <http://orcid.org/0000-0002-3212-8303> (LZ)

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Abstract. Although it is well known that team performance influences strategic decision making, little is known about its impact on ascriptive inequality. This study proposes a performance effect on racial bias: higher team performance reduces managers' performance pressure and therefore, leads to more managerial bias in the subsequent decisions. I find strong evidence for this proposition using a fine-grained data set from the National Basketball Association. In this highly competitive industry, team performance is positively associated with coaches' subsequent exercise of racial bias: players experience more favorable treatment from same-race coaches after their teams win games. This study shows an important relationship between performance feedback and racial bias and suggests that, even in highly competitive industries, managerial bias may persist in high-performing teams and organizations.

Supplemental Material: The online appendices are available at <https://doi.org/10.1287/orsc.2018.1232>.

Keywords: racial bias • discrimination • performance feedback • NBA basketball

Introduction

Racial bias should be costly. By indulging in racial preference, employers and managers forgo the opportunity to use the best available workers, undermining the performance of their organizations and teams (Becker 1957). This has led many to assume a competitive effect on racial bias: competition should lead employers and managers to either restrain their racial preference or face the prospect of being driven out of the market (Becker 1957, Fernandez and Campero 2014, Baert et al. 2015). However, empirical evidence shows that racial bias remains prevalent in highly competitive industries (Kumar et al. 2015, Zhang 2017). This study offers an explanation by theorizing that a manager's exercise of racial bias is contingent on the performance of his or her team and organization.

I draw from the literature on organizational performance feedback to suggest a performance effect on racial bias (Greve 2003b). The performance of an organization or team is known to strongly influence a manager's engagement with risk and strategic change, but this literature has yet to consider its impact on managers' ascriptive bias in decision making. I propose that higher team performance leads managers to exercise greater racial bias. Managers tend to experience more performance pressure and have less self-confidence and credibility when their teams have performed poorly. They are, therefore, more incentivized to use the best workers available to maximize performance, and they use objective criteria to avoid criticism.

However, these same managers may be more insulated from performance pressure and have greater confidence and credibility when their teams have performed well, giving them more room to exercise their racial preference. This performance effect predicts that racial bias in competitive markets would mostly come from managers of higher-performing teams.

I examine this argument in the context of the National Basketball Association (NBA), a highly competitive industry in which head coaches are under tremendous performance pressure. Using data from 1990 to the present, I find that as many as 20% of NBA head coaches lose their jobs every year, and the majority do not survive beyond their third year. Team performance is a crucial criterion in these termination decisions. Among those who lost their head coaching positions, more than 80% had failed to make the playoffs in the previous year.

However, despite the market's competitiveness, NBA coaches still exhibit significant racial bias in their lineup decisions (Schroffel and Magee 2012, Zhang 2017). In a previous paper (Zhang 2017), I showed that a player gets 34 seconds more playing time per game playing for a same-race coach than for an other-race coach. This pattern remains robust even after accounting for various alternative explanations and selection issues. In that study, coaches' racial bias declines as the number of closely contested games increases, suggesting that competitive pressure helps reduce racial bias. However, that study's focus is the relationship between

repeated interaction and racial bias; it does not explain how racial bias can persist in such a competitive market. In this article, I apply performance feedback theory to offer an explanation.

Team Performance and Racial Bias

Racial bias refers to the unequal treatment of persons or groups on the basis of their race (Pager and Shepherd 2008). As an important source of organizational inequality, it contributes to racial gaps in hiring (Pager 2003, Bertrand and Mullainathan 2004, Pager et al. 2009), opportunity allocation (DiTomaso et al. 2007b, Schroffel and Magee 2012, Zhang 2017), performance evaluation (Elvira and Town 2001, DiTomaso et al. 2007b), promotion and wage setting (Wilson 1997, Castilla 2008), and dismissal (Elvira and Zatzick 2002, Giuliano et al. 2011).

Broadly speaking, there are two kinds of racial bias. The first, commonly referred to as taste-based bias, comes from a decision maker's preference for some racial groups over others (Charles and Guryan 2008). The second type comes from a decision maker's association of some racial groups with higher quality than other racial groups, and it is often referred to as either statistical discrimination (Phelps 1972, Aigner and Cain 1977, Rubineau and Kang 2012) or performance stereotyping (England and Lewin 1989, Correll and Benard 2006), depending on whether the decision maker has the correct group average (Zhang 2017).¹

In this paper, I focus on taste-based bias. A common example is in-group preference: people generally feel more comfort, trust, and obligation toward members of their own race and treat them more favorably (Reskin 2000, Reskin 2005). This has been consistently observed in laboratory experiments and recently, also documented in field studies (Reskin 2000, DiTomaso et al. 2007a). For example, black and white hiring agents are more likely to hire black and white job applicants, respectively (Stoll et al. 2004, Giuliano et al. 2009), and managers tend to give same-race employees higher performance evaluations (Elvira and Town 2001). Similar evidence of same-race favoritism appears in sports refereeing (Price and Wolfers 2010, Parsons et al. 2011, Pope et al. 2013), patient care (Chen et al. 2001), and jury verdicts (Anwar et al. 2012).

