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CONSUMER AND EMPLOYER DISCRIMINATION IN PROFESSIONAL SPORTS MARKETS – NEW EVIDENCE FROM MAJOR LEAGUE BASEBALL

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Consumer and employer discrimination in professional sports markets – New evidence from Major League Baseball*

Abstract: We investigate the relationship between consumer discrimination, racial matching strategies, and employer discrimination in Major League Baseball (MLB) from 1985 to 2016. To this end, we assess the extent to which both fan attendance and team performance respond to changes in teams' and their local market areas' racial compositions. We innovate by using a significantly enhanced data basis with individual player data that we derive from combining web scraping and using facial recognition techniques to identify player race and using County-level Census data instead of Metropolitan Statistical Area data. We find that fans in both MLB Leagues developed a taste for racial diversity in the late 1980s; since the 2000s, discrimination starts to increase again. However, this discrimination is not fully rationalizing the performance gap across athletes of different race and ethnicity; employer discrimination is not primarily driven by fans' racial preferences.

Key words: Consumer preferences, Discrimination, Race, Ethnicity, Facial recognition, Ticket sales
JEL: *C5, J1, Z2*

1 Introduction

A number of studies show that employers account for consumer-based discrimination in their employee selection procedure, presumably in attempt to increase profits (see, e.g., Combes et al. (2016), Laouénan (2017), and Leonard et al. (2010)).[1] Likewise, it is often assumed that sport fans prefer players to be of similar race as their own (Kerr, 2019; Parsons et al., 2011) and previous research substantiates the belief that fan driven discrimination can impact merchandise and collectibles purchases (Nardinelli & Simon, 1990), All-Star voting (Hanssen, 2001), TV ratings (Kanazawa & Funk, 2001;

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[1] Going back to Becker (1957), the theory of segregation states that employers can increase profits by accounting for potential customer discrimination. Becker further identifies employers and coworkers as potential sources of labor market discrimination. In contrast to consumer discrimination, employer discrimination is likely to decrease profits in competitive markets (Leonard et al., 2010), and given that workers are mobile in the long run, employee self-sorting causes coworker discrimination to likely disappear in the long run (Nardinelli & Simon, 1990). As a consequence, many economists assume that employer discrimination does not last in competitive labor markets; persistent discrimination would therefore most likely originate from consumer discrimination rather than employer or coworker discrimination (Holzer & Ihlanfeldt, 1998).

Konjer et al., 2017), and stadium attendance behavior (Tainsky & Winfree, 2010). However, evidence is mixed, and it is unclear whether sport teams can effectively increase their revenues by matching employees' to markets' racial profiles (Burdekin & Idson, 1991; Nutting, 2012; Tainsky & Winfree, 2010).

In this study, we investigate the relationship between consumer discrimination, racial matching strategies, and employer discrimination in Major League Baseball (MLB) from 1985 to 2016. First, we predict team-specific mean regular season home game attendance to assess the potential impact of consumer discrimination against minority players on ticket demand that originates from changes in the racial composition of home teams and their local market populations. Second, we test for the presence of employer discrimination by examining the link between winnings, team diversity, and fans' racial preferences. Third, we measure the extent to which team owners engage in racial matching strategies in their player selection procedure. These comparisons offer three complementary ways in which the presence of consumer and labor market discrimination may realize in our panel data.

Extending previous studies on consumer and employer discrimination in sports markets, we allow for discrimination effects to evolve non-linearly over time, depend on local market area racial demographics, and vary across the National League (NL) and the American League (AL). Moreover, most of previous discrimination studies use relatively short time periods, do not take into account information on local markets' racial compositions, and do not investigate potential differences in discrimination against black and non-black minority players (for an overview, see, e.g., Kahn (1991) and (Tainsky & Winfree, 2010). While Hanssen (1998) analyzes League-specific consumer and employer discrimination in MLB between 1950 and 1984, no research exists that systematically investigates the relationship between ticket sales, team performance, and discrimination for a more recent period of time. This study aims to close this gap.

A central problem in the empirical analysis of discrimination in sports markets is the scarcity of publicly available data on player race and ethnicity (Foley & Smith, 2007; Hamrick & Rasp, 2015; Kahn, 1992). As a consequence, racial and ethnic affiliations are typically determined by manually assessing individual pictures of players and/or players' names and birthplaces (Hanssen & Andersen, 2007; Parsons et al., 2011; Tainsky et al., 2015). Two innovations of our study address these issues by combining automated data acquisition and racial profiling methods to reduce data collection costs and mitigate subjective bias in human race classification. First, we use web scraping techniques to collect data and pictures on more than 7,000 individual players; second, we use a deep-learning driven facial recognition application programming interface (API) to identify groups of players with similar racial and ethnic profiles. This unique data set then allows us to analyze potential differences in fans' racial preference for various types of athlete-groups that differ in their degree of visibility, position and frequency of appearance. Furthermore, while previous studies analyze data of large market areas, such as Metropolitan Statistical Areas, this is the first study to exploit County-level Census data. The resulting county-to-team mapping allows us to analyze local market area demographics that more closely resemble the population characteristics of teams' local fan bases.

Baseball has several features that allow to empirically test different forms of consumer discrimination in fans' attendance behavior. First, starting lineup players are often associated with a higher visibility, skill, and fan interest than bench players and non-key positions (Kahn, 1992; Rosen & Sanderson, 2001), and they are important to society's perception of racial equality (Guardian, 2019; Medoff, 1986). Furthermore, similar to quarterbacks in NFL, starting pitchers are by far the most highlighted position in MLB, and fans place greatest attention to their performance (Andersen & Croix, 1991; Berri & Simmons, 2009). As a result, evaluating differences in discrimination against minorities across player positions provides a way for uncovering heterogeneity in fans' racial preferences that depend on player appearance, visibility, and fan interest (Burdekin & Idson, 1991; Hamilton, 1997; Nutting, 2012).

Summarizing our main findings, this study provides evidence for the presence of consumer as well as employer discrimination. In contrast to finding discrimination against minorities to consistently increase for positions associated with higher visibility, fans' and team owners' racial preferences differ across minority and athlete groups, Leagues, and substantially change over time. While our findings indicate that baseball franchises engage in racial matching strategies, employer discrimination is not primarily driven by fans' racial preferences — differences in fans' attendance behavior resulting from consumer discrimination are not sufficient to rationalize the performance gap across athletes of different race and ethnicity.

The remainder of the paper is organized as follows: Section 2 reviews the literature on consumer-driven discrimination in professional sports markets, and Section 3 describes the data and our empirical strategy. In Section 4, we show and discuss our results. Last, in Section 5, we summarize our findings and conclusions, thereby addressing relevant policy implications.

2 Discrimination, consumer preferences, and sports markets

Sports market data often allow to analyze the presence of discrimination in a much more detailed way than it is possible in other industries, mainly because they provide various information on players' and managers' salaries, performances and their socio-economic characteristics over a long period of time (Kahn, 2000). As a consequence, there exist numerous studies that analyze discrimination in professional sports markets. To give some examples for employer discrimination, Wilson and Ying (2003) and Preston & Szymanski (2000) investigate nationality and racial labor market discrimination in professional English soccer leagues; Hoang & Rascher (1999), McCormick & Tollison (2001) and Hill & Groothuis (2017) examine the relationship between wage discrimination and player performance in the National Basketball Association (NBA); Jones & Walsh (1988) measure the extents to which player salary is affected by player skill, franchise characteristics, and employer discrimination in the National Hockey League (NHL), and Groothuis & Hill (2015) investigate exit discrimination and players career length in the National Football League (NFL). Similarly, and directly related to employer discrimination, several studies analyze diversity effects on team performance (e.g., Prinz & Wicker (2016), Kahane et al. (2013), and Papps et al. (2011)). Moreover, examples for studies on coworker, coach and referee discrimination include the analysis of labor migration (Orlowski et al., 2016) and potential effects of racial bias in MLB umpire (Hamrick & Rasp, 2015; Parsons et al., 2011; Tainsky et al., 2015), NBA referee (Price & Wolfers, 2010) and Women's National Basketball Association (WNBA) coach decisions (Harris & Berri, 2016). A general overview of earlier research on discrimination in professional sports markets is provided by Kahn (1991).

Previous studies have analyzed different forms of fan-driven discrimination against minority players with mixed evidence. First, several studies examine whether fan discrimination against minority players has an effect on tradable collectibles, such as baseball cards. For instance, Nardinelli & Simon (1990) use baseball cards price data from 1970 and find discrimination against black pitchers, but they do not find significant discrimination against black hitters pitchers. Conversely, Andersen

& Croix (1991) use data from 1960-61 and 1977 and find significant discrimination against black hitters and pitchers.

An alternative approach analyzes fan discrimination in All-star voting patterns. For example, Hanssen (2001) and Hanssen & Andersen (2007) analyze All-Star votes in baseball from 1970 to 1996 and find evidence for substantial discrimination against minority players for the early 1970s, but no significant discrimination between 1979 to 1996. In contrast, Depken & Ford (2006) suggest that there was no discrimination against minority players in baseball All-star voting between 1990 and 2000.

Another strand of the discrimination literature uses Television ratings to measure the extents of consumer prejudice. To give examples, Kanazawa & Funk (2001) uses television Nielsen ratings on basketball games from 1996 to 1997 and find that more white players on a team significantly increases TV ratings, and Konjer et al. (2017) provide evidence for positive nationality discrimination in German tennis broadcasting between 1999 and 2010. Further approaches for detecting fan driven discrimination include the analysis of fantasy sport consumers' team selection decisions (Kotrba, 2021) and social media platform activities (Watanabe et al., 2017).

Arguably the most prominent strategy for assessing consumer discrimination in professional sports markets is testing for the existence of discrimination in fans' attendance behavior. The vast majority of this strand of research concentrates on baseball and basketball. Examples concerning basketball include Burdekin & Idson (1991) and Burdekin et al. (2005); analyzing the link between NBA game attendance, racial composition effects, and minority population demographics between 1980 and 1999, they find evidence for the profitability of racial matching strategies.

In MLB, until 1947 black and other non-white players were banned from participating. During the following process of racial integration from 1947 to 1970s a great number of black players entered the MLB. As a consequence, earlier research focused on consumer prejudice against Afro-American players. For instance, Gwartney & Haworth (1974) analyze seasons between 1950 and 1959 and find that employing black players increased home attendance. Though, these positive discrimination effects appear to be partially driven by non-discriminating teams with higher shares of black players that performed better than discriminating teams, thereby increasing winnings and attendance. In contrast, Hanssen (1998) analyzes League-specific differences in consumer and employer discrimination in MLB using data from 1950 to 1984 and finds that, in both Leagues, fans show prejudice against black players. Moreover, discrimination appears to be pronounced more strongly in the American League (AL) than in the National League (NL).

The number of black players in MLB peaked in the early 1970s, remained at those levels, and began to shrink from the 1990s on until today. At the same time, there was a large increase in the numbers of Hispanic and Latino players in MLB and the US population. Consequently, researchers have extended their analyses to differences in discrimination against black and Hispanic players. However, as with earlier research, more recent studies provide mixed evidence for the existence of fan-driven discrimination in MLB (e.g., Foley & Smith (2007) and Nutting (2012). Tainsky & Winfree (2010) analyze the effect of changes in the number of a team's international players on yearly stadium attendance between 1985 and 2005. While they find no significant evidence for an impact of matching players' to metropolitan areas' racial compositions, their results show a quadratic trend for the effect of the number of a team's international players on ticket sales: the effect is negative at the beginning of the sample, turns positive in 1992, peaks in 2000, and then decreases until the end of their data sample in 2005.

Moreover, both Tainsky & Winfree (2010) and Hanssen (1998) investigate the relationship between a team's season performance and its racial composition to test for the potential existence of employer discrimination. Hanssen (1998) finds that black players have a significant and approximately equal positive impact on team performance in both the NL and AL between 1950 and 1985, indicating the presence of employer discrimination against black players. Conversely, using data from 1985 to 2005, Tainsky & Winfree (2010) do not find international players to significantly impact team performance. Furthermore, previous research on labor market discrimination in MLB has found little evidence for salary discrimination against minority athletes after the period of racial integration has ended; though, some studies highlight the presence of discrimination at the lower end of the salary distribution (Holmes, 2011; Kahn, 2000).

3 Data and empirical strategy

3.1 Data acquisition, racial classification and descriptive analysis

Our data stem from various sources: baseballreferences.com (player pictures), census.gov (population characteristics), retrosheet.org (game-log data), seamheads.com (information on stadiums), and seanlahman.com (player data). Moreover, in this study we only consider US MLB teams and their corresponding local market populations for reasons of data availability and comparability.

The main dependent variable of interest, team-specific mean home game regular season attendance, is computed from aggregated game ticket sales and the corresponding number of home games.[2] In contrast to relying on yearly total attendance numbers, this procedure allows to control for individual season and game schedule irregularities such as cancelled or relocated home games. The attendance data are derived from all 73,409 games that were played over the course of the 32 MLB regular seasons from 1985 to 2016. To assure that we exclusively measure the effects linked to a team's corresponding home local market areas' fan population, we discard a few games per season that were not played at the corresponding home team venue. Likewise, we restrict our analysis to US teams that did not change their home city between 1985 and 2016 or after moving to the US or entering the MLB in the course of a league expansion. This procedure results in 69,239 individual games that we aggregate to 866 yearly observations. A detailed description of the data cleaning process and additional summary statistics are provided in the Appendix, Section 2.

We use US Census County-level data to approximate the racial compositions of teams' local home fans and specify three mutually exclusive race groups: w*hite*, *black*, and *other* non-black minorities (see Appendix, Table A2 for the team-county mapping). [3] Our analysis includes all 7,137 players that played for the 29 US teams during the seasons from 1985 to 2016. To this end, we employ a strategy that combines automated data acquisition and race classification with manual hand coding to reduce data collection costs and mitigate subjective bias that is often associated with human race classification (Fort & Gill, 2000; Tainsky et al., 2015). First, we scraped 7,026 player pictures that

[2] The publicly available attendance numbers refer to the total number of sold tickets (and free tickets), not the actual number of spectators that were present at a game. In this study, we use the terms attendance and ticket sales synonymously. For discussion on the differences between attendance and ticket sales, see, e.g., Mueller (2020) and Schreyer et al. (2019).

[3] A limiting factor in using US Census County-level data is that the early surveys (before 1991) do not provide information on Hispanic heritage. Moreover, while the US Census Bureau officially classifies Hispanic heritage as an ethnicity and not as a race, two-thirds of American Hispanic adults view being Hispanic as part of their racial background (Pew Research Center, 2015). In addition, there has been much confusion on what actually determines Hispanic race and ethnicity, respectively (Pew Research Center, 2019). As an example, the 2010 Census survey first asked for Hispanic, Latino, or Spanish origin. A follow-up question asked survey respondents to which race they belong to, and over a third of American Hispanics checked the box for "Some other race" (The Economist, 2013).

were available on baseball-reference.com; the remaining 111 players were downloaded from MLB.com and Trademark-cards.com. In the second step, we used a deep learning based face recognition API (Kairos.com) to determine groups of players with similar racial profiles. Specifically, to match our racial classification of the County-level population data, we classify players' race on the basis of their pictures as either w*hite*, *black*, or *other*.[4] We define *white* as strictly Caucasian and *black* as African or African American appearance. *Other* includes all other non-white and non-black players; however, in addition to a few Asian players, the vast majority of other players are of Hispanic race and ethnicity, respectively. Third, based on our preliminary race mapping, two researchers independently checked each picture to correct for misclassifications using information on players' names and birth-places. Last, a small number of ambiguous cases were discussed together with a third researcher until agreement on a final assessment was reached.

We investigate the impact of changes in teams' racial compositions with respect to three different groups of athletes that vary with player visibility and fan interest. In the first and second group-specification, we measure a team's percentages of black and other non-black regular season home game starting pitchers (1) and starting non-pitchers (2). The third group includes a team's percentages of all black and other (non-black) minority athletes that played in a given season (3), and we refer to this specification as roster. To account for within-season player changes across teams in the roster model, athletes are weighted by the number of games they played for each team. For an overview of the development of MLB local market areas' and teams' racial compositions, see Appendix, Section 2.

3.2 Model specification and variable description

The model and variable specifications that we employ in this study are based on the works of Hanssen (1998), Burdekin & Idson (1991), Burdekin et al. (2005), and Tainsky & Winfree (2010). The regression function that we separately estimate for each of the three athlete groups (starting pitchers, starting non-pitchers, and roster) equates to:

$$Attendance_{it} = \beta_0 + Controls_{it}'\beta_C + Team.Comp_{it}'\beta_T + Team_t'\beta_{FE} + Pop.Comp_{it}'\beta_P + \epsilon_{it} \quad (1)$$

[4] The face recognition API Kairos provides percentage values for four race categories: Asian, black, Hispanic, white, and other. We iteratively tested and evaluated different combinations of cutoff values to determine the player to race mapping.

$Attendance_{it}$ is the mean regular season home game attendance for a team i in year t, and β_0 is a constant term. The vector $Cont$rols includes the following variables: $Wins_{it}$ is a team's corresponding winning percentage for that season. $Playoffs_{it-1}$ is a dummy variable that equals one for teams that made it to the playoffs in the previous season. Likewise, $Strike_t$ indicates a strike year and $Stadium_{it}$ indicates whether a team opened a new stadium. $Trend_t$ is a trend variable that equals zero for $t = 1985$ and increases by one unit per year, and $Trend_t^2$ is the corresponding squared term.

The vector $Team.Comp$ comprises our main variables of interest: a team's percentage shares of black [other] players $Black_{it}$ [$Other_{it}$], as well as interaction term between $Black_{it}$ [$Other_{it}$] and $Trend_t$, and an interaction term between $Black_{it}$ [$Other_{it}$] and $Trend_t^2$. In addition, we allow for differences in team racial composition effects across Leagues by including corresponding interaction terms for the AL teams; the NL is chosen as the reference League.

$Team_t'$ is a vector of home team dummy variables that capture time-invariant team and city specific characteristics (team fixed effects). As an example, ticket price data are not available for the entire sample; however, while prices vary over time, consistent differences in ticket prices across teams exists that are captured by the team fixed effects. Likewise, we highlight that our sample exclusively features stable team-city combinations and, in addition to accounting for differences in monetary prices, team fixed effects also largely control for non-monetary costs such as average travel times to the stadium as well as other leisure substitutes (Beckman et al., 2012). In this context, in favor of accounting for team fixed effects and aiming for a preferably parsimonious model, we desist from including variables that are largely team- and city-specific such as a League-membership dummy and the number of MLB teams per city or State.

Last, in addition to an error term ϵ_{it} (addressed in more detail in the next Section), $Pop.Comp_{it}$ is a vector that includes the percentage shares of black and other non-black minority residents in a team's local market area, as well as interaction terms between the share of a team's black [other] players and its corresponding local market area's share of black, other, and white residents:

$$Pop.Comp_{it}'\beta_P = Pop.Black_{it}\beta_1 + Pop.Other_{it}\beta_2 + Black_{it} * Pop.Black_{it}\,\beta_3 +$$
$$Other_{it} * Pop.Other_{it}\beta_4 + Black_{it} * Pop.White_{it}\beta_5 + Other_{it} * Pop.White_{it}\beta_6$$

3.3 Estimation strategy and standard error correction procedure

Typical concerns regarding the error term structure in regression analysis of sport attendance data include serial correlation, cross-sectional dependence, and heteroscedasticity (Hanssen, 1998; Wallrafen et al., 2019). In this paper, we investigate these issues by applying different test procedures that account for our panel data design. Concisely, the tests' results strongly indicate team-specific heteroscedasticity (variance of error terms differs across teams) and serial correlation (errors within team-specific panels are temporally correlated) as well as contemporaneous correlation across teams (cross-sectional errors are correlated due to temporal shocks common to all teams within the same period). The corresponding results are reported in the Appendix, Table A3.

In our estimation strategy, we account for disturbance serial correlation within-panels by including team-specific first order autoregressive error processes using the transformation method proposed by Prais and Winsten (1954). The final model coefficients are estimated by least-squares dummy variable (LSDV) regression. To account for the contemporaneously correlated error term structure and team-specific heteroscedasticity, we estimate the error variance-covariance matrix by feasible generalized least squares (FGLS) using panel-corrected standard errors (PCSEs) (Beck & Katz, 1995). Hence, in addition to accounting for time-invariant home team fixed effects and panel-specific first order autocorrelated error terms, the employed standard error estimation procedure is robust to differences in the variances of the disturbances across teams and to each teams' observations being correlated with those of the other teams over time.

4 Results

First, in our main analysis we assess the potential impact of consumer discrimination against minority players on ticket demand that originates from changes in the racial composition of home teams (Section 4.1) as well as their local market populations (Section 4.2). In the second step of our analysis we test for the presence of employer discrimination by examining the link between winnings and team diversity (Section 4.3). Third, we analyze whether team owners account for racial matching strategies in their player selection procedure (Section 4.4). Last, to complement our analysis, we provide the results of various robustness tests (Section 4.5).