Economic theory views such bias as costly. Managers who indulge in their racial preferences forgo the opportunity to use the best workers available, undermining organizational performance by introducing inefficiency (Becker 1957). Managers who do not express a racial taste should, therefore, perform better than those who do. Given the economic cost of racial bias, there has been much interest in its relationship with competition (Ashenfelter and Hannan 1986, Neumark 1999, Levine et al. 2008, Buchak and Jørring 2016, Pager 2016). Because discriminating managers

are at a competitive disadvantage, competition should eventually drive them out of business (Becker 1957). Alternatively, it is possible that, instead of being eliminated by the market, biased managers would simply refrain from exercising their racial preferences in competitive environments (Fernandez and Campero 2014, Baert et al. 2015). Thus, competition should either select out biased managers from the market or discourage them from indulging in their bias: “tastes for discrimination should only be sustained in sectors of the economy with little market competition” (Fernandez and Campero 2014, p. 3).

All the same, racial bias remains prevalent in many competitive industries. In finance and sports, for example, poor-performing managers and coaches can easily lose their positions. However, research shows that many managers and coaches in these industries continuously exhibit significant racial bias in selecting workers and allocating opportunities (Kahn 1991, Schroffel and Magee 2012, Kumar et al. 2015, Zhang 2017). These findings seem to contradict the prediction that intense competition should either drive out biased managers and coaches or force them to restrain their biases (England and Lewin 1989). However, there is an alternative scenario if we consider the social psychology of performance feedback: it is possible that managers and coaches exercise racial bias only when their teams have performed well, in which case racial bias would still exist in these competitive markets.

The proposition that managers adjust their levels of racial bias depending on their teams' performance speaks to performance feedback theory, which suggests that recent organizational and team performance has important influences on subsequent managerial decision making (Cyert and March 1963, Greve 1998, Greve 2003b). However, this theory has mostly focused on strategic decision making, and as I propose below, there are reasons to believe that performance has an impact on managers' exercise of racial bias as well.

A Performance Effect on Racial Bias

Performance feedback theory suggests that managers and organizations are highly attentive to their performance and make decisions based on whether it exceeds their aspirations (Greve 2003b). At an individual level, the theory predicts that managers take on riskier strategies when performance is below aspiration. This argument draws from prospect theory, which argues that individuals are risk averse when winning and risk seeking when losing (Kahneman and Tversky 1979). At an organizational level, the performance feedback process is based on problemistic search in the behavioral theory of the firm: organizations are more likely to search for new strategies and make changes when performing below their aspirations (Cyert and March 1963). Together, these

two theoretical frameworks have led to a rich literature that examines how organizational or group performance influences strategic decision making. In particular, it has been well documented that performance influences risk taking (March and Shapira 1987, Bromiley 1991, Lim and McCann 2013, Kacperczyk et al. 2015, Zhang 2018), strategic change (Greve 1998), investment in assets (Audia and Greve 2006), acquisitions (Iyer and Miller 2008), investments in research and development (Chen and Miller 2007, Chatterjee and Hambrick 2011), and product innovation (Greve 2003a).

The performance feedback literature shows that recent performance has a significant influence on subsequent managerial decision making. However, this literature has mostly focused on firm strategy as the outcome and paid little attention to inequality. This is unfortunate, because managers' allocation of opportunities and rewards is an important source of inequality within organizations and groups (Pager and Shepherd 2008), and there are reasons to believe that recent performance can influence managers' exercise of racial bias in making these decisions. In particular, higher performance can give managers less performance pressure, more confidence, and more credibility, all of which can contribute to the expression of their racial preference.

Performance Pressure. Foremost, a team's recent performance can influence its manager's performance pressure, especially in competitive environments.² Managers whose teams have performed poorly relative to aspirations face more pressure to perform, because failure to immediately improve may result in being fired and other adverse outcomes (Chevalier and Ellison 1999). However, managers whose teams have exceeded expectations have earned some "breathing space" and are more likely to experience satisfaction and complacency (Audia et al. 2000). This pattern can occur even in highly competitive industries. For example, NBA coaches and players show much more performance urgency after losing a game than after winning one (Mizruchi 1991). In the performance feedback literature, this difference in performance pressure leads lower-performing and higher-performing managers to take different approaches to problemistic search and strategic change. I expect it to also affect their exercise of racial preference. When teams have performed poorly, managers face much stronger performance pressure and therefore, have less latitude to indulge in their personal "taste": they have every incentive to use the best workers available and put aside their racial preferences. However, managers whose teams have performed well have more room to express their personal likings and may be more willing to pay the cost of bias; therefore, their

decisions may be more influenced by their racial preferences.

Self-Confidence and Credibility. Other than performance pressure, there are two additional processes—self-confidence and credibility—that may contribute to a performance effect on racial bias. According to the theory of capability cues, managers often use past performance as an indicator of their competence, and therefore, higher-performing managers tend to be more confident in their ability (Feather 1966, Schmalensee 1976, Chatterjee and Hambrick 2011). The more-confident managers are likely to perceive less competition and challenge in the environment than the less-confident ones and thus, have less incentive to maximize performance. They may also place more trust in their own judgment and rely less on objective performance metrics, a choice that could lead to more racial bias (Reskin 2000). Thus, by feeding managers' self-confidence, improvement in team performance can contribute to racial bias in decision making.

Similarly, a team's recent performance may influence its manager's credibility to outsiders. Managers can gain authority and avoid criticism when their teams have performed well, and they can face questioning and skepticism when their teams have performed poorly. Higher-performing managers may feel more comfortable expressing their individual preferences, because they are less likely to be questioned, whereas lower-performing ones may opt to use more objectivity to avoid criticism (Monin and Miller 2001). This credibility effect can reinforce the performance effect on racial bias.

Hypothesis. *The better a team performs, the more racial bias its manager exercises in subsequent decision making.*

A Boundary Condition

There is an important exception to higher team performance leading to less performance pressure in the subsequent round. Certain markets give increasingly higher rewards for higher performance. For example, in most sports tournaments (such as NBA playoffs), there are increasingly higher returns to top finishers. Coaches may feel a higher performance pressure as they progress further in the tournament (for example, more pressure in a tournament final than in a semifinal). In these markets, I expect managers to maintain high performance pressure after winning, and the performance effect on racial bias may be significantly weaker in these situations.

Racial Bias in the NBA

I examine the behavior of head coaches in the NBA. This setting offers important advantages in identifying racial bias, which has long been a challenge in

observational studies (Pager and Shepherd 2008, Pager et al. 2009). Typically, researchers measure racial bias using residual differences between races after controlling for observable individual characteristics (Tomaskovic-Devey et al. 2005). However, there may be important differences between individuals of different races that are visible to decision makers but not to researchers, and this unobserved heterogeneity can confound the effect of race (Charles and Guryan 2008, Pager and Shepherd 2008). For this reason, claims of racial bias in observational studies have frequently been questioned (Farkas and Vicknair 1996, Charles and Guryan 2008).

The NBA setting helps minimize the issue of unobserved heterogeneity (Zhang 2017). First, because NBA coaches and players frequently change teams, researchers can use player fixed effects to examine how a player’s treatment (for example, playing time) changes as he moves from a same-race coach to an other-race coach and vice versa. Observing within-player changes allows one to account for time-invariant individual traits (Halaby 2004). Second, the NBA context offers objective measures of individual performance: namely, detailed performance statistics on each player, including points, rebounds, and assists (Kahn 1991, Staw and Hoang 1995). These measures help control for a player’s time-variant performance level.

One of a coach’s primary roles is to allocate playing time (Staw and Hoang 1995, Camerer and Weber 1999, Schroffel and Magee 2012, Zhang 2017). As past studies suggest, playing time is important to players, because it gives them opportunities to perform and showcase their value (Staw and Hoang 1995, Zhang 2017). For instance, playing time contributes to a player’s likelihood of staying on the team, becoming an All Star, and getting a raise (Zhang 2017). Therefore, playing time is an important and meaningful outcome in this context, and I will use it as the dependent variable to examine the performance effect on racial bias.

Methods

My analysis uses the NBA’s game-by-game data from the 1990–1991 season through the 2014–2015 season.

Unlike most NBA studies that use season-by-season statistics (e.g., Staw and Hoang 1995, Camerer and Weber 1999, and Zhang 2017), this study offers more fine-grained analyses by examining coaches’ treatment of their players in each game. I scraped the data from basketball-reference.com, a reliable site for sports statistics (Kubatko et al. 2007). For each player, I gathered performance statistics for every game, including points, rebounds, assists, fouls, and minutes played. I recorded whether a player is active or injured for each game and excluded those player-game cases in which a player is injured. For each team, I identified its head coach and current win-loss record. For each game, I recorded whether it was a regular season or playoff game and its final score.

I coded the race of every player and coach in the data set using online photos. A colleague conducted the coding separately: we had an intercoder reliability of 99%. Each player and coach was coded as either “black” or “white.” Because there are few Hispanic or Asian players in the NBA (less than 1%), I simply excluded them from the analysis. I also excluded the few cases that my colleague and I coded differently. The final sample has 2,106 players and 645,672 player-game observations. As Table 1 shows, there are more black players than white players in the sample but more games under white coaches than black coaches.

Fixed Effects Models

My main models are linear panel models with player fixed effects, which observe how a player’s playing time changes as he moves from playing under a white coach to a black coach or vice versa. In the sample, 1,185 players have played under both white and black coaches, accounting for 521,103 player-game observations (80.7% of the sample). Because fixed effects cannot account for time-varying within-cluster correlations, I clustered standard errors at both the player and coach levels. As a robustness check, I included both coach and team fixed effects in additional models; their inclusion does not substantially change the results.