4.1 Attendance and team racial composition effects

Table 1 displays the athlete-group specific attendance regression results based on the model specification described in equation (1) without including variables on local market areas' racial demographics.

Table 1. Racial composition effects on average home game attendance

	(1) Starting Pitchers		(2) Starting Non-Pitchers		(3) Roster	
Wins (%)	274.47***	(19.22)	276.03***	(19.42)	275.97***	(19.50)
Playoffs	2395.95***	(272.29)	2368.83***	(278.69)	2390.85***	(284.26)
Stadium	5416.94***	(651.09)	5411.45***	(651.71)	5408.42***	(664.88)
Strike	-683.43	(705.35)	-603.29	(712.58)	-681.51	(701.42)
Trend (1985=0)	694.40***	(180.99)	368.71	(299.47)	680.60**	(332.26)
$Trend^2$	-14.55**	(5.69)	-3.94	(9.05)	-12.86	(10.35)
Black (%)	26.08	(68.99)	-35.01	(54.86)	38.89	(85.87)
Black*Trend	5.51	(10.93)	7.58	(7.86)	-2.36	(12.95)
$Black*Trend^2$	-0.22	(0.33)	-0.19	(0.24)	-0.02	(0.41)
Other (%)	125.36**	(50.90)	131.47	(91.61)	51.78	(120.91)
Other*Trend	-15.85**	(6.23)	-2.80	(11.35)	-5.82	(14.78)
$Other*Trend^2$	0.42**	(0.19)	-0.07	(0.31)	0.11	(0.42)
AL Black	47.36	(97.33)	28.42	(53.22)	95.77	(85.41)
AL Black*Trend	-10.22	(14.22)	-5.83	(7.14)	-6.89	(11.71)
AL Black* $Trend^2$	0.33	(0.42)	0.13	(0.23)	0.23	(0.38)
AL Other	-101.18	(63.96)	-199.54**	(91.43)	29.18	(125.92)
AL Other*Trend	18.91***	(7.23)	18.01*	(10.26)	8.34	(13.19)
AL $Other*Trend^2$	-0.55***	(0.20)	-0.35	(0.27)	-0.20	(0.35)
Constant	11018.29***	(3690.99)	12439.42***	(4211.96)	8760.96**	(3597.98)
Team FE	Yes		Yes		Yes	
R2	0.800		0.810		.795	

Notes: Dependent variable is team-specific MLB mean regular season home game attendance. Results are based on aggregated game data from 1985 to 2016. Model (1-2) relate to starting lineups, whereas model (3) includes all athletes that were playing during a given season. National League teams are chosen as reference (vs. American League). Estimates are derived from Prais-Winsten regression using panel-corrected standard errors (in parentheses; see Section 3.3 for details). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In all three model specifications (starting pitchers, starting non-pitchers, and roster), both winning percentage and reaching the previous season's play offs have a significant positive effect on a team's mean season home game attendance — fans prefer winning (home) teams. The trend variable estimates are both significantly different from zero for the starting pitchers specification (1), not significant for the starting non-pitchers model (2), and only the linear trend coefficient is significant for the roster specification (3). The combined second-degree polynomial trend estimates show the expected positive concave effect on mean attendance over time in each of the three model specifications. Furthermore, we use Wald joint significance tests incorporating both trend variables and find that the combined trend effect is significant in each of the three athlete group specifications (p-value < 0.01).

For both NL and AL teams, we do not find significant estimates for the percentage share of black players (individual as well as trend polynomial interactions) on mean home game attendance for any of the three athlete group specifications. With respect to a team's percentage of other non-black minority athletes, we find significant effects for starting pitchers in the NL that significantly differ to the corresponding AL estimates, and we find significant effects for starting non-pitchers in the AL. The corresponding individual coefficient estimates for the roster specification are all insignificant.

Similar to testing the combined time trend effect, in the next step of our analysis, we investigate the combined racial composition trend effects by League-specific joint significance tests to assess the relevance of non-linear changes over time: we test whether the NL combined coefficients are statistically different from zero, whether the AL coefficients differ from the NL coefficients, and whether the AL coefficients are different from zero. The corresponding results are presented in Table 2.

Table 2. Racial composition effects on average home game attendance

Specification	Black			Other		
	(1)	(2)	(3)	(1)	(2)	(3)
First degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. Zero	0.132	0.512	0.694	0.768	0.021	0.674
AL vs. NL	0.985	0.556	0.458	0.214	0.072*	0.038**
AL vs. Zero	0.112	0.793	0.422	0.140	0.024**	0.023**
	(4)	(5)	(6)	(4)	(5)	(6)
Second degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. Zero	0.226	0.526	0.834	0.075*	0.040**	0.869
AL vs. NL	0.887	0.643	0.534	0.009***	0.080*	0.059*
AL vs. Zero	0.241	0.850	0.513	0.014**	0.017**	0.059*
	(7)	(8)	(9)	(7)	(8)	(9)
Third degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.126	0.736	0.946	0.049**	0.064*	0.796
AL vs. NL	0.843	0.846	0.712	0.011**	0.150	0.131
AL vs. zero	0.245	0.967	0.780	0.015**	0.041**	0.142

Notes: This Table shows p-values from joint significance Wald tests for linear combinations of League-specific racial composition effects. National League (NL) is chosen as reference (vs. American League (AL)). Models (4-6) correspond to the regression results presented in Table 1 and include second-degree polynomial trend interactions with the percentages of black and other non-black minority athletes, whereas model (1-3) and model (7-9) include first and third degree interactions (see Appendix, Table A4). Models (1-2), (4-5) and (7-8) relate to starting lineups, models (3), (6) and (9) include all athletes that were playing during a given season. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

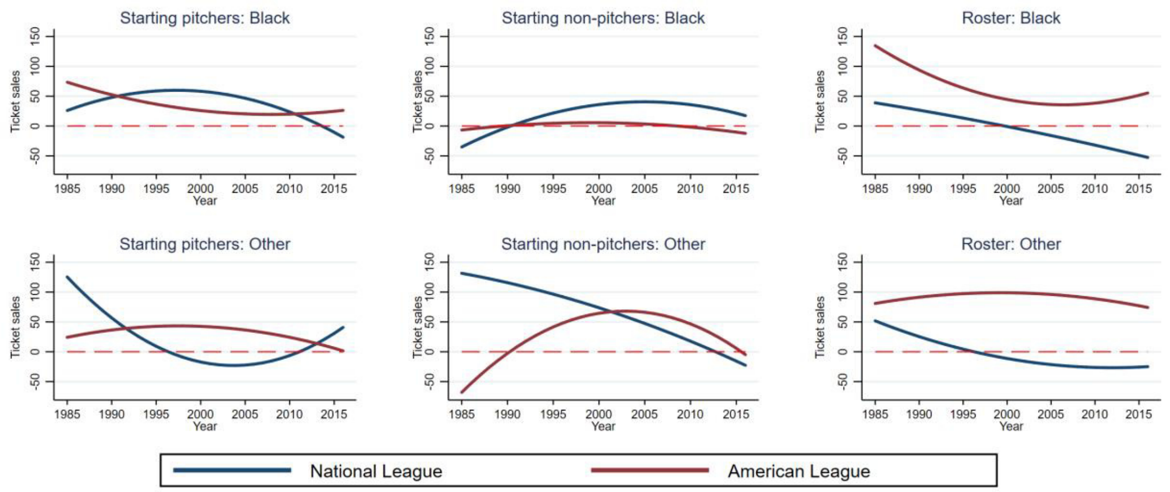
Models (4-6) are derived from the regressions that include second-degree polynomial trend racial composition effects presented above in Table 1. The combined effects for the share of black athletes is insignificant across all three athlete groups. In contrast, the League-specific effects for the percentage of other (non-black) athletes are both significantly different from zero, as well as significantly different to each other.

In addition to the second-degree polynomial trend racial composition interactions, which is our favorite specification in constructing a preferably parsimonious model that allows to account for the likely existence of non-linear discrimination patterns in MLB attendance over time (Hanssen & Andersen, 2007; Tainsky & Winfree, 2010), we also evaluate alternative polynomial degree specifications. Analogously to models (4-6), the models (1-3) and (7-9) in Table 2 are based on regressions using first and third-degree polynomial racial trend interactions. The corresponding results and joint significance tests are in line with the second-degree specifications; the complete regression results for the alternative model specifications are included in the Appendix (Section 3.1, Table A4).

Finally, using the second-degree polynomial racial trend regression results presented in Table 1, we illustrate the development of the combined racial percentage share coefficient estimates (i.e., marginal effects) as a function of time in Figure 1.

Both the individual and joint significance tests for the impact of the percentage shares of black athletes do not significantly differ from zero, suggesting that fans in both Leagues are indifferent to changes in teams' shares of black athletes. Therefore, in the following, we focus on the interpretation of the development of other non-black minority athletes. However, while our results indicate that fans rather positively discriminated against black athletes, we find fans preference for black athletes in the NL to gradually decrease for the roster specification. For the 2000 season, the corresponding marginal effect (ME) is approximately zero.

Figure 1. League-specific marginal racial composition effects on attendance over time



Notes: Marginal effect (ME) plots are derived from the three attendance regressions presented in Table 1. League-specific ME estimates are based on second-degree polynomial trend interactions with the percentages of black and other (non-black) minority players and are plotted as a function of time. The first two columns relate to starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 for details). As an example, ME estimates for other (non-black) minority athletes in the NL are computed as $\hat{\beta}_{ME}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$.

The ME for other starting pitchers in the NL shows a convex development: The ME for NL teams in 1985 is positive with an average increase of around 125 ticket sales per mean regular season home game for a 1 %-point increase in the share of other non-black minority starting pitchers, reaches its minimum with –23.00 tickets in 2004, and ends with a positive ME of 40.78 in 2016. Conversely, the ME for AL teams shows a concave development and is positive throughout the entire sample. Between 1992 and 2013, baseball fans in the AL relatively stronger preferred non-black minority (other) starting pitchers than fans in the NL.

Considering other non-black minority starting non-pitchers, the ME for NL teams is positive in 1985 and gradually decreases until 2016. In contrast to the NL, the corresponding ME in the AL follows a concave development. Hence, although the average development of the share of other starting non-pitchers does not strongly differ across Leagues (see Appendix Section 2, Figure A1), there exist differences in discriminatory fan behavior for the first half of the sample: NL fans preferred other non-black minority starting non-pitchers, whereas AL fans discriminated against them. This discrimination differential, however, declined sharply as time passed, and beginning in the early 2000s, the League-specific MEs start to follow the same approximately linear downward trend.

Looking at the development of the ME for other non-black minority athletes for our roster specification: in the NL, the ME is positive in 1985, and then follows a convex development of small curvature. In the AL, the ME follows a slightly concave trend but is relatively stable. Moreover, as with the joint significance tests presented in Table 2, the developments of the ME estimate for first and third-degree polynomial racial trend specifications are very similar to the second-degree models. Furthermore, instead of polynomial trend interactions, we also evaluate individual interaction effects between the percentage share of black and other athletes and individual year dummy variables. Fitting polynomial regressions of the corresponding estimates on year as an integer variable results in only minor differences to our baseline ME estimations (see Appendix, Section 3.1).

4.2 Attendance and local market area racial composition effects

After analyzing the effects of team racial composition on attendance we now investigate the relationship between teams' local market area racial compositions and attendance. Table 3 shows the corresponding results of the athlete-group specific attendance regressions.

Table 3. Team and local market area racial composition effects on attendance

	(1) Starting Pitcher	(2) Starting Pitcher	(3) Starting Non-Pitcher	(4) Starting Non-Pitcher	(5) Roster	(6) Roster
Black (%)	29.71	-436.19*	-26.95	-548.00***	54.11	-22.36
	(67.83)	(255.46)	(54.43)	(205.82)	(85.34)	(359.15)
Black*Trend	4.90	3.39	6.45	6.87	-4.73	-5.63
	(10.76)	(10.61)	(7.90)	(8.00)	(13.02)	(13.12)
Black*Trend^2	-0.19	-0.13	-0.15	-0.11	0.07	0.13
	(0.32)	(0.32)	(0.24)	(0.25)	(0.42)	(0.42)
AL*Black (%)	31.58	-4.00	22.24	11.01	87.99	78.55
	(96.77)	(95.99)	(53.62)	(54.44)	(85.63)	(86.58)
AL*Black*Trend	-8.25	-7.16	-5.36	-2.85	-5.58	-2.81
	(14.13)	(13.99)	(7.19)	(7.37)	(11.79)	(12.04)
AL*Black*Trend^2	0.25	0.26	0.12	0.04	0.19	0.07
	(0.42)	(0.42)	(0.23)	(0.23)	(0.38)	(0.39)
Other (%)	134.39***	213.12***	122.25	45.38	61.80	53.35
	(49.78)	(70.16)	(91.63)	(131.78)	(120.38)	(169.06)
Other*Trend	-16.53***	-16.44***	-1.60	-0.33	-6.95	-8.40
	(6.20)	(6.24)	(11.39)	(11.69)	(14.80)	(15.07)
Other*Trend^2	0.43**	0.42**	-0.12	-0.15	0.12	0.11
	(0.19)	(0.19)	(0.32)	(0.32)	(0.42)	(0.43)
AL*Other	-110.06*	-108.42*	-188.32**	-186.88**	43.52	47.79
	(64.27)	(65.10)	(92.67)	(93.40)	(129.61)	(131.32)
AL*Other*Trend	19.47***	19.29***	16.54	15.89	6.33	6.31
	(7.29)	(7.36)	(10.35)	(10.55)	(13.58)	(13.82)
AL*Other*Trend^2	-0.55***	-0.54***	-0.30	-0.28	-0.13	-0.12
	(0.21)	(0.21)	(0.28)	(0.28)	(0.36)	(0.36)
Pop.Black (%)	-292.40	-297.40	-455.01**	-460.79**	-377.83**	-373.50**
	(182.32)	(183.06)	(181.12)	(187.82)	(180.35)	(181.08)
Pop.Other (%)	294.60	278.30	125.36	208.55	233.69	89.48
	(220.54)	(224.74)	(232.34)	(259.31)	(218.23)	(254.88)
Black*Pop-Black		3.36		4.92***		0.64
		(2.41)		(1.90)		(3.32)
Black*Pop.White		5.86**		5.69**		0.91
		(2.78)		(2.25)		(3.90)
Other*Pop.Other		0.52		-0.48		4.77*
		(1.30)		(1.75)		(2.81)
Other*Pop.White		-1.18*		1.18		-0.13
		(0.69)		(1.18)		(1.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	.806	.796	.813	.805	.801	.782

Notes: Dependent variable is team-specific MLB mean regular season home game attendance. Results are based on aggregated game data from 1985 to 2016. Model (1-4) relate to starting lineups, whereas models (5-6) include all athletes that were playing during a given season. National League is chosen as reference (vs. American League (AL)). The control variables are the same as for the attendance regressions presented in Table 1. Estimates are derived from Prais-Winsten regression using panel-corrected standard errors (in parentheses; see Section 3.3 for details). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Considering the percentage share of black and other (non-black) minority local market residents, Table 3 shows that the share of black [other] residents is negative [positive] across all model specifications, regardless of including interactions between team and local market area racial composition variables; only the coefficient estimates for the share of black residents in the starting non-pitchers and the roster specification are statistically different from zero. Hence, consistent with previous findings and anecdotal evidence (Armour, 2002; Hanssen, 1998; Lanning, 2010), we find black residents to relatively less frequently attend baseball games than other non-black minority residents.

Regarding the model specifications including interactions between team and local market racial composition variables (models (2), (4), and (6)), the interaction between a team's share of black athletes and a team's local market area's share of black residents is positive across all model specifications, but significant only for the starting non-pitcher specification. Similarly, white baseball fans are inclined to fancy black starting lineup players: the corresponding coefficients are significantly positive for the starting pitchers and for the non-pitchers specification.

Similar to the results for black starting non-pitchers, for the roster specification, the racial matching coefficient for other non-black minority players is positive and weakly significant. Thus, to some extent, we find matching team racial profiles to local market racial demographics to increase ticket sales. Moreover, the interaction effect between the share of other starting pitchers and the share of white residents is negative and weakly significant, indicating that white fans prefer white and black starting pitchers over other (Hispanic and Asian) starting pitchers. However, when interpreting these results, it is important to consider the consistently low numbers of black starting pitchers in the MLB.[5]

Last, as with the visualization of the ME estimates in the previous section, we compute the corresponding combined second-degree polynomial racial trend effect estimates on the basis of Table 3, models (1), (3), and (5). The corresponding partial effect (PE) estimates (Figure A8) only differ marginally to the ME estimates of our baseline specification (Figure 1). Likewise, the PE estimates derived from Table 3, models (2), (4), and (6) are very similar to our baseline estimates when taking into account the impact of the full set of local market areas racial demographic variables (Figure A9). For brevity, the corresponding analyses, as well as additional League-specific joint significance test results, are relegated to the Appendix, Section 3.2.

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[5] We also tested for time dependent local market racial compositions effects. For the share of black residents, we did not find any significant first or second-degree trend interactions. In contrast, other non-black minority residents' preference for attending baseball games significantly increase over time. The corresponding results, as well as further alternative model specifications, are included in the Appendix, Section 3.2.

4.3 Season success and team racial composition effects

In this section, we test whether team owners' willingness to employ minority players affects team success. If an increase in a team's share of, e.g., black athletes, has a positive [negative] effect on winning, teams with more black players relative to their competitors should win [lose] a higher percentage of games (Hanssen, 1998); given competitive sport labor markets, a positive [negative] effect then would indicate the presence of negative [positive] labor market discrimination against black athletes. Since team owners are incentivized to take into account fans' racial preferences in their hiring practice, and given that workers are mobile in the long run, any persistent labor market discrimination would therefore result from consumer discrimination (Becker, 1957; Holzer & Ihlanfeldt, 1998; Nardinelli & Simon, 1990). Furthermore, assuming that starting lineup players are relatively more important for winning than substitute players, labor market discrimination against starting lineup players may be relatively less pronounced because team owners have to differently balance the potentially diametrical effects of minority players on attendance and team success (Burdekin & Idson, 1991).

In Table 4, we show the results from regressing a team's winning percentage on its percentage share of black and other non-black minority players by athlete group for different model specifications that vary with the degree of polynomial racial trend interactions to control for the existence of non-linear labor market discrimination effects over time. As with our attendance regressions, we first apply a series of different panel-data error structure test procedures; the corresponding results indicate team-specific heteroscedasticity and serial correlation as well as cross-sectional correlation (for details, see Appendix, Section 4). Consequently, in addition to including team fixed effects to account for team-specific characteristics that may affect regular season performance, we model team-specific AR(1) serial correlated disturbance terms using Prais-Winsten transformation and estimate the error-covariance matrix using FGLS to account for PCSEs (Beck & Katz, 1995).

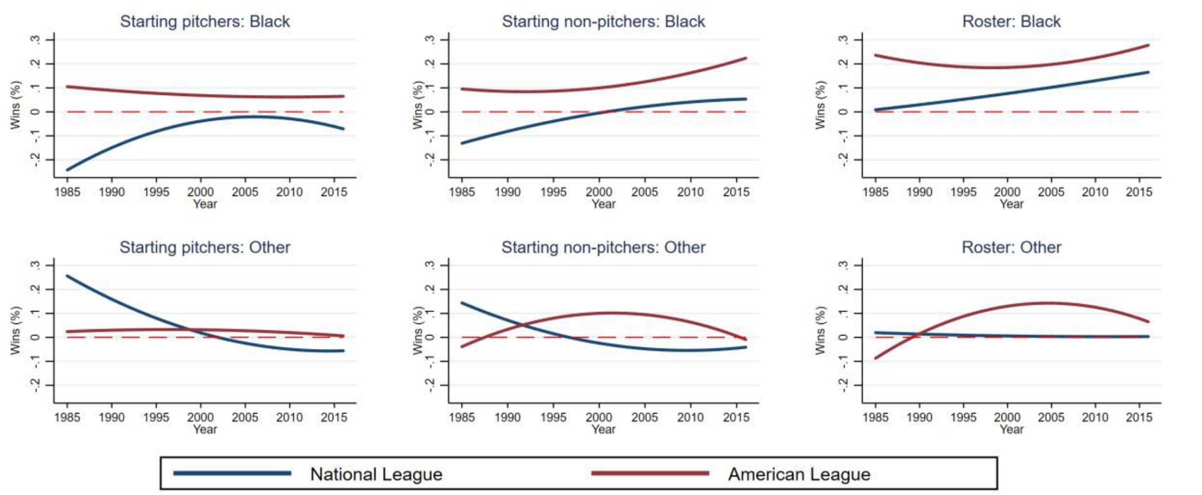
Table 4. League-specific racial composition effects on mean regular season winning percentage

	(1) Starting Pitcher	(2) Starting Pitcher	(3) Starting Pitcher	(4) Starting NPitcher	(5) Starting NPitcher	(6) Starting NPitcher	(7) Roster All	(8) Roster All	(9) Roster All
Black (%)	-0.243**	-0.151**	-0.084**	-0.347***	-0.157**	-0.018	0.003	-0.001	0.080
	(0.109)	(0.069)	(0.035)	(0.123)	(0.073)	(0.034)	(0.183)	(0.114)	(0.058)
Black*Trend	0.021	0.005		0.040**	0.009**		0.003	0.005	
	(0.016)	(0.005)		(0.017)	(0.004)		(0.025)	(0.006)	
Black*Trend²	-0.001			-0.001*			0.000		
	(0.001)			(0.000)			(0.001)		
AL*Black	0.348**	0.245**	0.155***	0.384**	0.217**	0.162***	0.103	0.162	0.152*
	(0.163)	(0.111)	(0.056)	(0.160)	(0.102)	(0.048)	(0.258)	(0.164)	(0.081)
AL*Black*Trend	-0.025	-0.006		-0.032	-0.003		0.014	0.000	
	(0.023)	(0.007)		(0.022)	(0.006)		(0.036)	(0.009)	
AL*Black*Trend²	0.001			0.001			-0.000		
	(0.001)			(0.001)			(0.001)		
Other (%)	0.256***	0.179***	0.003	0.098	0.015	-0.040	0.187	-0.044	-0.027
	(0.077)	(0.055)	(0.022)	(0.156)	(0.088)	(0.034)	(0.229)	(0.145)	(0.054)
Other*Trend	-0.021**	-0.009***		-0.011	-0.002		-0.035	0.001	
	(0.010)	(0.003)		(0.020)	(0.004)		(0.028)	(0.007)	
Other*Trend²	0.000			0.000			0.001		
	(0.000)			(0.001)			(0.001)		
AL*Other	-0.233**	-0.144*	0.022	-0.208	0.037	0.109**	-0.382	0.111	0.157**
	(0.117)	(0.081)	(0.035)	(0.195)	(0.123)	(0.047)	(0.312)	(0.202)	(0.078)
AL*Other*Trend	0.023	0.009**		0.039	0.003		0.084**	0.003	
	(0.015)	(0.004)		(0.025)	(0.006)		(0.040)	(0.010)	
AL*Other*Trend²	-0.000			-0.001			-0.002**		
	(0.000)			(0.001)			(0.001)		
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	.800	.807	.808	.805	.810	.811	.789	.794	.795

Notes: Dependent variable is team-specific MLB mean regular season winning percentage. Results are based on aggregated game data from 1985 to 2016. Team-specific percentage shares of black [other] minority athletes are centered by the League-specific yearly mean shares of black [other] athletes. Trend=0 in 1985 and increases in one unit per year. Models (1-6) relate to starting pitchers and starting non-pitchers (NPitchers), whereas models (7-9) include all athletes that were playing during a given season. National League is chosen as reference (vs. American League (AL)). Estimates are derived from Prais-Winsten regression using panel-corrected standard errors (in parentheses; see Section 3.3 for details). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results presented in Table 4 show significant negative coefficient estimates for the share of black starting pitchers in the NL ((1), (2), and (3)) as well as for the share black starting non-pitchers ((4) and (5)) — NL team owners prefer black starting players beyond their impact on team success. In contrast, AL team owners discriminate against black players. As an example, the coefficient estimate for the share of black starting pitchers in model (3) is positive significant. Joint significance tests not only provide further evidence for the existence of labor market discrimination against black athletes but also against other non-black minority players. However, allowing for a better assessment of the degree of labor market discrimination over time, in Figure 2 we plot the League-specific ME estimates derived from the models (1), (4), and (7). [6]

Figure 2. League-specific marginal racial composition effects on winning percentage over time



Notes: Marginal effect (ME) plots are derived from the three winning percentage regression models (1), (4), and (7) in Table 4. League-specific ME estimates are based on second-degree polynomial trend interactions with the percentages of black and other (non-black) minority athletes and are plotted as a function of time. The first two columns relate to starting lineups, while the third column relates to all athletes that were playing during a given season. As an example, ME estimates for other (non-black) minority athletes in the National League are computed as $\hat{\beta}_{ME}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$.

Figure 2 suggests that AL team owners have been constantly discriminating against black athletes. In addition, discrimination against black non-starting pitchers starts to increase since 1995. In general, we find NL team owners' preference for hiring black players to decrease over time; though, the NL-specific black starting pitchers ME estimate is concave and turns to become more negative again in the early 2000s.

Figure 2 further shows that, for NL team owners, the ME for other starting pitchers and non-pitchers is convex and our results suggest that NL team owners discriminating behavior against Hispanic and Asian starting pitchers decreases over time. Around the early 2000s, NL team owners start actively preferring other non-black minority starting players. For the starting non-pitcher and roster specifications, however, we do not find any significant NL-specific estimates for the share of other non-black minority athletes. Hence, except for starting-pitchers, our findings indicate that NL team

[6] Detailed results for joint significance tests and different polynomial degree specifications are included in the Appendix, Section 4.

owners do not prefer or discriminate against other athletes. In contrast, that AL team owners tend to discriminate against other non-black minority athletes across all athlete group specifications: the three ME curves are concave and indicate that labor market discrimination against Hispanics and Asians in the AL peaked around 2000 to 2005.[7]

Furthermore, the NL-specific winning percentage ME estimates for the share of black athletes (starting pitchers, non-pitchers, and roster) are in line with the NL-specific consumer discrimination patterns reported in Section 4.1 and 4.2. In general, NL team fans like watching black starting pitchers and non-pitchers and NL team owners show a preference for employing them. Conversely, on average, NL fans show a decreasing preference for other (non-black) minority athletes, whereas the extent to which NL team owners discriminate against Hispanic and Asian players decreases until a moderate negative effect on team performance is reached. AL fans, on the other hand, generally show more positive but concave developing racial preferences for both black and non-black minority athletes, whereas AL team owners tend to consistently discriminate against black as well as Hispanic and Asian players over the entire sample.

5 Team selection and racial matching strategies

To further investigate the extent to which team-owners may adapt their hiring of minority players to the rational of racial matching, similar to Burdekin et al. (2005), we estimate the impact of local market demographics on teams' racial compositions. To this end, we specify six different outcomes: a team's athlete-group specific shares of black and other non-black minority players. In addition to League-specific coefficients for the percentage shares of black and other local market residents, we account for team fixed effects to control for time-invariant team- and city-specific attributes that may affect teams' racial compositions. Moreover, we include a time trend and its squared value to capture general trends in local markets' minority population growth.

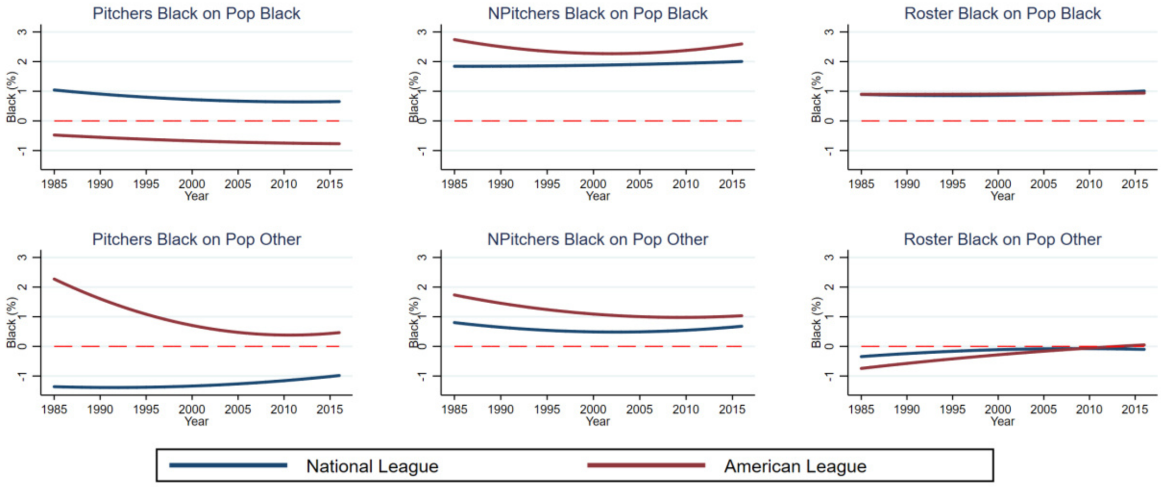
We apply the same set of panel-data tests that as we do for the attendance and winning percentage regressions and find substantial evidence for team-specific heteroscedasticity and error term serial

[7] As with our attendance regression, for our winning percentage regression analysis, we also evaluate individual interaction effects between the percentage share of black and other athletes and individual year dummy variables. Polynomial regression curves fitted on the corresponding estimates highly resemble the ME estimates presented in Figure 2 (see Appendix, Section 4).

correlation as well as well as contemporaneously correlated error terms. As a consequence, we model team-specific AR(1) disturbances via Prais-Winsten transformation and estimate the error covariance matrix using FGLS using the PCSEs approach (Beck & Katz, 1995). The tests' results are included in the Appendix, Section 5, together with detailed results for different regression specifications that vary with the number of considered interactions.

In Figure 3 and 4, we show the League-specific ME estimates for the second-degree specification for the share of black and other minority players by athlete group over time.

Figure 3. League-specific market area racial composition effects on teams' share of black athletes over time



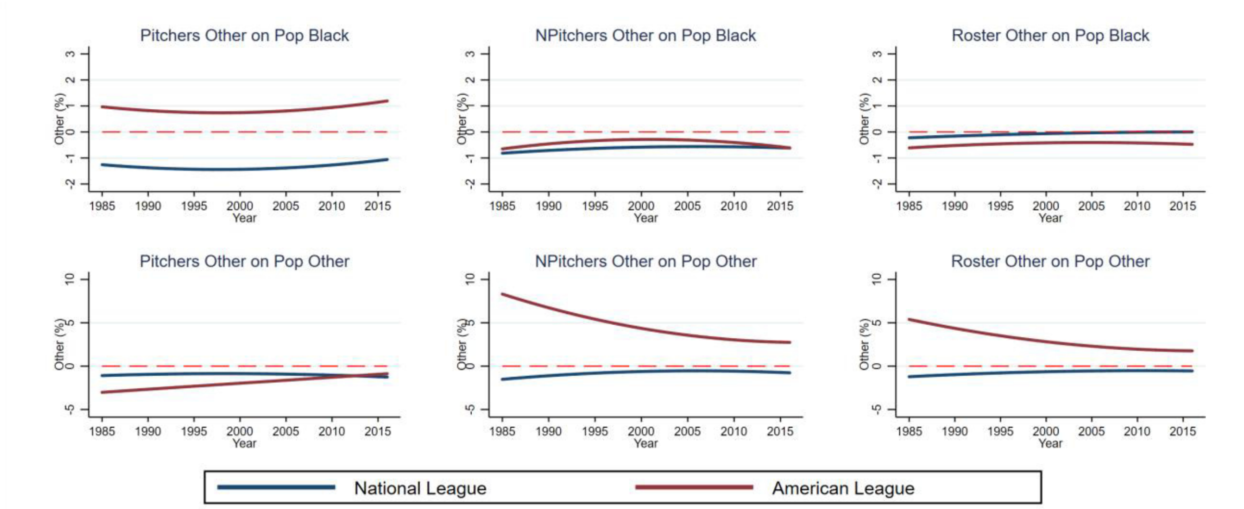
Notes: Dependent variable is a team's percentage share of black athletes; the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 for details). Marginal effect (ME) estimates are based on League-specific second-degree polynomial trend interactions with the percentages of black or other (non-black) local market area residents and are plotted as a function of time (detailed results are included in the Appendix, Section 5).

Figure 3 shows that, except for the AL-specific ME estimate for the black starting pitchers specification, higher shares of black local market area residents are consistently linked to higher shares of black athletes and do not differ much across Leagues. In addition, the corresponding ME estimates do not vary largely across time. Joint significance tests indicate that the League-specific combined effects for the share of black residents are significantly different from zero for each athlete-group specification ($p \leq 0.01$) and, furthermore, that the League-specific ME estimates for the starting pitcher model significantly differ to each other ($p \leq 0.05$).

Turning to the impact of other non-black minority residents on teams' share of black athletes: the ME estimates for non-starting pitchers and the roster specification do not vary significantly between Leagues and across time. For the percentage of black starting pitchers, the AL-specific ME curve is convex; it starts around 2% but decreases to and remains around 0.5%. In contrast, the ME for the share of other minority residents is negative, but increases from approximately –1.5% to –1%. The results of joint significance tests do only indicate weakly significant estimates for the black starting pitcher specification; the League-specific combined effects for the impact of other residents in the black starting non-pitchers and roster specification are both insignificant (see Appendix, Section 5, Table A16).

Figure 4 shows that the AL-specific ME estimate for the starting non-pitchers and the roster model, higher shares of Hispanic and Asian athletes are associated with higher shares of other (non-black) minority residents. However, for both athlete-group specifications, the AL-specific ME estimate decreases substantially over time. The NL-specific ME for the share of other residents is negative across all three athlete-groups. Yet, except for the starting pitchers specification, based on joint significance tests, none of the NL-specific combined effects for the share of other residents is statistically different from zero at $p \leq 0.05$. In contrast, the AL-specific combined effects are statistically different from zero and significantly differ to the corresponding NL estimates.

Figure 4. League-specific market area racial composition effects on teams' share of other non-black minority athletes over time



Notes: Marginal effect (ME) plots are derived from the three winning percentage regression models (1), (4), and (7) in Table 4. League-specific ME estimates are based on second-degree polynomial trend interactions with the percentages of black and other (non-black) minority athletes and are plotted as a function of time. The first two columns relate to starting lineups, while the third column relates to all athletes that were playing during a given season.

The AL-specific effect of black residents on a team's share of Hispanic and Asian starting pitchers is positive throughout the entire period; all other ME estimates for the effect of an increase in the share of black residents on a team's share of other (non-black) minority players are negative (or close to zero) and do not significantly differ between Leagues. Moreover, confirmed by joint significance tests, our results suggest that ME estimates for the share of black athletes do not largely vary across time. Depending on the degree of the specified polynomial racial trend interactions, for the black starting pitchers and non-pitchers models, the NL- and AL-specific estimates are both significantly different from zero and from each other. For the roster specification, we find (weakly) significant effects for the share black resident that do not appear to substantially differ across Leagues (see Appendix, Section 5, Table A17).

In general, our results provide evidence for team owners in both Leagues to engage in racial matching practices. Moreover, except for the NL-specific ME for a team's share of black starting pitchers, higher levels of other non-black minority residents are linked to higher shares of black athletes, whereas higher levels in an AL team's black local market population are linked to higher shares of other (non-black) minority starting pitchers.

6 Hispanic players and additional robustness tests

In our racial-group specification of other non-black minorities we do not distinguish between Hispanic and Asian athletes, because we attempt to investigate racial matching effects and the early US County level Census data do not provide information on Hispanic origin (see Section 3.1 for details). In addition, with the exception of a few Asian players, the group of other non-black minority athletes mainly includes player who are of Hispanic ethnicity (on average, 93.4% across athlete groups). Consequently, we do only find marginal differences when evaluating Hispanic players by excluding Asians from the group of other non-black minority athletes (see Appendix, Section 6).

Furthermore, our findings concerning the relationship between winnings and teams' racial composition suggest that League-specific differences in the share of employed minority players significantly impact team success (see Section 4.2), and our analysis of racial matching strategies indicates that teams owners account for local market population demographics in their employer selection strategies (see Section 4.3). Hence, when investigating the linkages between ticket sales, team racial composition effects and winnings, excluding information on the teams' market area minority populations potentially biases coefficient estimates. However, in Section 4.2, we find that our main results are robust to including local market racial composition variables. Likewise, as an additional robustness check to our analysis of the relationship between winnings and teams' racial compositions, we extend the baseline model to account for black and other (non-black) minority population shares as additional explanatory variables. The resulting estimates are nearly identical to the baseline results that do not include local markets' minority population shares (see Appendix, Section 4). Last, we note that local market's minority population shares change rather slowly over time. As a consequence, although not explicitly accounting for market area racial structure variables in the attendance and winnings regressions analyses in Section 4.1 and 4.3, the included team-city fixed effects certainly account for some of the information linked to differences in local market area racial compositions.

7 Summary and conclusions

Analyzing MLB data from 1985 to 2016, this study shows that changes in teams' racial compositions significantly impact fans' attendance behavior and teams' performance, indicating the presence of consumer discrimination as well as employer discrimination.

First, at the beginning of our sample, except for non-pitchers, fans more frequently attend games of teams with increasing shares of minority players in both MLB Leagues. Hence, fans started developing a taste for racial diversity during the period following the racial integration in the late 1980s. In the AL, fans' preference for Hispanic and Asian (other non-black) athletes shows a concave trend that peaked around the early 2000s. Moreover, for fan preferences against Hispanics and Asians in the AL, we find consumer prejudice against minority players to increase for athlete groups associated with higher visibility and importance. In contrast, NL fans' preferences for other non-black minority starting pitchers follow a convex trend, whereas their taste for Hispanic and Asian starting non-pitchers and roster players steadily decreases over time. Similar to the trends observed in the AL, around the 2000s, NL fans started to relatively attend less games for teams with higher roster shares of black and other minority players.

Second, concerning League-specific employer discrimination, AL team owners discriminate against black players: we find a positive relationship between team performance and black players across all athlete groups that persists over time. Conversely, NL team owners have a taste for black players with high visibility and fan interest; the corresponding results suggest a negative impact of black starting players on team winnings. Given these findings, employer discrimination cannot be exclusively driven by consumer discrimination; consumer discrimination in fans' attendance behavior is not sufficient to rationalize the performance gap across athlete groups of players of similar race and ethnicity.

Third, we do not find strong evidence for fans' attendance behavior to significantly respond to changes in the number of black players. However, when including information on teams' local market minority population, both white and black fans show a significant taste for black players. Similarly, we find non-black minority fans prefer players matching their own racial background. In line with these results, analyzing the extent to which team owners consider local market demographics in their hiring of minority players indicates a positive significant relationship between teams' and their local market areas' racial composition. Hence, despite the existence of contrasting racial preferences between MLB fans and team owners, baseball franchises engage in racial matching strategies.

Concerning contemporaneous discriminatory trends and associated policy implications: in line with the decreasing numbers of black players in the MLB, black local market residents less frequently attend baseball games than other non-black minority residents, indicating a general decrease in black fans' and athletes' interest in baseball when compared to the period of racial integration (Chicago Tribune, 2002). Moreover, given the current demographic trends in the US, the white population share is projected to further decrease, the black population share is projected to slightly increase, whereas the Hispanic and Asian population shares are both expected to continue growing more strongly (US Census Bureau, 2020). However, considering the distribution of player race for starting pitchers — arguably the most prestigious and important position in MLB — white players continue to remain largely overrepresented. In the light of these projections and the overall decline in MLB attendance during the recent years (Bloomberg, 2019), it is important for MLB franchises to acknowledge the trend of discrimination against Hispanic players and the decreasing interest in baseball among the black community. Similar to research that links growing NFL popularity ratings to the visibility of black quarterbacks and an increases in fans' racial preferences for team diversity (Aldrich et al., 2006), promoting the leadership role of playing as starting pitcher to more black athletes may refurbish fans' interest in baseball, particularly among blacks.

As a final remark, while our results are robust to alternative athlete-minority group specifications and functional forms, race and ethnicity are ambiguous concepts that are hard to quantify. Therefore, it is important to acknowledge that results derived from using categorical race measures can be sensitive to racial coding schemes and miss-classifications (Berri et al., 2014; Fort & Gill, 2000; Tainsky et al., 2015). However, in addition to exploiting a large number of aggregated player data, our semi-automated racial coding procedure likely allows for a more robust identification of player race when compared to traditional race classification approaches. Specifically, we consider that applying automated facial recognition techniques to video data or a larger set of pictures per individual may prove useful in creating novel race measures and mitigating potential racial coding bias in future discrimination research.

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Consumer discrimination, racial matching strategies and employer discrimination – New evidence from professional sports markets

Appendix

1 Introduction

This Appendix includes concise information on the data cleaning process, descriptive statistics, the results that we omitted from the main text for brevity, and complements our analysis by providing the results of additional analyses and robustness tests. We note that this Appendix reproduces some text and results from the main paper; however, it is not meant to stand alone.