Table 1. Comparison of Black and White Players

Variable	Black players	White players	All players
<i>Number of Players</i>	1,594	512	2,106
<i>Games Under Black Coaches</i>	149,437	34,790	184,227
<i>Games Under White Coaches</i>	359,015	102,430	461,445
<i>All Games</i>	508,452	137,220	645,672
<i>Minutes per Game</i>	23.9	20.5	23.2
<i>Years in the League</i>	6.0	5.5	5.9
<i>Points per Minute</i>	0.38	0.35	0.37
<i>Rebounds per Minute</i>	0.17	0.19	0.17
<i>Assists per Minute</i>	0.09	0.08	0.08
<i>Team Record (Current Season)</i>	0.5	0.5	0.5

Variables

I used a player’s playing time in each game as the dependent variable. The main independent variable is whether a player has a same-race coach. As Table 1 shows, in 251,867 player-game observations (39% of the sample), the coach and the player are of the same race. Of these, 102,430 observations involve white coaches and players, and 149,437 involve black coaches and players. Of the remaining observations, 34,790 involve black coaches and white players, and 359,015 involve white coaches and black players. To measure team performance, I created two variables: a team’s current win-loss percentage in the season and its win-loss percentage in the previous 10 games. The two measures are correlated at 0.8, and I placed them in separate models to avoid collinearity.

Although the inclusion of player fixed effects eliminates the need to control for time-invariant individual characteristics, such as height, position, and playing style, it does not take into account time-varying individual performance. To control for players’ performance, I used the three standard performance statistics in basketball: points, rebounds, and assists per minute (Staw and Hoang 1995, Kubatko et al. 2007, Price and Wolfers 2010, Zhang 2017). I measured them using two time horizons: a player’s cumulative performance under the current coach and his performance in the previous 10 games. In addition to performance statistics, I included the number of years that a player has been in the league and its squared term, the number of years that a player has worked with the current coach, the number of games that a player has played for the team, whether the player is in his first year with the team, the player’s foul rate per minute, and a dummy variable indicating the team’s current ranking in the conference. Table 2 shows summary statistics and correlations of the key variables.

Results

Results support the hypothesis. A player receives more playing time under a same-race coach than under an other-race coach, but the magnitude of this bias depends on team performance; it is much stronger when the team has performed better.

Table 3 uses panel linear models with player fixed effects to predict playing time. Model 1 shows that a player gets 25 more seconds ($0.41 \times 60 = 25$) per game when playing under a same-race coach than under an other-race coach. This effect is smaller than that found in my previous study, which uses season-by-season data from 1955 to 2000 (Zhang 2017). Nonetheless, this is a significant disparity that can accumulate into a significant gap in the course of an entire season (Zhang 2017). Moreover, as I show next, this disparity increases significantly when the team has performed well.

In Models 2 and 3, I examine the effect of recent performance on coaches’ exercise of racial bias. I interacted *Same-Race Coach* with a team’s win-loss record in the previous 10 games in Model 2 and with its record in the current season in Model 3. Both interaction terms have large, positive, and statistically significant coefficients. To give a visual illustration, Figure 1 plots the effect of performance on racial bias based on Model 2. When a team has performed poorly in the previous 10 games, racial bias is quite minimal. A separate analysis shows that the same-race effect is statistically insignificant when the team has won fewer than five of the previous 10 games but becomes larger and statistically significant as the number of wins increases. When a team has won nine or 10 of the previous 10 games, having a same-race coach gives a player more than a minute of additional playing time. Models 2 and 3 are consistent with my theory that, in competitive contexts, better performance increases coaches’ indulgence in racial bias.

Table 2. Variable Summary and Correlation

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Minutes Played	23.2	12.39	1												
2 Same-Race Coach	39%	NA	-0.05	1											
3 Points per Minute (Under Current Coach)	0.4	0.15	0.40	-0.06	1										
4 Rebounds per Minute (Under Current Coach)	0.2	0.09	0.04	0.02	0.05	1									
5 Assists per Minute (Under Current Coach)	0.1	0.06	0.25	-0.04	0.19	-0.40	1								
6 Points per Minute (Previous 10 Games)	0.4	0.14	0.37	-0.04	0.67	-0.02	0.15	1							
7 Rebounds per Minute (Previous 10 Games)	0.2	0.09	-0.02	0.03	-0.04	0.76	-0.46	-0.03	1						
8 Assists per Minute (Previous 10 Games)	0.1	0.06	0.21	-0.03	0.14	-0.41	0.87	0.14	-0.44	1					
9 Fouls per Minute	0.1	0.35	-0.08	0.01	0.01	0.04	-0.05	-0.04	0.04	-0.05	1				
10 Years in the League	5.9	3.91	0.12	-0.03	0.05	0.02	0.08	-0.01	0.00	0.06	-0.02	1			
11 Years of Coach-Player Collaboration (Logged)	0.4	0.56	0.19	-0.02	0.17	0.05	0.10	0.14	0.02	0.08	-0.02	0.22	1		
12 Team Record (Current Season)	0.5	0.19	-0.01	-0.07	0.04	0.01	0.04	0.04	0.01	0.03	-0.00	0.19	0.27	1	
13 Team Record (Previous 10 Games)	0.5	0.22	-0.01	-0.06	0.04	0.01	0.04	0.05	0.02	0.04	-0.00	0.16	0.22	0.84	1

Note. SD, standard deviation.