2 Data cleaning and descriptive analysis

In this study, we focus on population characteristics and therefore only consider US MLB teams and their corresponding Counties for reasons of data availability and comparability. Hence, we do not consider the two Canadian teams the Toronto Blue Jays (TOR) and the Montreal Expos (MON). However, MON relocated to Washington D.C. after the 2004 season and thus became an US team, named Washington Nationals (WSN). Moreover, our considered time period includes two league expansions, in which two teams each entered the MLB. In 1993 the Colorado Rockies (COL) and Miami Marlins (MIA), and in 1998 the Arizona Diamondbacks (ARI) and the Tampa Bay Rays (TBR). In addition, in 1998 the Milwaukee Brewers (MIL) switched from the AL to the NL, and in 2013, the Houston Astros (HOU) switched from the NL to the AL. Since we expect historically rooted differences in fan-based racial preferences across Leagues, we choose a mutually exclusive team to League mapping in our main analyses and classify MIL as an AL team and HOU as an NL team. To assure that we exclusively measure the effects linked to a team's corresponding home local market areas' fan population, we restrict our analysis to home games that were played at the corresponding home teams' stadiums. Likewise, we restrict our analysis to US teams that did not change their home city between 1985 and 2016 or after moving to the US or entering the MLB in the course of a league expansion. However, we note that some teams changed their names between 1985 and 2016.

We use mean home team specific regular season attendance that we compute from aggregated game ticket sales and the number of home games.[1] The information that we use in this study are derived from all 73,409 games that were played over the course of the 32 MLB regular seasons from 1985 to 2016 with 69,257 home games played by the corresponding 29 US teams that we consider in our analysis. In advance of a regular season, each team has scheduled 81 home games. If a game has to be cancelled or cannot be continued due to bad weather conditions or other special events, it is usually rescheduled to a later date or played at the visiting team's or another team's stadium. However, a few games are cancelled at the end of each season, but only if they cannot affect team rankings. Since the number of played home games is certainly a major driving force for yearly ticket sales, we correct the number of played home games for cancelled games as well as home games that were not played at a home team's stadium and discard the corresponding observations. Moreover, we follow common practice and set the game attendance of second game day double headers to their corresponding first game day attendance for double header games with missing or zero second game day attendance. Lastly, there is one game that shows an attendance of zero because fans were prohibited from attending the game and are there are two games with missing attendance data for unknown reasons that we also drop from our sample. This procedure results in 69,239 individual games that we aggregate to 866 yearly observations. However, we consider all played games for computing the number of teams' winning percentages per season.

The data that we use in this study are collected from baseballreferences.com (player pictures), census.gov (population characteristics), retrosheet.org (game-log data), seamheads.com (information on stadiums), seanlahman.com (player data).[2]

[1] The publicly available attendance numbers refer to the total number of sold tickets and free tickets, not the actual number of spectators that were present at a game. In this study, we use the terms attendance and ticket sales synonymously. For a general discussion of spectator no-show behavior, see, e.g. (Schreyer, 2019).

[2] https://www.baseball-reference.com, http://www.retrosheet.org, https://www.census.gov, https://sites.google.com/site/rodswebpages/, http://www.seamheads.com, http://www.seanlahman.com

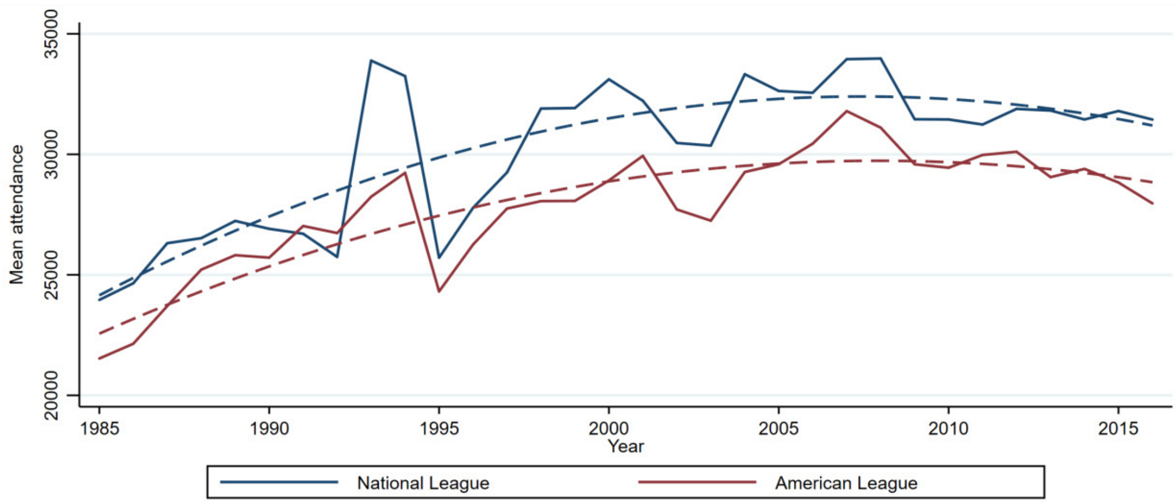
Table A1 shows descriptive summary statistics for the main variables that we employ in our analysis, and Figure A1 shows the, approximately quadratic development of League-specific mean regular season home game attendance developments from 1985 to 2016.

Table A1. Descriptive summary statistics

	Mean	SD	Min	Max
Mean season attendance	29188	8637	8726	58535
Wins (%)	49.94	6.93	26.54	71.60
Playoffs	0.24	0.43	0.00	1.00
New.Stadium	0.03	0.16	0.00	1.00
Strike.Year	0.12	0.32	0.00	1.00
Trend (1985=0)	16.15	9.14	0.00	31.00
Black population (%)	23.41	15.30	1.63	65.56
Black players in team roster (%)	9.02	8.10	0.86	40.90
Black starting lineup non-pitchers (%)	15.64	7.20	0.00	48.15
Black starting lineup pitchers (%)	24.17	12.68	0.00	59.26
Other population (%)	5.56	8.41	0.00	50.85
Other players in team roster (%)	20.21	8.74	0.00	54.25
Other starting lineup non-pitchers (%)	21.64	12.99	0.00	59.31
Other starting lineup pitchers (%)	17.38	15.94	0.00	79.01
Hispanic players in team roster (%):	19.04	8.04	0.00	48.10
Hispanic starting lineup non-pitchers (%)	20.61	12.33	0.00	58.85
Hispanic starting lineup pitchers (%)	15.53	14.77	0.00	79.01

Notes: Data are derived from 69,239 individual games that we aggregate to 866 observations from the 29 US teams that played during the 32 MLB regular seasons from 1985 to 2016. Excluding Asian players from the group of other non-black minority players equals the group of Hispanic players. Section 3 in the main text provides detailed descriptions on the data cleaning procedure and variable specifications.

Figure A1. League-specific mean MLB regular season home game attendance from 1985 to 2016



Notes: Dashed lines corresponds to second-degree polynomial regression curves.

In Table A2 we present the team to County and local market area mapping. Moreover, we note that multiple Counties can be represented by the same MLB team and, a single County or local market area can be affected by more than one local MLB team. Precisely, the Chicago Cubs and the Chicago White Sox both are located in the same County, and we use all of the Counties that comprise New York City as one local market area for both the New York Mets and the New York Yankees.

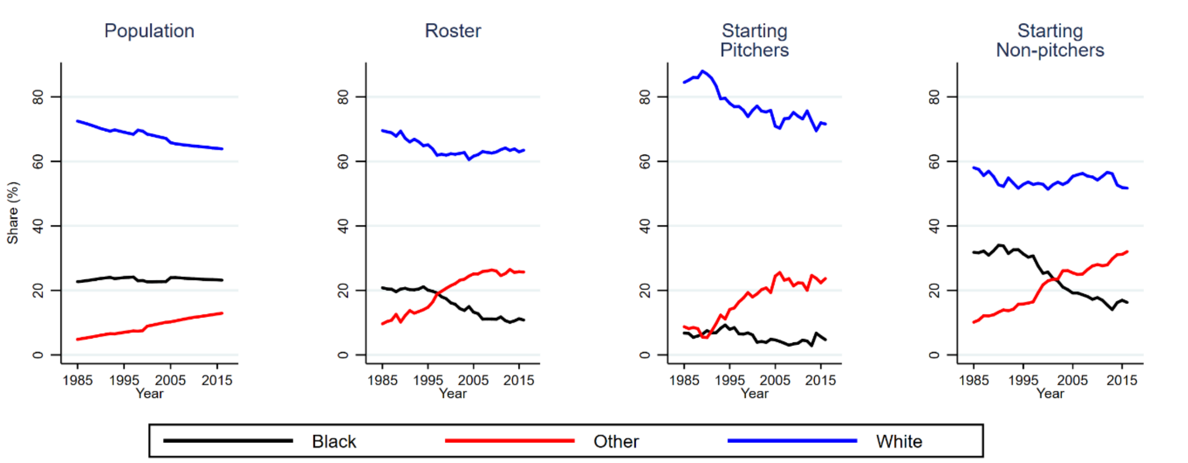
Table A2. Racial composition effects on average home game attendance

Team / Market Area	City	County	State	League
Arizona Diamondbacks	Phoenix	Maricopa	Arizona	NL
Atlanta Braves	Atlanta	Fulton	Georgia	NL
Baltimore Orioles	Baltimore	Baltimore	Maryland	AL
Boston Red Sox	Boston	Suffolk	Massachusetss	AL
Chicago Cubs, Chicago White Sox	Chicago	Cook	Illinois	NL, AL
Cincinnati Reds	Cincinnati	Hamilton	Ohio	NL
Cleveland Indians	Cleveland	Cuyahoga	Ohio	AL
Colorado Rockies	Denver	Denver	Colorado	NL
Detroit Tigers	Detroit	Wayne	Michigan	AL
Houston Astros	Houston	Harris	Texas	NL
Kansas City Royals	Kansas City	Jackson	Missouri	AL
Los Angeles Angels	Anaheim	Orange	California	AL
Los Angeles Dodgers	Los Angeles	Los Angeles	California	NL
Miami Marlins	Miami	Dade	Florida	NL
Milwaukee Brewers	Milwaukee	Milwaukee	Wisconsin	AL
Minnesota Twins	Minneapolis	Hennepin	Minnesota	AL
New York Mets, New York Yankees	New York City	New York, Bronx, Brooklyn, Queens, Richmond	New York	NL, AL
Oakland Athletics	Oakland	Alameda	California	AL
Philadelphia Phillies	Philadelphia	Philadelphia	Pennsylvania	NL
Pittsburgh Pirates	Pittsburgh	Allegheny	Pennsylvania	NL
San Diego Padres	San Diego	San Diego	California	NL
Seattle Mariners	Seattle	King	Washington	AL
San Francisco Giants	San Francisco	San Francisco	California	NL
St. Louis Cardinals	St. Louis	St. Louis	Missouri	NL
Tampa Bay Rays	Saint Petersburg	Pinellas	Florida	AL
Texas Rangers	Arlington	Tarrant	Texas	AL
Washington Nationals	Washington D.C.	District of Columbia	District of Columbia	NL

Notes: Our data comprise 29 MLB teams that we map to 27 local market areas on the basis of 32 US Counties. NL refers to National League, and AL refers to American League.

Figure A2 shows the development of MLB local market areas' mix up and teams' racial compositions for the three athlete group specifications between 1985 and 2016.

Figure A2. League-specific mean MLB regular season home game attendance from 1985 to 2016

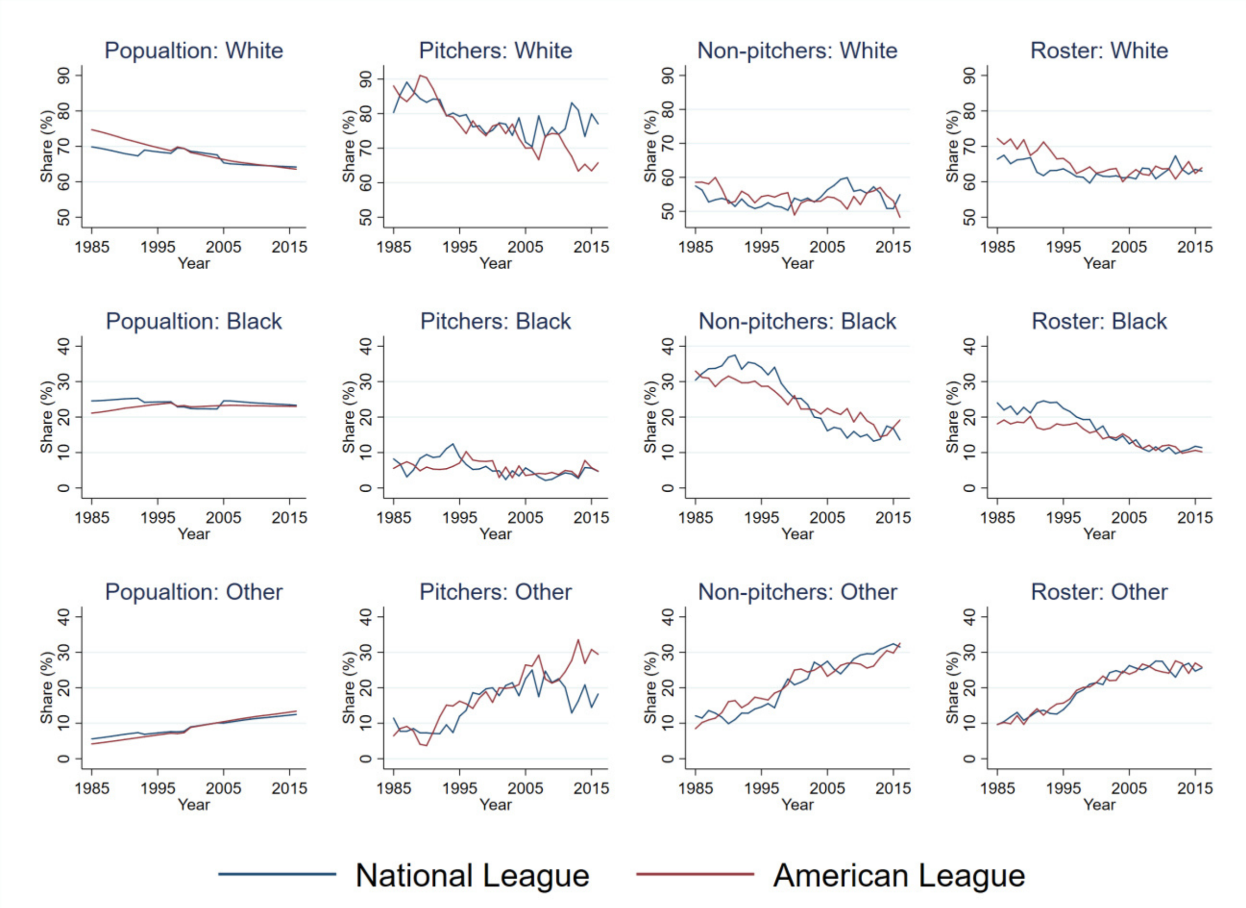


Notes: MLB Team and local market area mean racial composition percentages derived from US Census County level data and individual player racial profiles. Plots are based on 29 US MLB teams and their local market area demographics between 1985 and 2016. Pitchers and non-pitchers relate to home game starting lineups, whereas Roster includes all athletes that were playing during a given season.

Figure A2 shows that the mean share of other non-black minority [white] local market area residents gradually increases [decreases] from around 5% [72%] in 1985 to 13% [64%] in 2016; the share of black residents remains relatively stable at 23%. Considering average team racial compositions, for the roster [starting non-pitchers] specification the mean share of black athletes is decreasing from around 20% [30%] in 1985-1995 to 10% [20%] in 2016, while there is relatively low variation in the otherwise small percentages of black starting pitchers (3-8%). In contrast to black athletes, there has been a large increase in the share of other (non-black) minority players across all three athlete groups that was mainly driven by a great influx of Hispanic players (Armour & Levitt, 2016). Most strikingly, MLB has experienced a substitution of black players with other (non-black) minority players that started around 1995, and since the 2000s, the number other (non-black) minority athletes passed the number of black players. For the starting non-pitcher positions the mean share of other (non-black) minority athletes increases from 8% in 1985 to 28% in 2016. Similarly, from the early 1990s until 2006 a substantial share of white starting pitchers has been replaced with Hispanic and other non-black minorities. Since 2007, the share of other (non-black) minority starting pitchers varies around 19%.

Last, complementing Figure A2, Figure A3 shows the League-specific development of MLB teams' and their local markets' racial compositions by race from 1985 to 2016.

Figure A3. League-specific team and market area racial compositions over time



Notes: League-specific team and local market area mean racial composition percentages derived from US Census County-level data and individual player racial profiles. Plots are based on 29 US MLB teams and their local market area demographics between 1985 and 2016. We consider three different athlete group specifications: pitchers and non-pitchers relate to home game starting lineups, whereas roster includes all athletes that were playing during a given season.

In general, there are only minor differences in the average team and local market area racial compositions across Leagues. The most striking differences exist for the share of white and other non-black starting pitchers: the share of other starting pitchers in the AL increases throughout the entire sample, whereas the corresponding share in the NL starts to decline in ca. 2007. Likewise, while the share of white starting pitchers in the AL gradually decreases throughout the sample, the share of white starting pitchers in the NL only decreased until around 2000 and then, on average, starts to slightly increases until 2016.

3 Attendance and consumer discrimination

In this section, in addition to the detailed results of our attendance regression analysis together with additional extensions and variations of the main model specifications. First, in Table A3 we show the panel-data tests for serial correlation, heteroscedasticity, and cross-sectional dependence of error terms.

Table A3. Serial correlation, heteroscedasticity, and cross-sectional dependence tests I

	(1) Starting Pitchers	(2) Starting Pitchers	(3) Starting Non Pitchers	(4) Starting Non Pitchers	(5) Roster All	(6) Roster All
Wald	417.87	334.00	404.15	277.05	512.72	390.56
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Preusch-Pagan*	850.59	825.13	867.99	780.55	809.04	723.76
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Wooldridge	119.46	129.00	111.63	110.00	130.62	128.00
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Born-Breitung*	6.63	6.49	6.35	6.50	6.36	6.61
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Pop. controls	-	Yes	-	Yes	-	Yes

Notes: The selected test procedures are designed for panel data models and are computed on the basis of fixed effects attendance regressions that we specify in accordance with the model specifications reported in equation (1) in the main text, Section 3.2. Hence, all models include second-degree polynomial trend interactions with League-specific racial composition effects. De-pendent variable is team-specific mean regular season home game attendance. Regressions are based on aggregated US Cen-sus County level and MLB game data from 1985 to 2016. We consider three different athlete group specifications: models (1-4) relate to home game starting lineups, whereas models (5-6) relate to all athletes that were playing during a given season. Wald reports the Wald test statistic for groupwise heteroscedasticity within the panel residuals. Likewise, Breusch–Pagan tests for cross-sectional independence, Wooldridge is a test for within-panel serial correlation, and Born-Breitung is a hetero-scedasticity-robust test for within-panel serial correlation. * Test requires balanced panel data; the corresponding test statis-tic is computed on the basis of the 24 teams that we observe over the full set of 32 seasons. Tests statistics' p-values are in parentheses.

3.1 Team racial composition effects

In this section we present the detailed results of the athlete-group specific attendance regressions based on the model specification described in equation (1) in the main text without including variables on local market areas' racial demographics.

First, in Table A4 we present the corresponding coefficient estimates derived from different model specifications that vary with the degree of included polynomial racial trend interactions.

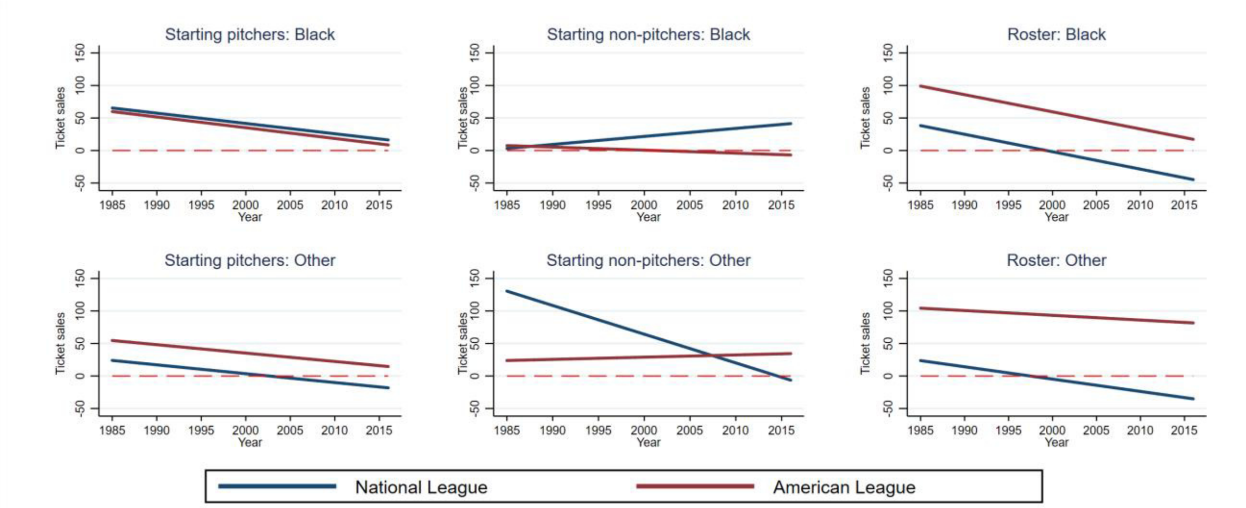
Table A4. Racial composition effects on average home game attendance

	(1) Starting	(2) Starting	(3) Starting	(4) Starting	(5) Starting	(6) Starting	(7) Roster	(8) Roster	(9) Roster
Black (%)	65.37	26.08	-54.08	3.16	-35.01	-38.71	38.31	38.89	-6.96
	(40.54)	(68.99)	(88.24)	(35.97)	(54.86)	(70.75)	(58.99)	(85.87)	(106.01)
Black*Trend	-1.58	5.51	33.31	1.23	7.58	8.87	-2.68	-2.36	11.78
	(2.58)	(10.93)	(22.85)	(1.94)	(7.86)	(17.49)	(3.10)	(12.95)	(25.55)
Black*Trend²		-0.22	-2.48		-0.19	-0.29		-0.02	-1.02
		(0.33)	(1.77)		(0.24)	(1.29)		(0.41)	(1.92)
Black*Trend³			0.05			0.00			0.02
			(0.04)			(0.03)			(0.04)
AL*Black	-5.50	47.36	105.14	4.42	28.42	34.41	60.79	95.77	113.50
	(59.95)	(97.33)	(118.15)	(39.64)	(53.22)	(68.66)	(66.63)	(85.41)	(104.69)
AL*Black*Trend	-0.07	-10.22	-26.82	-1.70	-5.83	-7.79	0.04	-6.89	-10.60
	(3.57)	(14.22)	(29.90)	(1.88)	(7.14)	(16.38)	(3.28)	(11.71)	(24.77)
AL*Black*Trend²		0.33	1.61		0.13	0.29		0.23	0.44
		(0.42)	(2.36)		(0.23)	(1.27)		(0.38)	(1.98)
AL*Black*Trend³			-0.03			-0.00			-0.00
			(0.05)			(0.03)			(0.04)
Other (%)	23.96	125.36**	179.00***	130.53**	131.47	138.60	23.67	51.78	156.10
	(34.64)	(50.90)	(62.81)	(50.94)	(91.61)	(127.75)	(69.10)	(120.91)	(151.34)
Other*Trend	-1.36	-15.85**	-33.23**	-4.42**	-2.80	-5.05	-1.90	-5.82	-34.90
	(1.86)	(6.23)	(15.22)	(2.24)	(11.35)	(28.89)	(3.16)	(14.78)	(33.73)
Other*Trend²		0.42**	1.71		-0.07	0.09		0.11	2.12
		(0.19)	(1.10)		(0.31)	(1.84)		(0.42)	(2.21)
Other*Trend³			-0.03			-0.00			-0.04
			(0.02)			(0.03)			(0.04)
AL*Other (%)	30.64	-101.18	-166.87**	-106.73**	-199.54**	-192.67	80.64	29.18	-26.29
	(41.16)	(63.96)	(77.44)	(54.12)	(91.43)	(127.57)	(68.49)	(125.92)	(169.23)
AL*Other*Trend	0.07	18.91***	40.21**	4.76**	18.01*	16.65	1.17	8.34	24.64
	(2.07)	(7.23)	(16.69)	(2.18)	(10.26)	(27.60)	(2.94)	(13.19)	(33.65)
AL*Other*Trend²		-0.55***	-2.10*		-0.35	-0.27		-0.20	-1.32
		(0.20)	(1.13)		(0.27)	(1.73)		(0.35)	(2.10)
AL*Other*Trend³			0.03			-0.00			0.02
			(0.02)			(0.03)			(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.80	0.80	0.80	0.82	0.81	0.81	0.80	0.80	0.80

Notes: Dependent variable is team-specific mean regular season home game attendance. Results are based on aggregated game data from 1985 to 2016. Models (1-6) relate to a team's home game starting lineups, whereas models (7-9) relate to all athletes that were actively playing during a given season. The National League is chosen as the reference League (vs. American League (AL)). The set of control variables is the same as for the attendance regressions presented in Table 1 in the main text. Coefficients' estimates are corrected for team-specific autocorrelated error terms using Prais-Winsten regression. Residual variance-covariance matrices are estimated using panel-corrected standard errors (PCSEs) (in parentheses) to account for cross-sectional dependence and team-specific heteroscedasticity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

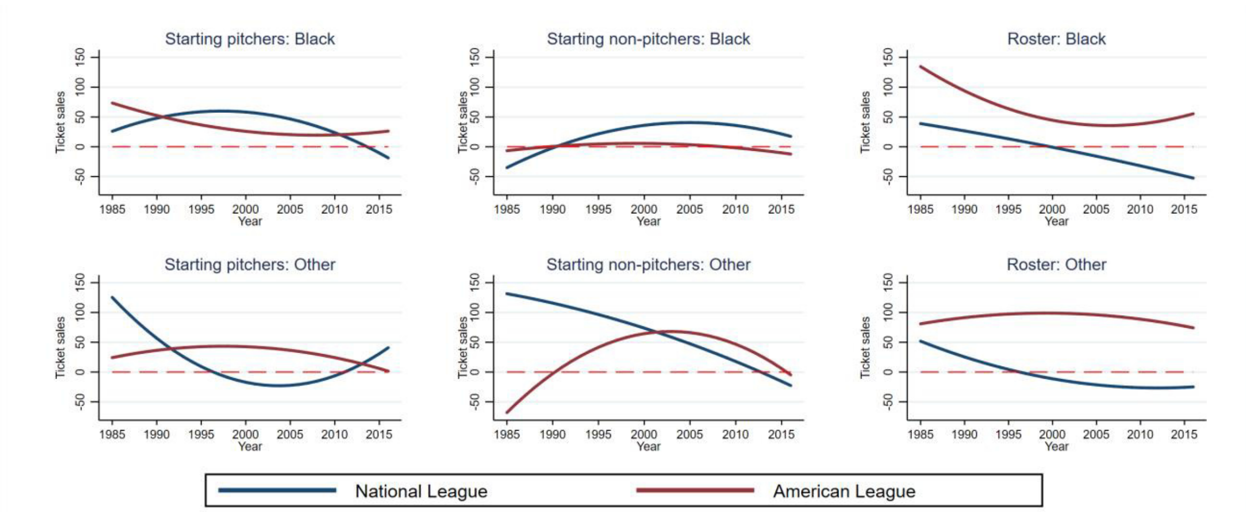
Next, in Figures A4, A5 and A6, we present the corresponding ME estimates derived from the first, second, and third degree of included polynomial racial trend interaction models (see Table A4).

Figure A4. League-specific marginal racial composition effects on attendance I



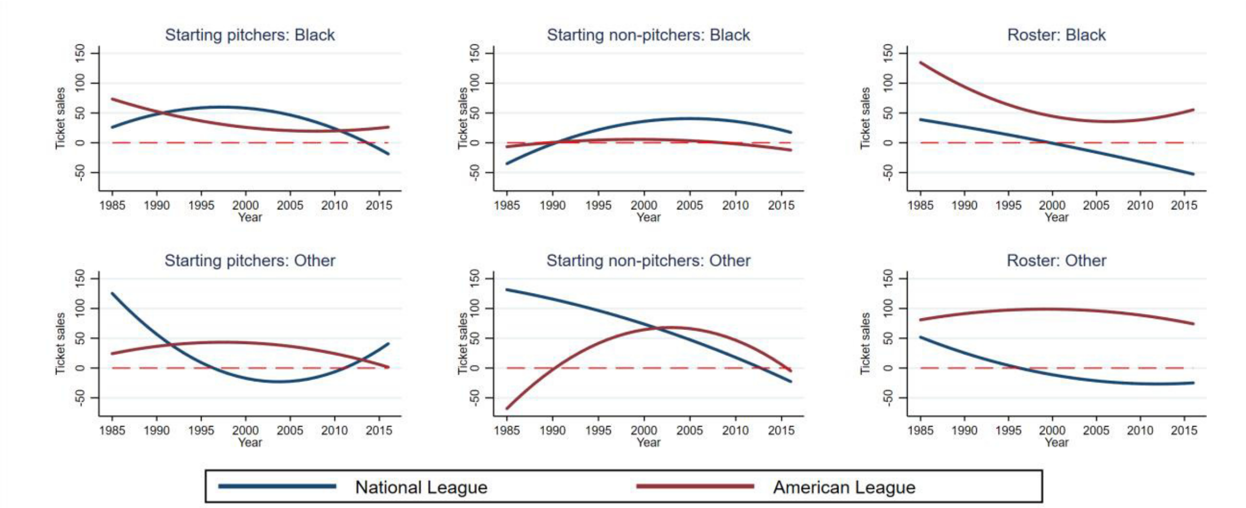
Notes: Marginal effect (ME) plots are derived from the three attendance regressions presented in Table A4, models (1), (4), and (7). League-specific ME estimates are based on first-degree polynomial trend interactions with the percentages of black and other (non-black) minority players and are plotted as a function of time. We consider three different athlete group specifications: the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season. As an example, ME estimates for other (non-black) minority athletes in the NL are computed as $\hat{\beta}_{ME}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend}$ with $Trend = 0$ in 1985.

Figure A5. League-specific marginal racial composition effects on attendance II



Notes: Marginal effect (ME) plots are derived from the three attendance regressions presented in Table A4, models (2), (5), and (8). League-specific ME estimates are based on second-degree polynomial trend interactions with the percentages of black and other (non-black) minority players and are plotted as a function of time. We consider three different athlete group specifications: the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season. As an example, ME estimates for other (non-black) minority athletes in the NL are computed as $\hat{\beta}_{ME}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$ with $Trend = 0$ in 1985.

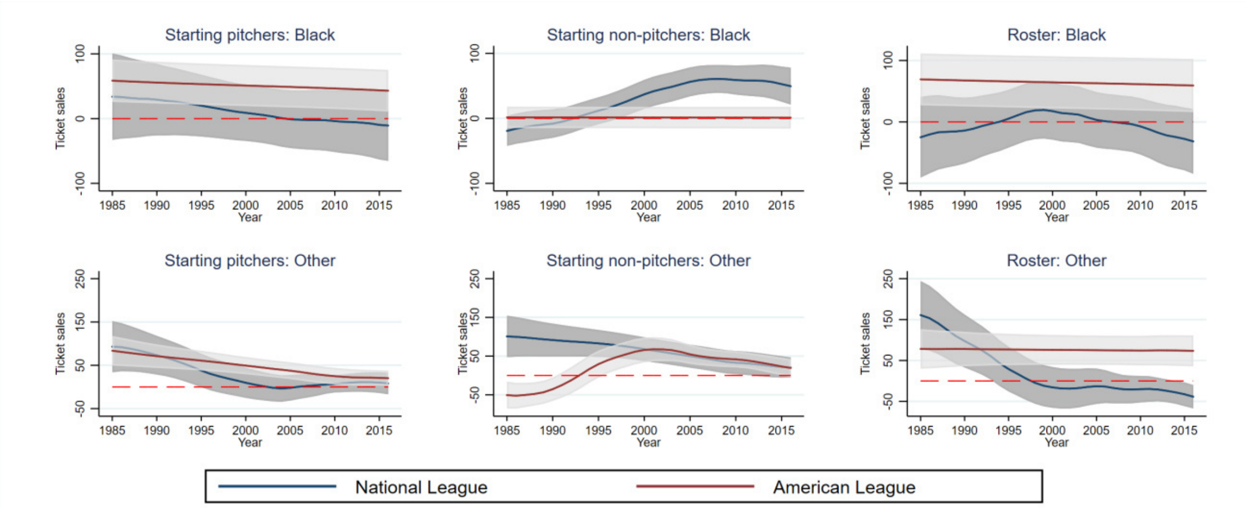
Figure A6. League-specific marginal racial composition effects on attendance III



Notes: Marginal effect (ME) plots are derived from the three attendance regressions presented in Table A4, models (3), (6), and (9). League-specific ME estimates are based on-third degree polynomial trend interactions with the percentages of black and other (non-black) minority players and are plotted as a function of time. We consider three different athlete group specifica-tions: the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season. As an example, ME estimates for other (non-black) minority athletes in the NL are computed as $\hat{\beta}_{ME}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2} + Trend^3 * \hat{\beta}_{OTrend^3}$ with $Trend = 0$ in 1985.

Furthermore, as alternative functional form specification, the CE estimates shown in Figure A7 are also derived from regressing mean season home game attendance on the same set of controls as in our baseline specification; however, instead of second-degree polynomial trend interactions with the percentages of black and other non-black minority (Hispanic and Asian) players, we include interactions with individual year dummy variables and the shares of black and other minority athletes (results omitted for brevity). The League-specific CE estimates are based on polynomial regressions using the dummy-racial-share coefficient estimates as outcome.

Figure A7. Alternative League-specific combined racial composition effects on attendance I



Notes: Combined effect (CE) plots are derived from regressing team-specific mean home game regular season attendance on the same set of controls as in our baseline specification, but instead of second-degree polynomial trend interactions, we include interactions with individual year dummy variables and the shares of black and other non-black minority athletes (results omitted for brevity). League-specific CE estimates are based on polynomial regressions using the dummy-racial-share coefficient estimates as outcome. Grey shaded areas indicate 95% confidence intervals. We consider three different athlete group specifications: the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details).

3.2 Team and local market area racial composition effects

In this section, we present the detailed results of the attendance regression including the set of variables on local market areas' racial composition.

Table A5 shows the results for the starting pitchers athlete-group specification, Table A6 includes the results for the starting non-pitchers specification, and last, in Table A7, we present the results for the roster specification. Considering local market racial compositions effects across Leagues, we only find some significant differences between starting pitchers in the NL and AL. Given a fixed white local market population share, higher levels of other non-black minority athletes in the NL are associated with lower attendance numbers than in the AL. Moreover, the AL-specific interaction effect between and a team's and its local market areas' share of other non-black minorities is negative,

Moreover, we also test for time dependent local market racial compositions effects in Table A8. For the share of black residents, we did not find any significant first or second-degree trend interactions. In contrast, our results show that other non-black minority residents' preference for attending baseball games significantly increase over time.

Table A5. Team and market area racial composition effects for starting pitchers

	(1) Starting Pitchers	(2) Starting Pitchers	(3) Starting Pitchers	(4) Starting Pitchers
Black (%)	29.71	36.73	-436.19*	-533.92*
	(67.83)	(69.48)	(255.46)	(317.43)
Black*Trend	4.90	4.33	3.39	3.16
	(10.76)	(10.85)	(10.61)	(10.57)
Black*Trend^2	-0.19	-0.18	-0.13	-0.12
	(0.32)	(0.32)	(0.32)	(0.32)
AL*Black (%)	31.58	25.85	-4.00	596.59
	(96.77)	(100.93)	(95.99)	(513.99)
AL*Black*Trend	-8.25	-7.63	-7.16	-8.75
	(14.13)	(14.48)	(13.99)	(14.30)
AL*Black*Trend^2	0.25	0.24	0.26	0.25
	(0.42)	(0.42)	(0.42)	(0.41)
Other (%)	134.39***	152.10***	213.12***	306.16***
	(49.78)	(50.84)	(70.16)	(85.09)
Other*Trend	-16.53***	-18.39***	-16.44***	-20.17***
	(6.20)	(6.26)	(6.24)	(6.28)
Other*Trend^2	0.43**	0.47**	0.42**	0.50***
	(0.19)	(0.19)	(0.19)	(0.19)
AL*Other	-110.06*	-129.48*	-108.42*	-293.12**
	(64.27)	(67.18)	(65.10)	(120.26)
AL*Other*Trend	19.47***	21.09***	19.29***	23.25***
	(7.29)	(7.49)	(7.36)	(7.66)
AL*Other*Trend^2	-0.55***	-0.57***	-0.54***	-0.58***
	(0.21)	(0.21)	(0.21)	(0.21)
Pop.Black (%)	-292.40	-287.19	-297.40	-279.11
	(182.32)	(201.23)	(183.06)	(201.03)
Pop.Other (%)	294.60	486.65	278.30	445.96
	(220.54)	(307.04)	(224.74)	(301.07)
AL*Pop.Black		155.20		161.97
		(311.85)		(301.05)
AL*Pop.Other		-177.79		-132.73
		(195.11)		(198.62)
Black*Pop.Black			3.36	4.62
			(2.41)	(2.94)
Black*Pop.White			5.86**	6.87*
			(2.78)	(3.55)
AL*Black*Pop.Black				-6.77
				(4.87)
AL*Black*Pop.White				-6.01
				(5.59)
Other*Pop.Other			0.52	2.37
			(1.30)	(1.76)
Other*Pop.White			-1.18*	-2.25**
			(0.69)	(0.97)
AL*Other*Pop.Other				-5.36**
				(2.72)
AL*Other*Pop.White				2.57*
				(1.41)
Controls	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes
R2	.81	.81	.80	.81

Notes: Dependent variable is team-specific mean regular season home game attendance. Results are based on aggregated game data from 1985 to 2016. Models (1-4) all relate to teams' percentage shares of home game starting pitchers. National League is chosen as reference (vs. American League (AL)). The set of control variables is the same as for the attendance regressions presented in Table 1 in the main text. Coefficients' estimates are corrected for team-specific autocorrelated error terms using Prais-Winsten regression. Residual variance-covariance matrices are estimated using panel-corrected standard errors (PCSEs) (in parentheses) to account for cross-sectional dependence and team-specific heteroscedasticity (see Section 3 in the main text for details). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Team and market area racial composition effects for starting non-pitchers

	(1) Starting Non-Pitchers	(2) Starting Non-Pitchers	(3) Starting Non-Pitchers	(4) Starting Non-Pitchers
Black (%)	-26.95	-9.28	-548.00***	-637.63**
	(54.43)	(57.74)	(205.82)	(266.74)
Black*Trend	6.45	5.39	6.87	5.01
	(7.90)	(8.05)	(8.00)	(8.11)
Black*Trend^2	-0.15	-0.15	-0.11	-0.10
	(0.24)	(0.24)	(0.25)	(0.25)
AL*Black (%)	22.24	-16.04	11.01	325.77
	(53.62)	(65.10)	(54.44)	(362.08)
AL*Black*Trend	-5.36	-2.34	-2.85	2.05
	(7.19)	(7.90)	(7.37)	(8.00)
AL*Black*Trend^2	0.12	0.09	0.04	-0.05
	(0.23)	(0.23)	(0.23)	(0.24)
Other (%)	122.25	131.18	45.38	205.07
	(91.63)	(92.88)	(131.78)	(163.44)
Other*Trend	-1.60	-2.34	-0.33	-3.05
	(11.39)	(11.62)	(11.69)	(11.79)
Other*Trend^2	-0.12	-0.12	-0.15	-0.11
	(0.32)	(0.32)	(0.32)	(0.33)
AL*Other (%)	-188.32**	-215.10**	-186.88**	-507.34**
	(92.67)	(95.59)	(93.40)	(198.62)
AL*Other*Trend	16.54	18.44*	15.89	22.58**
	(10.35)	(10.64)	(10.55)	(10.79)
AL*Other*Trend^2	-0.30	-0.31	-0.28	-0.37
	(0.28)	(0.28)	(0.28)	(0.28)
Pop.Black (%)	-455.01**	-395.30*	-460.79**	-329.89
	(181.12)	(208.70)	(187.82)	(230.64)
Pop.Other (%)	125.36	383.19	208.55	507.28
	(232.34)	(350.54)	(259.31)	(384.05)
AL*Pop.Black		-32.95		-144.24
		(348.26)		(358.63)
AL*Pop.Other		-358.86		-513.39
		(310.09)		(329.06)
Black*Pop.Black			4.92***	5.85**
			(1.90)	(2.56)
Black*Pop.White			5.69**	7.11**
			(2.25)	(2.96)
AL*Black*Pop.Black				-2.73
				(3.51)
AL*Black*Pop.White				-4.51
				(3.99)
Other*Pop.Other			-0.48	-0.22
			(1.75)	(2.42)
Other*Pop.White			1.18	-0.83
			(1.18)	(1.79)
AL*Other*Pop.Other				-0.91
				(3.08)
AL*Other*Pop.White				3.78
				(2.34)
Controls	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes
R2	.81	.80	.81	.80