Table 3. Panel Linear Models with Player Fixed Effects: Predicting Playing Time

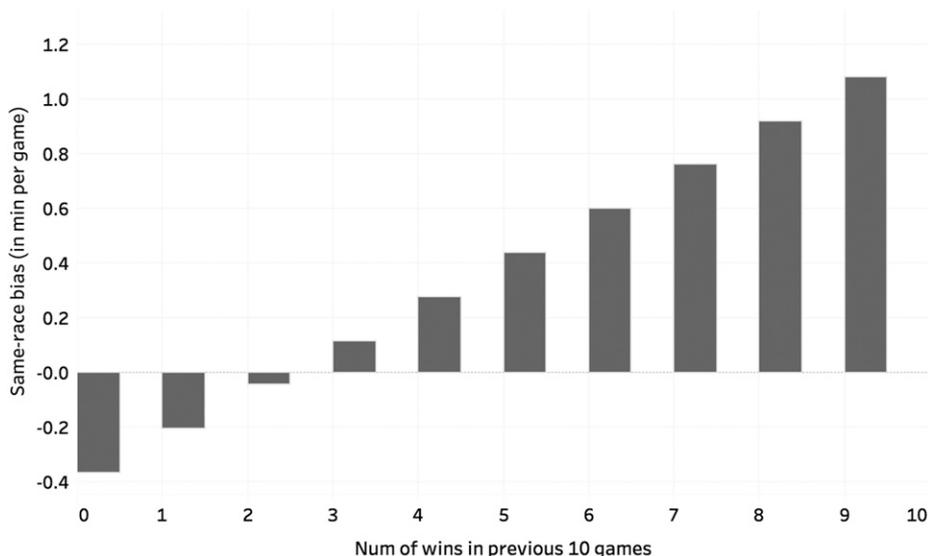
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
<i>Same-Race Coach</i>	0.41* (0.17)	0.44* (0.17)	0.45* (0.17)	0.45** (0.17)	0.47** (0.18)
<i>Same-Race Coach × Team Record in Previous 10 Games (Centered)</i>		1.61** (0.45)		1.64** (0.44)	
<i>Same-Race Coach × Team Record in Current Season (Centered)</i>			2.21** (0.69)		2.29** (0.67)
<i>Same-Race Coach × Playoff Game</i>				-0.34 (0.24)	-0.44* (0.22)
<i>Points per Minute (Under Current Coach)</i>	7.09* (2.93)	7.07* (2.93)	7.06* (2.93)	7.07* (2.93)	7.07* (2.93)
<i>Rebounds per Minute (Under Current Coach)</i>	5.94* (2.99)	5.93* (2.98)	5.93* (2.98)	5.93* (2.98)	5.92* (2.98)
<i>Assists per Minute (Under Current Coach)</i>	22.64** (2.54)	22.66** (2.53)	22.65** (2.53)	22.72** (2.54)	22.71** (2.54)
<i>Points per Minute (Previous 10 Games)</i>	10.37** (1.65)	10.37** (1.64)	10.38** (1.64)	10.34** (1.64)	10.35** (1.64)
<i>Rebounds per Minute (Previous 10 Games)</i>	-2.29 (1.49)	-2.25 (1.49)	-2.23 (1.49)	-2.26 (1.49)	-2.24 (1.49)
<i>Assists per Minute (Previous 10 Games)</i>	3.48* (1.68)	3.53* (1.68)	3.52* (1.68)	3.35* (1.70)	3.35* (1.69)
<i>Fouls per Minute</i>	-1.23** (0.27)	-1.23** (0.27)	-1.23** (0.27)	-1.23** (0.27)	-1.23** (0.27)
<i>Years in the League</i>	1.17** (0.10)	1.17** (0.10)	1.17** (0.10)	1.17** (0.10)	1.17** (0.10)
<i>Years in the League²</i>	-0.11** (0.01)	-0.11** (0.01)	-0.11** (0.01)	-0.11** (0.01)	-0.11** (0.01)
<i>Years of Coach-Player Collaboration (Logged)</i>	0.42** (0.12)	0.42** (0.12)	0.42** (0.12)	0.42** (0.12)	0.42** (0.12)
<i>Number of Games Played for This Team</i>	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)
<i>First Year on the Team</i>	-0.72** (0.17)	-0.72** (0.17)	-0.72** (0.17)	-0.71** (0.17)	-0.71** (0.17)
<i>Team Record in Previous 10 Games (Centered)</i>	-1.18** (0.20)	-1.82** (0.25)	-1.20** (0.20)	-1.87** (0.25)	-1.24** (0.20)
<i>Team Record in Current Season (Centered)</i>	-1.10* (0.55)	-1.04 (0.54)	-1.87** (0.62)	-1.14* (0.55)	-1.99** (0.62)
<i>Playoff Game</i>				-0.49** (0.13)	-0.45** (0.12)
<i>Constant</i>	10.44** (0.74)	10.43** (0.74)	10.43** (0.74)	10.57** (0.74)	10.56** (0.74)
Observations	645,672	645,672	645,672	645,672	645,672
R ²	0.14	0.14	0.14	0.14	0.14
Player fixed effects	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors clustered by player and coach.
 * $p < 0.05$; ** $p < 0.01$.