Notes: Dependent variable is team-specific MLB mean regular season home game attendance. Results are based on aggregated game data from 1985 to 2016. Models (1-4) all relate to teams' percentage shares of home game starting non-pitchers. National League is chosen as reference (vs. American League (AL)). The set of control variables is the same as for the attendance regressions presented in Table 1 in the main text. Coefficients' estimates are corrected for team-specific autocorrelated error terms using Prais-Winsten regression. Residual variance-covariance matrices are estimated using panel-corrected standard errors (PCSEs) (in parentheses) to account for cross-sectional dependence and team-specific heteroscedasticity (see Section 3 in the main text for details). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7. Team and market area racial composition effects for the roster specification

	(1) Roster	(2) Roster	(3) Roster	(4) Roster
Black (%)	54.11	101.35	-22.36	24.00
	(85.34)	(91.77)	(359.15)	(440.85)
Black*Trend	-4.73	-7.83	-5.63	-9.09
	(13.02)	(13.29)	(13.12)	(13.22)
Black*Trend^2	0.07	0.08	0.13	0.16
	(0.42)	(0.42)	(0.42)	(0.42)
AL*Black (%)	87.99	13.93	78.55	62.39
	(85.63)	(98.04)	(86.58)	(666.01)
AL*Black*Trend	-5.58	0.03	-2.81	5.04
	(11.79)	(12.64)	(12.04)	(12.94)
AL*Black*Trend^2	0.19	0.14	0.07	-0.05
	(0.38)	(0.39)	(0.39)	(0.40)
Other (%)	61.80	114.17	53.35	221.38
	(120.38)	(120.34)	(169.06)	(195.61)
Other*Trend	-6.95	-11.69	-8.40	-13.42
	(14.80)	(14.75)	(15.07)	(14.86)
Other*Trend^2	0.12	0.21	0.11	0.20
	(0.42)	(0.42)	(0.43)	(0.42)
AL*Other (%)	43.52	-40.48	47.79	-368.76
	(129.61)	(133.97)	(131.32)	(279.29)
AL*Other*Trend	6.33	13.38	6.31	19.24
	(13.58)	(13.76)	(13.82)	(14.00)
AL*Other*Trend^2	-0.13	-0.23	-0.12	-0.34
	(0.36)	(0.36)	(0.36)	(0.36)
Pop.Black (%)	-377.83**	-230.17	-373.50**	-247.10
	(180.35)	(202.32)	(181.08)	(226.90)
Pop.Other (%)	233.69	563.70	89.48	463.86
	(218.23)	(356.90)	(254.88)	(395.44)
AL*Pop.Black		-248.04		-265.82
		(339.44)		(361.58)
AL*Pop.Other		-486.71		-477.47
		(325.54)		(376.64)
Black*Pop.Black			0.64	0.18
			(3.32)	(4.20)
Black*Pop.White			0.91	1.04
			(3.90)	(4.93)
AL*Black*Pop.Black				0.51
				(6.35)
AL*Black*Pop.White				-1.21
				(7.45)
Other*Pop.Other			4.77*	5.11
			(2.81)	(3.65)
Other*Pop.White			-0.13	-1.89
			(1.58)	(2.19)
AL*Other*Pop.Other				-3.34
				(5.61)
AL*Other*Pop.White				4.56
				(3.36)
Controls	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes
R2	.80	.80	.78	.79

Notes: Dependent variable is team-specific MLB mean regular season home game attendance. Results are based on aggregated US Census County level and game data from 1985 to 2016. Models (1-4) all relate to teams' percentage shares of all athletes that were playing during a given season. National League is chosen as reference (vs. American League (AL)). The set of control variables is the same as for the attendance regressions presented in Table 1 in the main text. Coefficients' estimates are corrected for team-specific autocorrelated error terms using Prais-Winsten regression. Residual variance-covariance matrices are estimated using panel-corrected standard errors (PCSEs) (in parentheses) to account for cross-sectional dependence and team-specific heteroscedasticity (see Section 3 in the main text for details). * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A8. Team and market area racial composition trend effects

	(1) Starting Pitchers	(2) Starting Pitchers	(3) Starting Non-pitchers	(4) Starting Non-pitchers	(5) Roster	(6) Roster
Black (%)	-387.41	-412.14	-299.74	-296.61	253.03	272.98
	(261.57)	(254.98)	(209.64)	(210.11)	(347.34)	(342.62)
Black*Trend	2.49	2.21	3.25	2.79	-10.05	-10.45
	(10.66)	(10.58)	(8.29)	(8.25)	(13.31)	(13.21)
Black*Trend^2	-0.12	-0.11	-0.02	-0.00	0.27	0.29
	(0.32)	(0.32)	(0.26)	(0.26)	(0.43)	(0.43)
AL*Black (%)	197.98***	197.47***	-6.90	-7.00	61.95	63.17
	(70.24)	(70.72)	(54.80)	(54.78)	(88.19)	(87.12)
AL*Black*Trend	-16.17***	-16.22***	-0.55	-0.48	0.40	-0.06
	(6.15)	(6.25)	(7.42)	(7.43)	(12.21)	(12.10)
AL*Black*Trend^2	0.42**	0.42**	-0.02	-0.02	-0.03	-0.02
	(0.19)	(0.19)	(0.23)	(0.24)	(0.40)	(0.40)
Other (%)	-14.99	-19.20	-5.88	5.47	-48.88	-37.76
	(95.67)	(95.39)	(133.26)	(132.15)	(182.54)	(178.67)
Other*Trend	-6.70	-6.37	1.38	0.35	-4.46	-4.70
	(13.88)	(13.87)	(11.48)	(11.57)	(15.09)	(15.10)
Other*Trend^2	0.26	0.25	-0.18	-0.15	0.03	0.03
	(0.41)	(0.41)	(0.32)	(0.32)	(0.43)	(0.43)
AL*Other (%)	-111.21*	-115.03*	-167.13*	-178.08*	64.25	52.82
	(65.11)	(65.81)	(94.68)	(93.56)	(134.26)	(132.09)
AL*Other*Trend	19.93***	20.29***	14.47	15.46	5.46	6.48
	(7.36)	(7.47)	(10.61)	(10.55)	(14.06)	(13.86)
AL*Other*Trend^2	-0.56***	-0.57***	-0.25	-0.27	-0.09	-0.11
	(0.21)	(0.21)	(0.28)	(0.28)	(0.37)	(0.36)
Pop.Black (%)	-60.33	-139.04	-223.70	-324.95*	-227.42	-247.92
	(221.60)	(183.92)	(219.32)	(193.53)	(222.61)	(181.55)
Pop.Black*Trend	2.23	3.85*	0.67	4.30	4.46	3.53
	(7.40)	(2.31)	(7.71)	(2.79)	(7.45)	(2.54)
Pop.Black*Trend^2	0.06		0.12		-0.03	
	(0.22)		(0.23)		(0.22)	
Pop.Other (%)	-674.33	-572.57	-739.85*	-655.05	-936.62**	-845.45**
	(416.58)	(389.74)	(443.99)	(413.09)	(425.11)	(406.63)
Pop.Other*Trend	32.55*	22.70***	29.01	21.71***	31.46*	23.12***
	(18.42)	(6.22)	(17.90)	(6.69)	(18.57)	(6.67)
Pop.Other*Trend^2	-0.25		-0.17		-0.22	
	(0.51)		(0.50)		(0.51)	
Black*Pop.Black	2.85	3.11	2.83	2.80	-1.93	-2.06
	(2.49)	(2.44)	(1.92)	(1.92)	(3.24)	(3.17)
Black*Pop.White	5.52*	5.83**	3.21	3.17	-1.92	-2.16
	(2.85)	(2.79)	(2.27)	(2.27)	(3.78)	(3.73)
Other*Pop.Other	0.27	0.35	-0.87	-0.81	3.57	3.77
	(1.29)	(1.26)	(1.73)	(1.73)	(2.71)	(2.66)
Other*Pop.White	-1.04	-1.01	1.63	1.59	0.85	0.72
	(0.69)	(0.68)	(1.20)	(1.20)	(1.66)	(1.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	.80	.80	.81	.81	.79	.79

Notes: Dependent variable is team-specific MLB mean regular season home game attendance. Results are based on aggregated US Census County level and game data from 1985 to 2016. Models (1-6) relate to a team's home game starting lineups, whereas models (7-9) relate to all athletes that were actively playing during a given season. National League teams is chosen as reference (vs. American League (AL)). The set of control variables is the same as for the attendance regressions presented in Table 1 in the main text. Coefficients' estimates are corrected for team-specific autocorrelated error terms using Prais-Winsten regression. Residual variance-covariance matrices are estimated using panel-corrected standard errors (PCSEs) (in parentheses) to account for cross-sectional dependence and team-specific heteroscedasticity (see Section 3 in the main text for de-tails). * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A9 and A10 include the results of the joint significance tests that are based on the attendance regression coefficients' estimates presented in Table A5, A6, and A7. Specifically, Table A9 is based on the regression models that include the simple shares of local market areas' black and other non-black minority residents (model (1) in Table A5, A6, and A7), whereas Table A10 is derived from the regression specifications that include the simple minority shares in addition to the interaction between teams' and local market areas' minority racial shares (model (3) in Table A5, A6, and A7).

Table A9. Joint significant tests for League-specific consumer discrimination I

Test	Black			Other		
	(1)	(2)	(3)	(1)	(2)	(3)
First degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.089*	0.399	0.743	0.561	0.028**	0.566
AL vs. NL	0.891	0.632	0.471	0.210	0.045**	0.024**
AL vs. zero	0.092*	0.728	0.275	0.135	0.022**	0.014***
	(4)	(5)	(6)	(4)	(5)	(6)
Second degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.181	0.490	0.875	0.043**	0.039**	0.750
AL vs. NL	0.908	0.713	0.600	0.010***	0.059*	0.047**
AL vs. zero	0.249	0.834	0.459	0.010***	0.017**	0.047**
	(7)	(8)	(9)	(7)	(8)	(9)
Third degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.106	0.661	0.956	0.028**	0.075*	0.764
AL vs. NL	0.913	0.884	0.741	0.008***	0.099*	0.098*
AL vs. zero	0.239	0.951	0.619	0.010***	0.037**	0.105

Notes: This Table shows p-values from joint significance Wald tests for linear combinations of League-specific racial composition effects. We consider three different athlete group specifications: models (1-2), (4-5) and (7-8) relate to home game starting lineups, while models (3), (6) and (9) include all athletes that were playing during a given season. Estimates are based on the attendance regressions specifications described in Section 3 in the main text. Models (4-6) correspond to the regression results presented in Table 3 (models (1), (3), and (4)) and include second-degree polynomial trend interactions with the percentages of black and other non-black minority athletes as well as local market area percentage shares of black and other non-black minority residents. Instead of second-degree interactions, models (1-3) and models (7-9) include first and third-degree interactions (results omitted for brevity). National League (NL) is chosen as reference (vs. American League (AL)). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

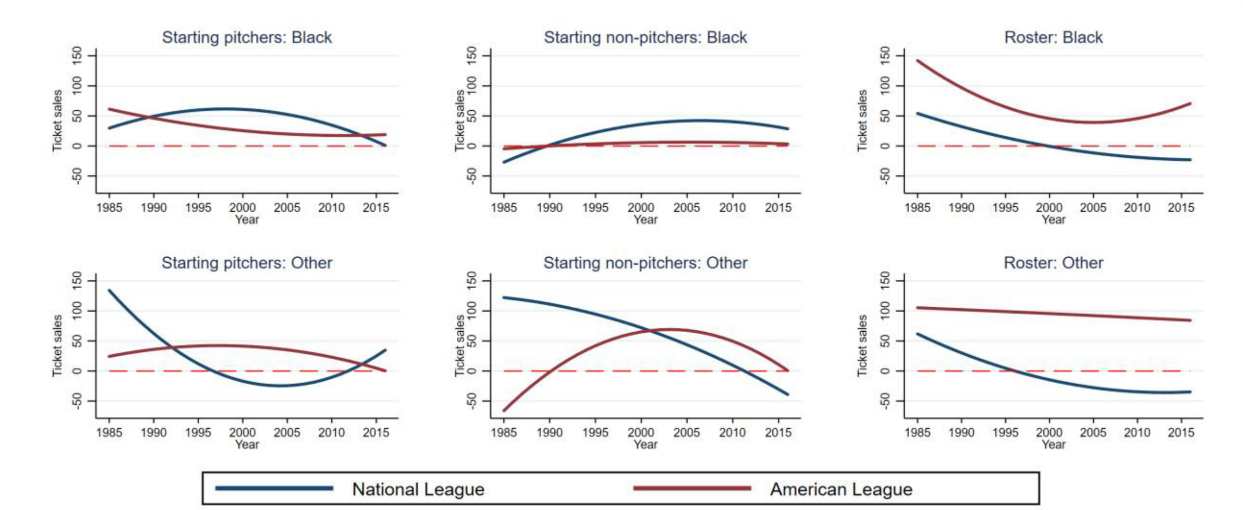
Table A10. Joint significant tests for League-specific consumer discrimination II

Test	Black			Other		
	(1)	(2)	(3)	(1)	(2)	(3)
First degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.183	0.036**	0.804	0.185	0.116	0.329
AL vs. NL	0.606	0.665	0.491	0.208	0.045**	0.018**
AL vs. Zero	0.307	0.127	0.701	0.113	0.161	0.039**
	(4)	(5)	(6)	(4)	(5)	(6)
Second degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.288	0.062	0.920	0.016**	0.115	0.535
AL vs. NL	0.715	0.801	0.680	0.011**	0.059*	0.039**
AL vs. Zero	0.503	0.249	0.874	0.007***	0.101	0.109
	(7)	(8)	(9)	(7)	(8)	(9)
Third degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.204	0.114	0.992	0.012**	0.161	0.609
AL vs. NL	0.794	0.910	0.728	0.007***	0.098*	0.076*
AL vs. zero	0.384	0.409	0.924	0.007***	0.185	0.200

Notes: This Table shows p-values from joint significance Wald tests for linear combinations of League-specific racial composition effects. We consider three different athlete group specifications: models (1-2), (4-5) and (7-8) relate to home game starting lineups, while models (3), (6) and (9) include all athletes that were playing during a given season. National League (NL) is chosen as reference (vs. American League (AL)). Estimates are based on the attendance regressions specifications described in Section 3 in the main text. Models (4-6) correspond to the regression results presented in Table 3 (models (2), (4), and (6)), and include second-degree polynomial trend interactions with the percentages of black and other non-black minority athletes, as well as local market area percentage shares of black and other non-black minority residents, and interactions be-tween team and local market area racial compositions. Instead of second-degree interactions, models (1-3) and models (7-9) include first and third-degree interactions (results omitted for brevity). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

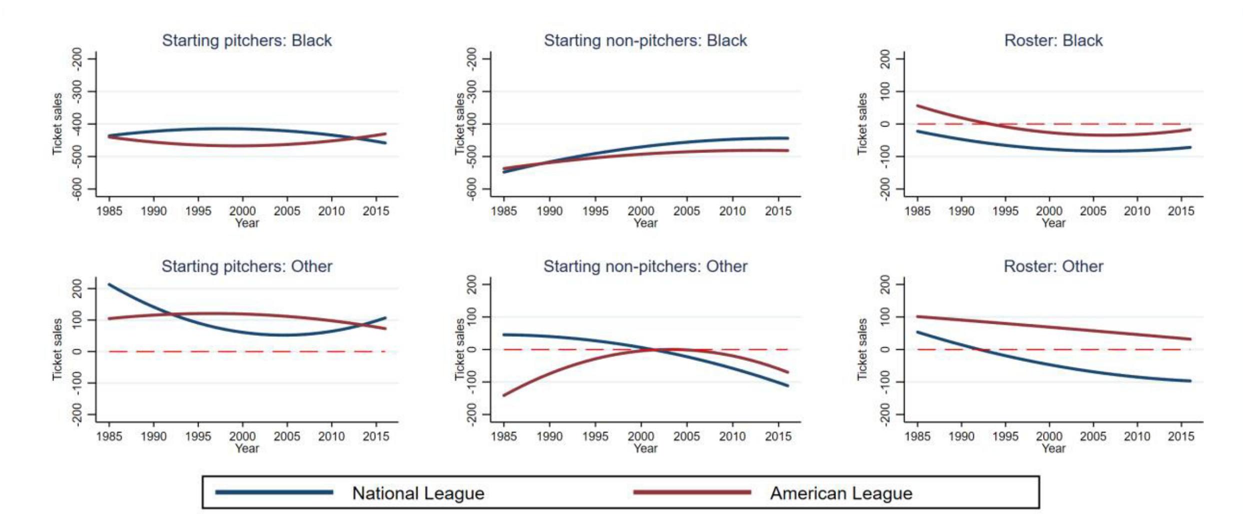
In Figures A8 and A9, we show the CE estimates derived from the second-degree polynomial racial trend interaction specifications that correspond to the same regression models as the ones presented in Table A8 and A9. Hence, Figure A8 is derived from the models that include the simple shares of local market areas' black and other non-black minority residents (model (1) in Table A5, A6, and A7), and Figure A9 is based on the models that include the simple minority shares in addition to the interaction between teams' and local market areas' minority racial shares (model (3) in Table A5, A6, and A7).

Figure A8. League-specific partial racial composition effect estimates on attendance I



Notes: Partial effect (PE) plots are derived from the three attendance regression in Table A5, A6, and A7, model (1). League-specific PE estimates are based on second-degree polynomial trend interactions with the percentages of black and other (non-black) minority athletes and are plotted as a function of time. We consider three different athlete group specifications: the first two columns relate home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 in the main for details). As an example, PE estimates for other (non-black minority athletes in the NL are computed as $\hat{\beta}_{CE}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$ with $Trend = 0$ in 1985.

Figure A9. League-specific partial racial composition effect estimates on attendance II



Notes: Partial effect (PE) plots are derived from the three attendance regression in Table A5, A6, and A7, model (3). League-specific PE estimates are based on second-degree polynomial trend interactions with the percentages of black and other (non-black) minority athletes and are plotted as a function of time. We consider three different athlete group specifications: the first two columns relate home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 in the main for details). As an example, PE estimates for other (non-black minority athletes in the NL are computed as $\hat{\beta}_{CE}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$ with $Trend = 0$ in 1985.

4 Performance and employer discrimination

In this Section, we provide the additional results from the team performance regressions that we omitted from the main text for brevity. Specifically, we estimate the (League-specific) effect of the difference between a teams' percentage share of black and other non-black minority athletes and its corresponding League-year-specific mean share on regular season winning percentage. Moreover, since teams typically compete against teams within their own League, in contrast to the attendance and team selection regressions, we account for the two League-membership changes in 1998 and 2013.

Table A11 shows the results of the panel-data tests for serial correlation, heteroscedasticity, and cross-sectional dependence, and Table A12 shows the joint significance tests derived from the winning percentage regressions in Table 4 in the main text.

Table A11. Serial correlation, heteroscedasticity, and cross-sectional dependence tests II

	(1) Starting Pitchers		(2) Starting NPitchers		(3) Roster	
Wald	64.19	(<.001)	58.60	(<.001)	66.16	(<.001)
Preusch-Pagan*	374.95	(<.001)	389.66	(<.001)	382.08	(<.001)
Wooldridge	27.19	(<.001)	29.11	(<.001)	22.96	(<.001)
Born-Breitung*	5.69	(<.001)	6.07	(<.001)	5.82	(<.001)

Notes: The selected test procedures are designed for panel data models and are computed on the basis of fixed effects regressions that we specify in accordance with the model specifications reported in models (3), (6) and (9) in the main text Table 4, Section 4.2. Dependent variable is team-specific MLB mean regular season winning percentage. Regressions are based on aggregated game data from 1985 to 2016. We consider three different athlete group specifications: models (1-2) relate to home game starting lineup, while model (3) relates to all athletes that were actively playing during a given season. Wald reports the Wald test statistic for groupwise heteroscedasticity within the panel residuals. Likewise, Breusch–Pagan is a tests for cross-sectional independence, Wooldridge is a test for within-panel serial correlation, and Born-Breitung is a heteroscedasticity-robust test for within-panel serial correlation. * Test requires balanced panel data; the corresponding test statistic is computed on the basis of the 24 teams that we observe over the full set of 32 seasons. Tests statistics' p-values are in parentheses.