In Models 4 and 5 of Table 3, I included an additional interaction term to compare the effect of race in regular season versus playoff games. In a normal NBA season, teams first play 82 regular season games to determine their regular season standings; the best eight teams in

each conference then proceed to the playoffs to play for the NBA championship.³ Coaches usually experience high performance pressure throughout the playoffs, because their teams have to continuously perform well to avoid elimination. I, therefore, expect coaches

Figure 1. Predicted Racial Bias Based on Recent Performance



Notes. Bars represent coefficient values for *Same-Race Coach* in Model 2 of Table 3. A higher bar suggests more same-race bias.

to exhibit less racial bias in the playoffs. The models mostly support this proposition. The interaction coefficients between *Playoff Game* and *Same-Race Coach* are negative in both models, and they are statistically significant in Model 5, providing some evidence that NBA coaches exhibit more racial bias in regular season games than in playoffs. A separate analysis finds that a team's performance does not have a significant effect on coaches' racial bias in playoffs. These findings suggest that team performance influences coaches' racial bias in regular season games but not in playoff games, where the pressure remains high or even increases after each win.

Table 4 accounts for the final score margin and difference in win-loss records between the two teams to ensure that the patterns observed in earlier models are not driven by coaches' decisions in blowout games—those won or lost by a large margin. In Models 1–3, I added two interaction terms: between *Same-Race Coach* and *Absolute Difference in Final Score* and between *Same-Race Coach* and *Absolute Difference in Team Records*. This does not substantively change the main findings: a team's performance is still positively correlated with the coach's same-race bias. In the remaining models, I examine only those games that have relatively close scores: Models 4 and 5 focus on games with a final score margin of less than 10 points, and Models 6 and 7 focus on games that have a final score margin of less than five points. These models are consistent with the main hypothesis, suggesting that the effect of team performance on racial bias is not driven by the dynamics of blowout games.

Table 4 also examines the competition hypothesis and offers some weak evidence showing that increased competitive pressure reduces coaches' racial bias. Although the NBA is a highly competitive market overall, games in which the teams have similar rankings should be more competitive than games in which the teams are far apart in ranking. Model 3 gives some indication that coaches exercise less racial bias in the more competitive games: the interaction term between *Same-Race Coach* and *Absolute Difference in Team Records* is positive and statistically significant at the 0.1 level. The competition effect is weak, probably because quality differences between NBA teams are so small that even games between two far-apart teams are highly competitive.

Controls are generally consistent with expectations. A player's points and assists per minute have a strong positive association with playing time, whereas his rebounds per minute have a weak association and fouls per minute have a negative association with playing time. In terms of tenure, a player initially gets more playing time as he spends more years in the league, although this effect diminishes as the player ages. Seniority on a team also matters: a player's playing

time increases as he spends more time on the team. Lastly, minutes per game have a negative correlation with team performance. This is likely because teammates on higher-performing teams are generally playing better, resulting in stronger competition for minutes. Overall, these patterns are similar to those found in previous studies (Staw and Hoang 1995, Zhang 2017).

Additional Analyses

Additional analyses further support the findings. First, I considered a team's performance in the previous season as a benchmark for current performance. A team that performed better in the previous season may have higher performance expectations than a team that performed poorly. In Online Appendix 1, I measured a team's performance using its current win-loss record minus its overall win-loss record in the previous season. For newly formed teams, I set their previous season record at 0.5, the league average. As Online Appendix 1 shows, accounting for previous season's performance weakens the effect of performance on racial bias, but the results still strongly support the hypothesis.

Second, one of the advantages of the NBA context is the availability of objective performance controls for individual players. Points, rebounds, and assists are the most salient dimensions of a player's performance and the ones to which coaches pay the most attention (Zhang 2017), but some coaches may also consider other aspects of a player's performance, such as field goal percentage, rebounding rate, and turnover ratio. In Online Appendix 2, I included player efficiency rating (PER), an advanced per-minute statistic developed by Hollinger (2005) that covers more than 10 dimensions of a player's performance (Staw and Hoang 1995, Ertug and Castellucci 2013). In constructing this variable, I calculated the unadjusted PER for each player and then standardized it within each team, because players on the same team are competing with one another for playing time. As shown in Online Appendix 2, using this fine-grained performance control does not substantively change the results.

Third, an analysis addresses possible serial correlation by considering a first-order autoregressive model. I used the method derived by Baltagi and Wu (1999), which relies on Cochrane–Orcutt transformations (*xtregar* module in Stata 15). This modeling strategy does not allow clustering. As Online Appendix 3 shows, these autoregressive models produce substantively similar results.