Table A12. Joint significant tests for League-specific employer discrimination by athlete group

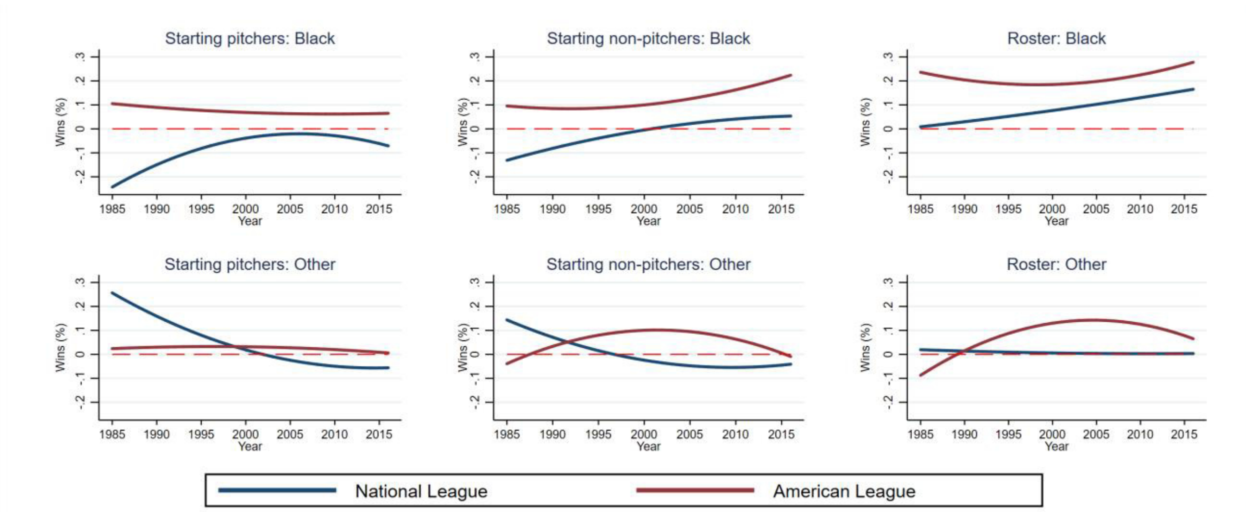
Test	Black			Other		
	(1)	(2)	(3)	(1)	(2)	(3)
Zero degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.018**	0.588	0.165	0.873	0.246	0.611
AL vs. NL	0.006***	0.001***	0.062*	0.536	0.020**	0.045**
AL vs. Zero	0.017**	0.000***	0.000***	0.639	0.047**	0.076*
	(4)	(5)	(6)	(4)	(5)	(6)
First degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.018**	0.091*	0.325	0.003***	0.561	0.842
AL vs. NL	0.011**	0.003***	0.132	0.133	0.100*	0.098*
AL vs. Zero	0.028**	0.000***	0.001***	0.013**	0.249	0.229
	(7)	(8)	(9)	(7)	(8)	(9)
Second degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.033**	0.040**	0.497	0.002***	0.597	0.554
AL vs. NL	0.027**	0.003***	0.174	0.147	0.054*	0.028**
AL vs. zero	0.075*	0.000***	0.002***	0.016**	0.111	0.120

Notes: This Table shows p-values from joint significance Wald tests for linear combinations of League-specific racial composition effects. We consider three different athlete group specifications: models (1-2), (4-5) and (7-8) relate to home game starting lineups, while models (3), (6) and (9) include all athletes that were playing during a given season. Models (1), (4), and (7) include second-degree polynomial trend interactions with the percentages of black and other non-black minority athletes. Instead of second-degree interactions, models (1-3) and models (4-6) include zero- and first-degree interactions. Estimates are based on the regression results presented in Table 4 in the main text. National League (NL) is chosen as reference (vs. American League (AL)). * $p \le 0.1$, ** $p < 0.05$, *** $p < 0.01$

The joint significance tests for the second-degree specification for the share of black starting players in the NL and AL are all significant at $p \leq 0.05$, and the joint test for the corresponding share of black athletes for the roster specification in the AL is significant at $p<0.01$. Regarding the joint tests for the second-degree polynomial racial trend interaction effects for the share of other non-black minority athletes, we find significant effects for the share of other starting pitchers in both the NL and AL, and we find a significant difference in the NL and AL effect for the share of other athletes in the roster specification. Moreover, we find a significant effect for the share of other starting non-pitchers in the AL ($p \leq 0.05$) that significantly differs to the NL effect ($p \leq 0.05$).

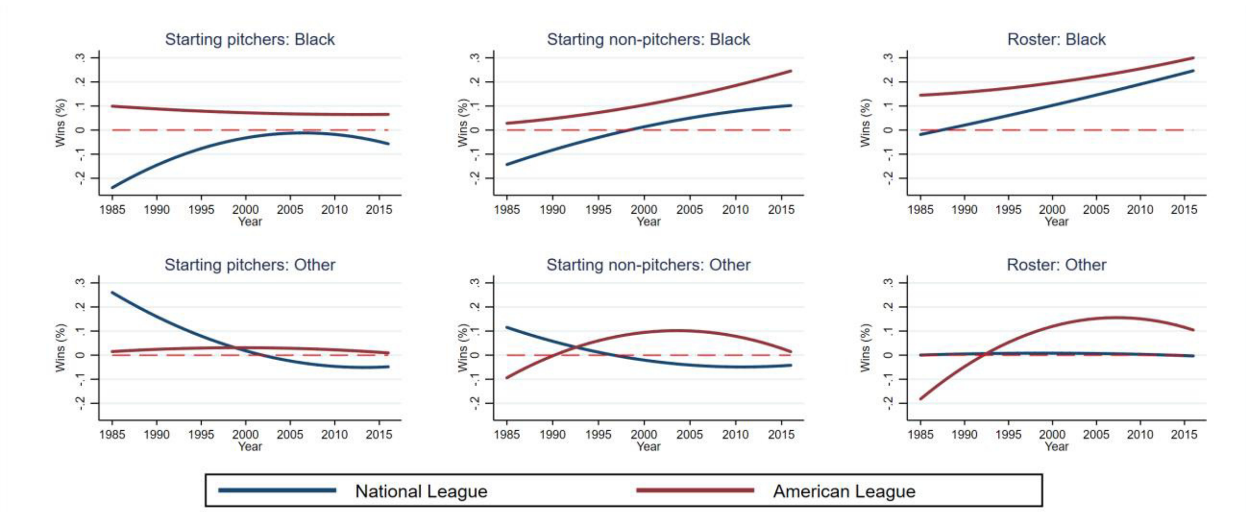
Figure A10 shows the ME estimates that are derived from our baseline model specification. In comparison, the CE estimates presented in Figure A11 are derived from regressing winning percentage on the same set of controls as in our baseline specification, but in addition, the set of explanatory variables includes the local market areas' percentage shares of black and other (non-black) minority residents.

Figure A10. League-specific marginal racial composition effects on team success over time



Notes: Marginal effect (ME) plots are derived from the three winning percentage regression models (1), (4), and (7) in Table 4 in the main text. League-specific ME estimates are based on second-degree polynomial trend interactions with the percentages of black and other (non-black) minority athletes and are plotted as a function of time. We consider three different athlete group specifications: the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details). As an example, ME estimates for other (non-black) minority athletes in the NL are computed as $\hat{\beta}_{CE}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$ with $Trend = 0$ in 1985.

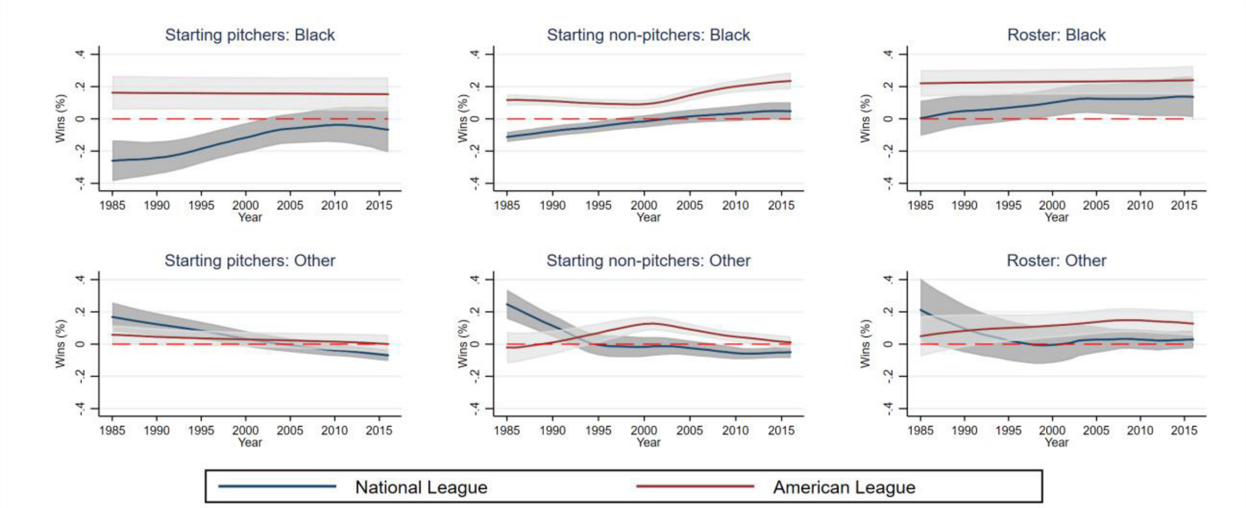
Figure A11. League-specific combined racial composition effects on team success over time I



Notes: Combined effect (CE) plots are derived from regressing winning percentage on the same set of controls as in our baseline specification (cf. Figure A10), but in addition, the set of explanatory variables includes the local market areas' percentage shares of black and other (non-black) minority residents. We consider three different athlete group specifications: the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details). As an example, CE estimates for other (non-black) minority athletes in the NL are computed as $\hat{\beta}_{CE}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$ with $Trend = 0$ in 1985.

Furthermore, as alternative functional form specification, the CE estimates shown in Figure A12 are as well derived from regressing winning percentage on the same set of controls as in our baseline specification; however, instead of second-degree polynomial trend interactions with the percentages of black and other (non-black) minority players, we include interactions with individual year dummy variables and the shares of black and other non-black minority athletes (results omitted for brevity). The League-specific CE estimates are based on polynomial regressions using the dummy-racial-share coefficient estimates as outcome.

Figure A12. League-specific combined racial composition effects on team success over time II



Notes: Combined effect (CE) plots are derived from regressing winning percentage on the same set of controls as in our baseline specification. However, instead of second-degree polynomial trend interactions, we include interactions with individual year dummy variables and the shares of black and other non-black minority athletes (results omitted for brevity). League-specific CE estimates are based on polynomial regressions using the dummy-racial-share coefficient estimates as outcome. Grey shaded areas indicate 95% confidence intervals. We consider three different athlete group specifications: the first two col-umns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details).

5 Team selection and racial matching strategies

Throughout this section, we present the detailed regression results and additional robustness tests for our analysis of the link between teams' and their local markets' racial compositions.

Table A13 shows the corresponding results of panel-data tests for serial correlation, heteroscedasticity, and cross-sectional dependence for our analyses of teams' shares of black and other non-black minority players by athlete group.

Table A13. Serial correlation, heteroscedasticity, and cross-sectional dependence tests III

	(1) Starting Pitchers: Black	(2) Starting Pitchers: Other	(3) Starting Npitchers: Black	(4) Starting Npitchers: Other	(5) Roster: Black	(6) Roster: Other
Wald	530.90	141.69	146.66	108.11	81.97	117.35
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
BP*	472.08	513.98	629.43	701.27	558.82	505.46
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
Wooldridge	45.384	128.420	135.510	101.925	42.835	56.242
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)
BB*	4.594	6.100	8.596	7.409	6.516	6.774
	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)	(<.001)

Notes: The selected test procedures are designed for panel data models and are computed on the basis of fixed effects regressions. Dependent variables are a team's percentage of black and other (non-black) minority athletes. Regressions are based on aggregated MLB game data from 1985 to 2016. The models (1-6) relate to home game starting pitchers and non-pitchers (NPitchers), whereas models (7-9) include all athletes that were playing during a given season. The models for black athletes ((1), (3), and (5)) and other (non-black) athletes ((2), (4), and (6)) are specified in accordance with the models (1), (4), and (7) in Table A14 and A15. Wald reports the Wald test statistic for groupwise heteroscedasticity within the panel residuals. Likewise, Breusch–Pagan (BP) is a tests for cross-sectional independence, Wooldridge is a test for within-panel serial correlation, and Born-Breitung (BB) is a heteroscedasticity-robust test for within-panel serial correlation. * Test requires balanced panel data; the corresponding test statistic is computed on the basis of the 24 teams that we observe over the full set of 32 seasons. Tests statistics' p-values are in parentheses.

In Tables A14 and A15, we present the results from regressing teams' percentage shares of black and other non-black minority athletes on their corresponding local market areas' percentage shares of black and other minority residents. Specifically, the presented model specifications vary with the considered positions (minority athlete groups) as well as the degree of interaction terms between local market areas' shares of minority residents and year as an integer variable.

Table A14. Market areas' racial composition and teams' racial shares of black athletes

Black athletes:	(1) Starting Pitchers	(2) Starting Pitchers	(3) Starting Pitchers	(4) Starting NPitchers	(5) Starting NPitchers	(6) Starting NPitchers	(7) Roster	(8) Roster	(9) Roster
Trend (1985=0)	0.853**	0.348	-0.028	-0.277	-0.989**	-0.985***	-0.530*	-0.689***	-0.692***
	(0.365)	(0.266)	(0.195)	(0.546)	(0.391)	(0.307)	(0.293)	(0.193)	(0.154)
Trend^2	-0.016	0.001	0.001	-0.020	0.007	0.007	-0.001	0.004	0.006*
	(0.011)	(0.005)	(0.004)	(0.016)	(0.007)	(0.006)	(0.007)	(0.004)	(0.003)
Pop-Black (%)	1.043**	0.671**	0.296	1.843***	2.071***	2.164***	0.893***	0.816***	0.805***
	(0.440)	(0.337)	(0.328)	(0.613)	(0.507)	(0.494)	(0.228)	(0.221)	(0.214)
Pop-Black*Trend	-0.030**	-0.010**		-0.000	0.002		-0.007	0.004	
	(0.013)	(0.005)		(0.019)	(0.007)		(0.008)	(0.003)	
Pop-B*Trend^2	0.001			0.000			0.000		
	(0.000)			(0.001)			(0.000)		
AL*Pop-Black	-1.519***	-1.087**	-0.623	0.900	-0.328	-0.589	0.006	0.105	0.035
	(0.546)	(0.446)	(0.433)	(0.876)	(0.741)	(0.692)	(0.373)	(0.335)	(0.313)
AL*Pop-Black*Trend	0.013	0.002		-0.056***	-0.004		0.007	-0.002	
	(0.013)	(0.004)		(0.022)	(0.008)		(0.010)	(0.003)	
AL* Pop-B*Trend^2	-0.000			0.001**			-0.000		
	(0.000)			(0.001)			(0.000)		
Pop-Other (%)	-1.359*	-1.708**	-0.621*	0.803	0.709	0.430	-0.344	-0.127	0.210
	(0.817)	(0.726)	(0.355)	(1.353)	(1.140)	(0.645)	(0.698)	(0.611)	(0.280)
Pop-Other*Trend	-0.009	0.014		-0.037	-0.008		0.023	0.006	
	(0.028)	(0.009)		(0.048)	(0.016)		(0.024)	(0.009)	
Pop-O*Trend^2	0.001			0.001			-0.000		
	(0.001)			(0.001)			(0.001)		
AL*Pop-Other	3.632*	1.515*	0.575**	0.932	-0.775	-0.268	-0.399	0.006	0.153
	(1.997)	(0.881)	(0.254)	(2.426)	(1.198)	(0.416)	(1.435)	(0.726)	(0.187)
AL*Pop- Other *Trend	-0.139	-0.022		-0.025	0.015		0.013	0.007	
	(0.091)	(0.017)		(0.100)	(0.021)		(0.062)	(0.014)	
AL*Pop-O*Trend^2	0.002			0.000			0.000		
	(0.002)			(0.002)			(0.001)		
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.12	0.110	0.093	0.36	0.351	0.351	0.45	0.442	0.454

Notes: Dependent variables is team-specific percentage share of black athletes. Results are based on aggregated US Census County level and MLB game data from 1985 to 2016. Models (1-6) relate to home game starting pitchers and non-pitchers (NPitchers), whereas models (7-9) include all athletes that were playing during a given season. National League is chosen as reference (vs. American League (AL)). Coefficients' estimates are corrected for team-specific autocorrelated error terms using Prais-Winsten regression. Residual variance-covariance matrices are estimated using panel-corrected standard errors (PCSEs) (in parentheses) to account for cross-sectional dependence and team-specific heteroscedasticity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15. Market areas' racial composition and teams' racial shares of other non-black minority athletes

Other (non-black) minority athletes:	(1) Starting Pitchers	(2) Starting Pitchers	(3) Starting Pitchers	(4) Starting NPitchers	(5) Starting NPitchers	(6) Starting NPitchers	(7) Roster	(8) Roster	(9) Roster
Trend (1985=0)	2.297***	1.553***	1.644***	-0.345	0.356	0.565**	0.587**	0.891***	1.113***
	(0.767)	(0.441)	(0.329)	(0.461)	(0.269)	(0.261)	(0.285)	(0.170)	(0.143)
Trend^2	-0.057**	-0.032***	-0.027***	0.031**	0.003	-0.000	-0.004	-0.015***	-0.016***
	(0.025)	(0.009)	(0.007)	(0.014)	(0.005)	(0.005)	(0.008)	(0.004)	(0.003)
Pop-Black (%)	-1.258*	-1.653***	-1.367**	-0.815	-0.727*	-0.897**	-0.222	-0.210	-0.299
	(0.716)	(0.609)	(0.589)	(0.516)	(0.425)	(0.409)	(0.262)	(0.246)	(0.241)
Pop-Black*Trend	-0.029	0.002		0.024	0.004		0.014	0.006**	
	(0.026)	(0.009)		(0.018)	(0.005)		(0.010)	(0.003)	
Pop-B*Trend^2	0.001			-0.001			-0.000		
	(0.001)			(0.001)			(0.000)		
AL*Pop-Black	2.225**	1.815*	1.440*	0.164	1.128	1.436**	-0.388	0.014	0.281
	(1.097)	(0.939)	(0.778)	(0.892)	(0.703)	(0.624)	(0.527)	(0.467)	(0.447)
AL*Pop-Black*Trend	-0.007	0.007		0.022	-0.000		0.007	-0.000	
	(0.026)	(0.009)		(0.020)	(0.006)		(0.013)	(0.004)	
AL* Pop-B*Trend^2	0.000			-0.001			-0.000		
	(0.001)			(0.001)			(0.000)		
Pop-Other (%)	-1.087	0.125	-1.578**	-1.517	0.086	0.523	-1.217*	-0.647	-0.016
	(1.926)	(1.622)	(0.736)	(1.041)	(0.922)	(0.596)	(0.634)	(0.511)	(0.290)
Pop-Other*Trend	0.034	-0.023		0.093**	0.010		0.054**	0.015**	
	(0.061)	(0.024)		(0.037)	(0.013)		(0.025)	(0.008)	
Pop-O*Trend^2	-0.001			-0.002**			-0.001*		
	(0.001)			(0.001)			(0.001)		
AL*Pop-Other	-1.932	-2.960	1.322**	9.831***	1.452	-0.305	6.608***	1.687*	-0.075
	(3.898)	(2.193)	(0.546)	(2.452)	(1.301)	(0.359)	(1.959)	(0.871)	(0.214)
AL*Pop- Other *Trend	0.036	0.086**		-0.436***	-0.039		-0.277***	-0.037**	
	(0.166)	(0.041)		(0.111)	(0.026)		(0.086)	(0.018)	
AL*Pop-O*Trend^2	0.001			0.007***			0.004***		
	(0.003)			(0.002)			(0.002)		
Team FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.19	0.185	0.178	0.32	0.311	0.304	0.50	0.486	0.469

Notes: Dependent variable is a team's percentage of other (non-black) minority athletes. Results are based on aggregated US Census County level and MLB game data from 1985 to 2016. Models (1-6) relate to home game starting pitchers and non-pitchers (NPitchers), whereas models (7-9) include all athletes that were playing during a given season. National League is chosen as reference (vs. American League (AL)). Coefficients' estimates are corrected for team-specific autocorrelated error terms using Prais-Winsten regression. Residual variance-covariance matrices are estimated using panel-corrected standard errors (PCSEs) (in parentheses) to account for cross-sectional dependence and team-specific heteroscedasticity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.0$

Table A16 and A17 show the joint significance tests derived from the regressions in Table A14 and A15.