Fourth, I included a lagged dependent variable in the model. A player's playing time in one game may also be influenced by his playing time in previous games. As Online Appendix 4 shows, the incorporation of a lagged dependent variable reduces the magnitude of the same-race effect but does not substantively change the main findings. A team's performance is still positively correlated with the coach's same-race bias. It is

Table 4. Account for Blowout Games

Variable	Full sample			Final score margin <10			Final score margin <5		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7		
<i>Same-Race Coach</i>	0.31 (0.19)	0.34 (0.19)	0.35 (0.19)	0.51** (0.18)	0.53** (0.18)	0.55** (0.19)	0.58** (0.19)		
<i>Same-Race Coach × Team Record in Previous 10 Games (Centered)</i>		1.49** (0.46)			1.61** (0.52)		1.73** (0.55)		
<i>Same-Race Coach × Team Record in Current Season (Centered)</i>			2.03** (0.69)						
<i>Same-Race Coach × Absolute Difference in Team Records</i>	0.24 (0.23)	0.33 (0.22)	0.36 (0.21)						
<i>Same-Race Coach × Absolute Difference in Final Score</i>	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)						
<i>Points per Minute (Under Current Coach)</i>	7.18* (2.93)	7.16* (2.93)	7.16* (2.93)	11.81** (2.69)	11.79** (2.70)	11.12** (3.08)	11.10** (3.09)		
<i>Rebounds per Minute (Under Current Coach)</i>	6.00* (3.00)	6.00* (3.00)	6.00* (3.00)	10.09** (2.73)	10.07** (2.72)	10.53** (2.66)	10.51** (2.65)		
<i>Assists per Minute (Under Current Coach)</i>	22.92** (2.52)	22.95** (2.52)	22.94** (2.52)	27.01** (2.56)	27.04** (2.56)	27.68** (2.96)	27.72** (2.95)		
<i>Points per Minute (Previous 10 Games)</i>	10.32** (1.65)	10.32** (1.65)	10.33** (1.65)	10.04** (1.56)	10.04** (1.56)	11.20** (1.74)	11.20** (1.74)		
<i>Rebounds per Minute (Previous 10 Games)</i>	-2.38 (1.50)	-2.34 (1.49)	-2.33 (1.49)	-3.17* (1.36)	-3.13* (1.35)	-3.74* (1.47)	-3.70* (1.47)		
<i>Assists per Minute (Previous 10 Games)</i>	3.72* (1.68)	3.77* (1.68)	3.76* (1.68)	4.64** (1.63)	4.69** (1.63)	6.32** (1.82)	6.36** (1.82)		
<i>Fouls per Minute</i>	-1.27** (0.28)	-1.27** (0.28)	-1.27** (0.28)	-1.03** (0.22)	-1.03** (0.22)	-0.82** (0.16)	-0.82** (0.16)		
<i>Years in the League</i>	1.16** (0.10)	1.16** (0.10)	1.16** (0.10)	1.27** (0.11)	1.27** (0.11)	1.28** (0.11)	1.28** (0.11)		
<i>Years in the League²</i>	-0.11** (0.01)	-0.11** (0.01)	-0.11** (0.01)	-0.11** (0.01)	-0.11** (0.01)	-0.11** (0.01)	-0.11** (0.01)		
<i>Years of Coach-Player Collaboration (Logged)</i>	0.41** (0.12)	0.40** (0.12)	0.40** (0.12)	0.43** (0.13)	0.43** (0.13)	0.36** (0.14)	0.36** (0.14)		
<i>Number of Games Played for This Team</i>	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)		
<i>First Year on the Team</i>	-0.71** (0.17)	-0.70** (0.17)	-0.70** (0.17)	-0.81** (0.18)	-0.81** (0.18)	-0.85** (0.21)	-0.85** (0.21)		
<i>Team Record in Previous 10 Games (Centered)</i>	-1.29** (0.19)	-1.88** (0.25)	-1.30** (0.19)	-1.39** (0.21)	-2.02** (0.29)	-1.28** (0.26)	-1.95** (0.35)		
<i>Team Record in Current Season (Centered)</i>	-5.24** (0.44)	-5.22** (0.44)	-6.00** (0.54)	-5.24** (0.51)	-5.22** (0.50)	-5.22** (0.54)	-5.19** (0.53)		
<i>Absolute Difference in Team Records</i>	-0.05 (0.15)	-0.08 (0.14)	-0.08 (0.14)						
<i>Absolute Difference in Final Score</i>	-0.09** (0.01)	-0.09** (0.01)	-0.09** (0.01)						
Constant	13.01** (0.74)	13.00** (0.74)	13.00** (0.74)	9.95** (0.76)	9.95** (0.76)	9.76** (0.91)	9.76** (0.91)		
Observations	645,672	645,672	645,672	326,827	326,827	134,345	134,345		
R ²	0.15	0.15	0.15	0.14	0.14	0.14	0.14		
Player fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes		

Note. Robust standard errors clustered by player and coach.

p* < 0.05; *p* < 0.01.

important to note that, although adding a lagged dependent variable to fixed effects models may introduce some concerns about endogeneity, it is significantly lessens by the large number of observations per player (Baltagi 2008).

Fifth, I added both team and coach fixed effects to the main models. As Online Appendix 5 shows, the inclusion of these additional fixed effects does not substantively change the findings.

I also considered a few alternative explanations.⁴ One possibility is that coaches may simply decide to use more variance in lineups after losing, which could dilute their initial preference and result in less same-race bias. However, additional analysis shows that a team's performance does not significantly affect its amount of playing time variance. Another possibility is that an influx of new players to the team may influence coaches' racial bias. However, incorporating an additional interaction term to account for any new players produced substantively similar findings. Finally, team performance may be somewhat correlated with team turnover. An additional analysis accounting for the interaction between *Years of Coach-Player Collaboration* and *Same-Race Coach* does not substantively change the main results.

Conclusion

Performance feedback theory suggests that the performance of a team or organization strongly influences its manager's subsequent decisions for organizational change, innovation, risk taking, and other strategic outcomes. This study shows that performance feedback influences not only firm strategies but also, social inequality within a group or organization. I hypothesize that higher team performance is associated with more racial bias in managers' subsequent decision making. Higher performance reduces a manager's performance pressure and raises his or her self-confidence and credibility, all of which increase his or her tendency to exercise racial preferences. Using a detailed NBA data set, I find that a team's winning percentage in recent games has a strong positive correlation with its coach's racial bias in the next game.

The performance effect on racial bias suggests that taste-based bias can persist in competitive markets. Because taste-based bias logically should be costly, economic theories have long predicted that biased employers and managers should be driven out of the market over time. This view assumes that employers and managers exercise the same level of taste-based bias in all situations unless their taste itself changes. A more recent version of this argument relaxes this assumption, suggesting that employers and managers can suppress their racial taste in competitive environments. However, both perspectives believe that little or no racial bias should exist in competitive

markets, a prediction largely inconsistent with empirical findings. This study offers an alternative perspective. I assume not only that managers can choose to exercise or suppress their racial taste but also, that they dynamically update their choices based on recent performance. In particular, they reduce their taste-based bias when team performance declines, whereas they increase it when performance improves. This proposition predicts racial bias in competitive markets but only among managers of higher-performing teams.

The findings in this paper have important implications for understanding organizational inequality. Teams or organizations tend to receive more rewards and opportunities when they have performed well. For example, winning mutual funds earn higher performance fees, higher-performing investment bank groups are allocated more total bonuses, and top-ranked sports teams get more media coverage. However, this study suggests that these additional rewards and opportunities are not distributed evenly between racial groups. Higher performance leads to more racial bias; hence, the additional rewards and opportunities afforded to higher-performing teams may be distributed unevenly to different racial groups. This suggests a pattern of racial inequality in organizations: in the most profitable teams and organizations, we may expect the highest levels of racial disparity.

Some limitations of this study offer opportunities for further research. First, although the NBA setting offers important advantages in identifying racial bias and measuring performance, we should keep in mind some of its unique features. For instance, compared with most other industries, it is more racially diverse and integrated, with a large proportion of black coaches and players. It is also a highly scrutinized industry; media and fans pay attention to even minor decisions that coaches make. The high level of racial diversity, transparency, and outside scrutiny should reduce racial bias, and therefore, this setting should be considered a conservative one. If racial bias occurs here, it is likely to appear in other contexts with less diversity and monitoring. Second, in the NBA context, it is difficult to tell if the observed racial bias is a result of same-race preference, other-race prejudice, or both. Playing time is zero sum; coaches who favor same-race players are penalizing other-race players, if only inadvertently, and vice versa. Third, it is difficult with this data set to distinguish if the bias comes from white coaches, black coaches, or both. A within-individual model can show that white and black coaches treat the same player differently, but it is not clear who is biased. A between-individual model would raise the issue of unobserved individual heterogeneity, because there could be differences between players that are important but difficult to measure (Price and Wolfers 2010, Zhang 2017).

To conclude, this study uses a unique data set to examine the role of race in NBA coaches' allocation of opportunities. I find that coaches exhibit more racial bias when their teams have performed better. This study should encourage future studies to consider the performance context when examining racial inequality in organizations.

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Endnotes

¹ Some studies use the term "statistical discrimination" to broadly refer to both performance stereotyping and true statistical discrimination. However, if we are to be precise about the definition, then true statistical discrimination occurs when decision makers draw from unbiased and objective group information to infer an individual's quality; performance stereotyping occurs when decision makers use biased perceptions of a group to infer an individual's quality.

² Throughout this discussion, I focus on a team's performance and its manager's subsequent decision making. However, a similar argument can be applied to an organization's performance and the behavior of its CEO and senior managers.

³ Historically, there has been some variation in the number of regular season games and the number of playoff teams. For example, there were only 66 regular season games during the 2011–2012 season because of a shortened schedule.

⁴ Analyses are available on request.

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Letian Zhang is an assistant professor at Harvard Business School. He received his PhD in sociology from Harvard University and his BS in mathematics from Stanford University. His current projects examine status, race, and gender dynamics in organizations and markets.