Table A16. Joint significance tests for League-specific matching effects for black athletes

Test	Black			Other		
	(1)	(2)	(3)	(1)	(2)	(3)
Zero degree	Pitchers	Non-Pitchers	Roster	Pitchers	Non-Pitchers	Roster
NL vs. Zero	0.367	0.001***	0.001***	0.080*	0.505	0.453
AL vs. NL	0.151	0.395	0.912	0.023**	0.519	0.413
AL vs. Zero	0.354	0.001***	0.001***	0.074*	0.786	0.112
	(4)	(5)	(6)	(4)	(5)	(6)
First degree	Pitchers	Non-Pitchers	Roster	Pitchers	Non-Pitchers	Roster
NL vs. Zero	0.005***	0.001***	0.001***	0.054*	0.824	0.569
AL vs. NL	0.050**	0.713	0.818	0.179	0.772	0.321
AL vs. Zero	0.001***	0.001***	0.001***	0.099*	0.910	0.088*
	(7)	(8)	(9)	(7)	(8)	(9)
Second degree	Pitchers	Non-Pitchers	Roster	Pitchers	Non-Pitchers	Roster
NL vs. zero	0.002***	0.005***	0.001***	0.082*	0.778	0.725
AL vs. NL	0.031**	0.066*	0.562	0.284	0.953	0.220
AL vs. zero	0.001***	0.001***	0.001***	0.049**	0.804	0.131

Notes: This Table shows p-values from joint significance Wald tests for linear combinations of League-specific racial composition effects. Models (1-2), (4-5) and (7-8) relate to home game starting lineups, while models (3), (6) and (9) include all athletes that were playing during a given season. Estimates are based on the regression results presented in Table A14. Models (7-9) include second-degree polynomial trend interactions with teams' local market area percentage shares of black and other non-black minority residents. Instead of second-degree interactions, models (1-3) and models (4-6) include zero- and first-degree interaction specifications. Dependent variable is a team's percentage share of black minority athletes. National League (NL) is chosen as reference (vs. American League (AL)). * $p \leq 0.1$, ** $p < 0.05$, *** $p < 0.01$

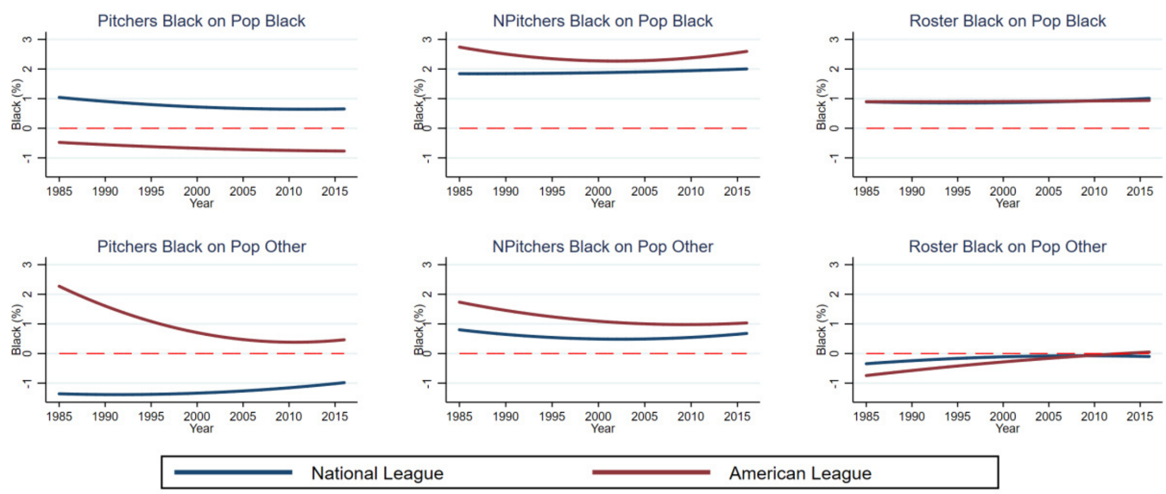
Table A17. Joint significant tests for League-specific matching effects for other athletes

Test	Black			Other		
	(1)	(2)	(3)	(1)	(2)	(3)
Zero degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. Zero	0.020**	0.028**	0.214**	0.032**	0.380	0.957
AL vs. NL	0.064*	0.021**	0.529	0.016**	0.395	0.728
AL vs. Zero	0.041**	0.026**	0.447	0.041**	0.656	0.861
	(4)	(5)	(6)	(4)	(5)	(6)
First degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. Zero	0.023**	0.176	0.070*	0.187	0.456	0.123
AL vs. NL	0.026**	0.230	0.996	0.036**	0.222	0.103
AL vs. Zero	0.013**	0.263	0.101	0.086*	0.398	0.181
	(7)	(8)	(9)	(7)	(8)	(9)
Second degree	Pitcher	Non-Pitchers	Roster	Pitcher	Non-Pitchers	Roster
NL vs. zero	0.012**	0.295	0.086*	0.360	0.082*	0.106
AL vs. NL	0.108	0.167	0.636	0.022**	0.001***	0.008***
AL vs. zero	0.030**	0.074*	0.065*	0.087*	0.002***	0.025**

Notes: P-values from joint significance Wald tests for linear combinations of League-specific racial composition effects. Models (1-2), (4-5) and (7-8) relate to home game starting lineups, while models (3), (6) and (9) include all athletes that were playing during a given season. Estimates are based on the regression results presented in Table A15. Models (7-9) include second-degree polynomial trend interactions with teams' local market area percentage shares of black and other non-black minority residents. Models (1-3) and models (4-6) include zero- and first-degree interaction specifications. Dependent variable is a team's percentage share of other non-black minority (Hispanic and Asian) athletes. National League (NL) is chosen as reference (vs. American League (AL)). * $p \leq 0.1$, ** $p < 0.05$, *** $p < 0.01$

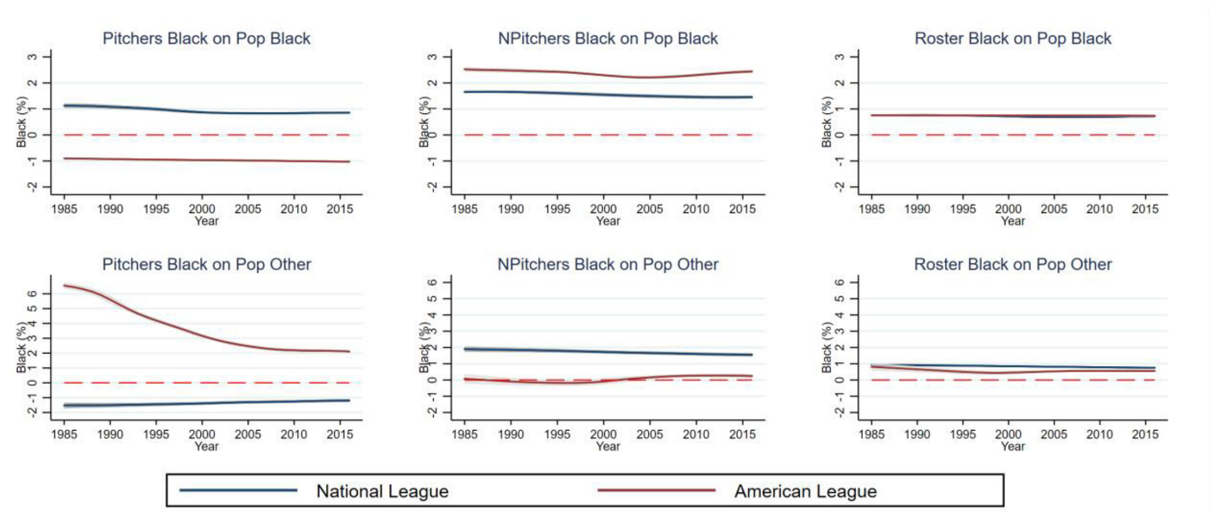
Furthermore Figure A13 and A15 show the ME estimates that are derived from our baseline model specification. In comparison, while the CE estimates included in Figure A14 and A16 are derived from the share of black and other players on the same set of controls as in our baseline specification, instead of second-degree polynomial trend interactions with the percentages of black and other (non-black) minority residents, we include interactions with individual year dummy variables and the shares of black and other non-black minority residents (results omitted for brevity). The presented League-specific CE estimates are based on polynomial regressions using the dummy-racial-share coefficient estimates as outcome.

Figure A13. League-specific marginal racial composition effects on a team racial structure I



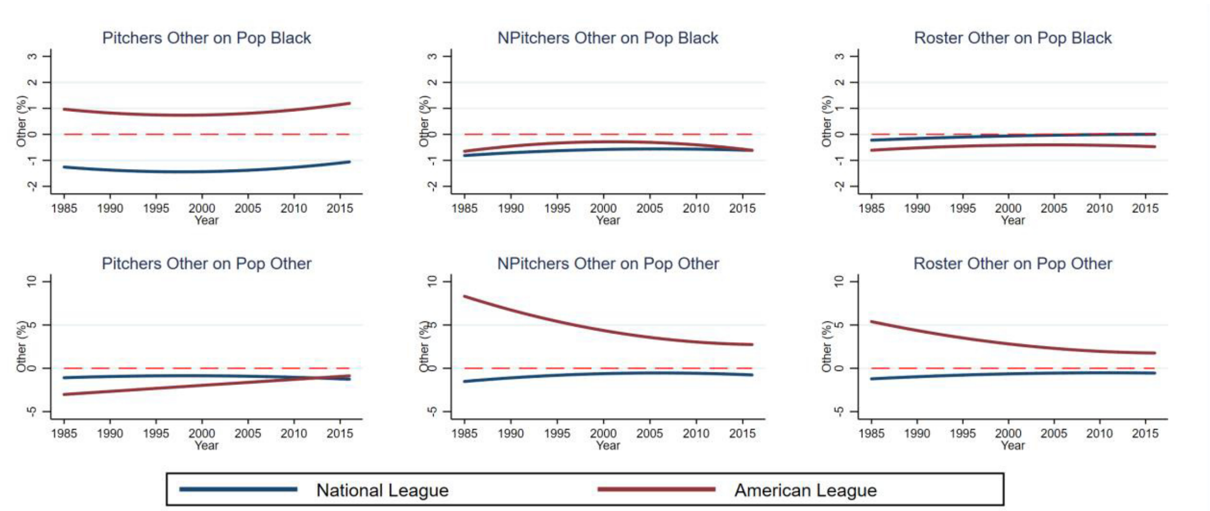
Notes: Dependent variable is a team's percentage share of black athletes; the first two columns relate to home game starting pitchers and non-pitchers (NPitchers), whereas the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details). In addition to League-specific racial composition variables and team fixed effects, the models include a simple trend and quadratic trend variable (Trend=0 in 1985). Marginal effect (*ME*) estimates are based on League-specific second-degree polynomial trend interactions with the percentages of black or other (non-black) local market area residents and are plotted as a function of time. The individual coefficient estimates are presented in Table A14, models (1), (4), and (7).

Figure A14. League-specific combined racial composition effects on team racial structure I



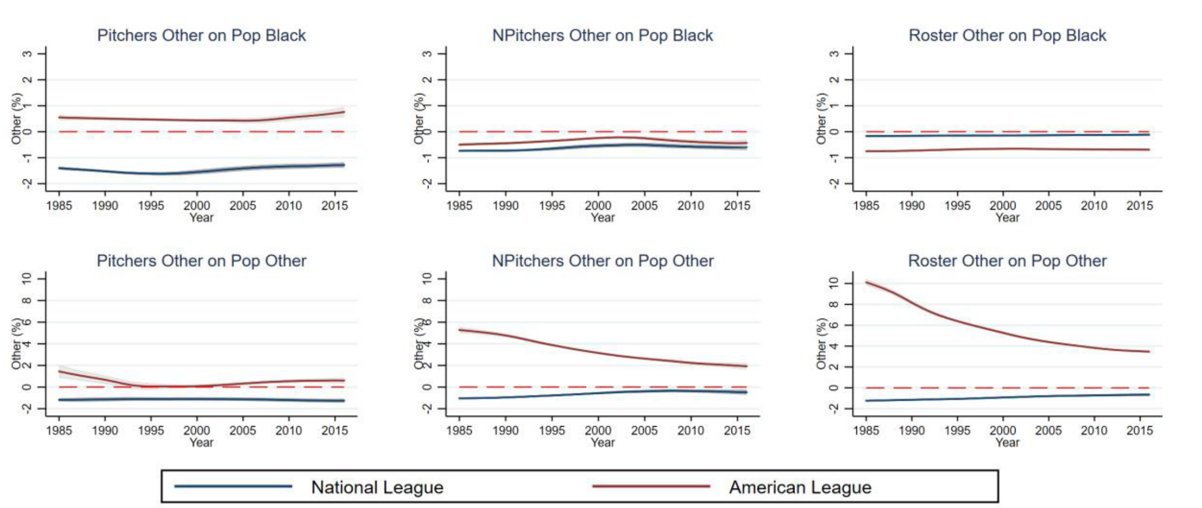
Notes: Combined effect (*CE*) plots are derived from regressing team's percentage share of black athletes on the same set of controls as in our baseline specification. However, instead of second-degree polynomial trend interactions, we include interactions with individual year dummy variables and the markets' black and other non-black minority population shares (results omitted for brevity). League-specific CE estimates are based on polynomial regressions using the dummy-racial-share coefficient estimates as outcome. Grey shaded areas indicate 95% confidence intervals. The first two columns relate to home game starting pitchers and non-pitchers (NPitchers), whereas the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details).

Figure A15. League- specific marginal racial composition effects on team racial structure II



Notes: Dependent variable is a team's percentage share of other non-black minority athletes (Hispanic and Asian players); the first two columns relate to home game starting pitchers and non-pitchers (NPitchers), whereas the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details). In addition to League-specific racial composition variables and team fixed effects, the models include a simple trend and quadratic trend variable (Trend=0 in 1985). Marginal effect (*ME*) estimates are based on League-specific second-degree polynomial trend interactions with the percentages of black or other (non-black) local market area residents and are plotted as a function of time. The individual coefficient estimates are presented in Table A15, models (1), (4), and (7).

Figure A16. League-specific combined racial composition effects on team racial structure II



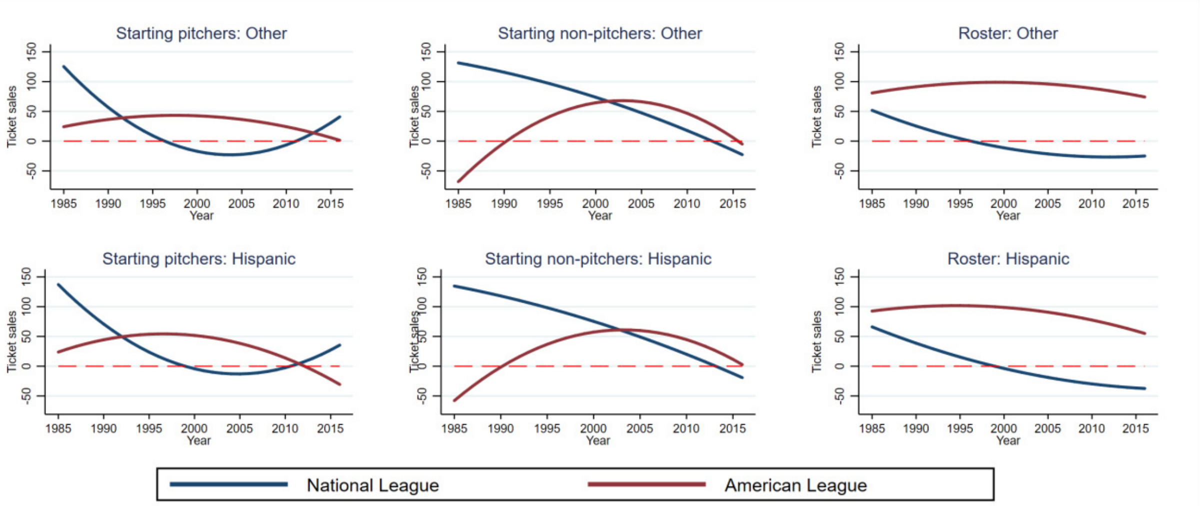
Notes: Combined effect (*CE*) plots are derived from regressing team's percentage share of other non-black minority athletes (Hispanic and Asian players) on the same set of controls as in our baseline specification. However, instead of second-degree polynomial trend interactions, we include interactions with individual year dummy variables and the markets' black and other non-black minority population shares (results omitted for brevity). League-specific CE estimates are based on polynomial regressions using the dummy-racial-share coefficient estimates as outcome. Grey shaded areas indicate 95% confidence intervals. The first two columns relate to home game starting pitchers and non-pitchers (NPitchers), whereas the third column relates to all athletes that were playing during a given season.

6 Discrimination against Hispanic players

In our main analyses, we do not distinguish between the different racial and ethnic groups that are included in the class of other non-black minority players, because the early US County level Census data do not provide information on Hispanic origin. As described in Section 3 in the main text, the group of other non-black minority athletes includes all other non-white and non-black players; however, in addition to a few Asian players, the vast majority of other players are of Hispanic race and ethnicity, respectively. The mean percentage share of Hispanic players with respect to the group of other non-black minority athletes for the roster specification is 94.4%, and the mean share of other [Hispanic] starting pitchers and starting non-pitchers is 95.2% and 89.4%, respectively.

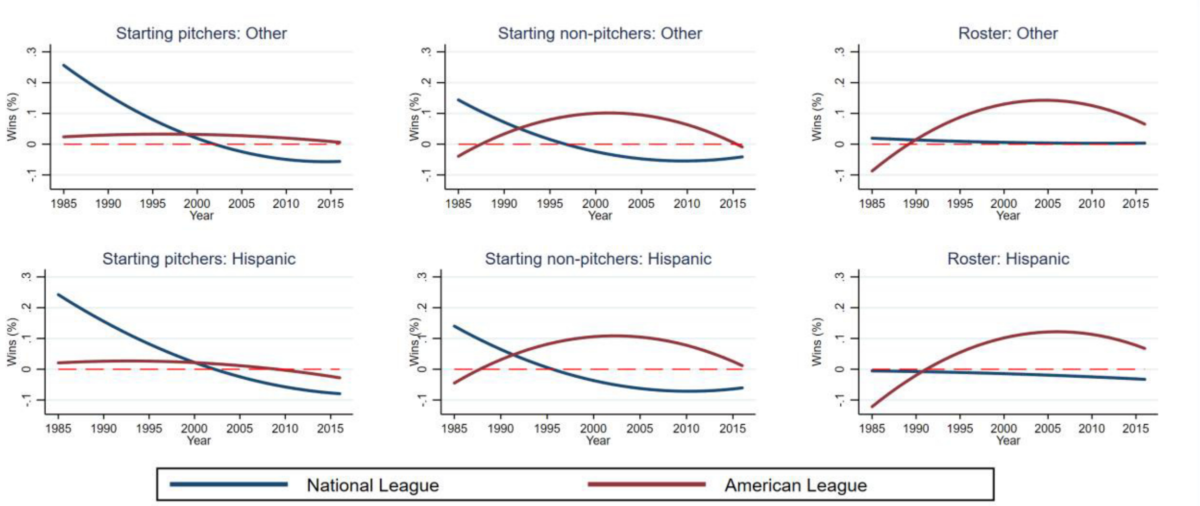
However, to specifically address discrimination against Hispanic players, we investigate the group of Hispanic players by excluding Asian players from the group of other non-black minority athletes (i.e., Hispanic players = Other – Asian players). Specifically, we compare our baseline second-degree polynomial racial trend specification for the attendance (Figure A17) and (Figure A18) winning percentage regressions between both racial-group classifications. The corresponding results show that there exist only marginal differences between the other non-black minority and the Hispanic racial specifications across time.

Figure A17. League-specific marginal racial composition effect estimates on attendance IV



Notes: The upper [lower] panel League-specific marginal effect (*ME*) estimates are based on second-degree polynomial trend interactions with the percentages of black and other non-black minority [Hispanic] athletes and are plotted as a function of time. Hispanic players are computed from excluding Asian players from the group of other non-black minority athletes. The upper panel plots are derived from the three attendance regression models in Table 1 in the main text. The lower panel regression results are omitted for brevity. We consider three different athlete group specifications: the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details). As an example, *ME* estimates for other (non-black) minority athletes in the NL are computed as $\hat{\beta}_{ME}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$ with $Trend = 0$ in 1985.

Figure A18. League-specific marginal racial composition effects on team success over time II



Notes: The upper [lower] panel League-specific marginal effect (*ME*) estimates are based on second-degree polynomial trend interactions with the percentages of black and other (non-black) minority [Hispanic] athletes and are plotted as a function of time. Hispanic players are computed from excluding Asian players from the group of other non-black minority athletes. The upper panel plots are derived from the three winning percentage regression models (1), (4), and (7) in Table 4 in the main text. The lower panel regression results are omitted for brevity. We consider three different athlete group specifications: the first two columns relate to home game starting lineups, while the third column relates to all athletes that were playing during a given season (see Section 3 in the main text for details). As an example, *ME* estimates for other (non-black) minority athletes in the NL are computed as $\hat{\beta}_{ME}^{Other}(Trend) = \hat{\beta}_{Other} + Trend * \hat{\beta}_{OTrend} + Trend^2 * \hat{\beta}_{OTrend^2}$ with $Trend = 0$ in 1985.

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