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Article — Published Version

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Contemporary Economic Policy

Suggested Citation: Creutzburg, Carsten; Maennig, Wolfgang; Mueller, Steffen Q. (2025) : From bias to bliss: Racial preferences and worker productivity in tennis, Contemporary Economic Policy, ISSN 1465-7287, Vol. 44, Iss. 2, pp. 380-393, <https://doi.org/10.1111/coep.70004>

This Version is available at:

<https://hdl.handle.net/10419/342177>

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From bias to bliss: Racial preferences and worker productivity in tennis

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Abstract

We investigate the impact of differences in consumers' racial preferences on worker productivity through the example of the home advantage (HA) effect using data on wins in men's tennis from 2001 to 2020 (pre-COVID-19). We identify players' racial affiliation as one of five distinct groups by combining clustering and facial recognition methods. Our empirical design allows us to distinguish among HA factors related to the presence of fans, referee bias, travel fatigue, and home-court familiarity. We provide evidence of social environments where Black players benefit more strongly from fan support than players of other races do, resulting in increased productivity.

KEYWORDS

consumer discrimination, home advantage, labor market discrimination, productivity, racial bias

JEL CLASSIFICATION

J15, J71, L83, Z22

1 | INTRODUCTION

It is frequently reported that consumers prefer to interact with same-race service workers (Combes et al., 2016; Laouénan, 2017; Leonard et al., 2010). Similarly, it is often believed that sport fans prefer players to be of a similar race as their own (Kahn, 1991; Parsons et al., 2011), and previous studies substantiate the belief that fan-driven discrimination can impact TV ratings (Kanazawa & Funk, 2001), ticket sales (Maennig & Mueller, 2022), collectible purchases (Nardinelli & Simon, 1990), and the construction of sports venues (Bodvarsson & Humphreys, 2013). Moreover, in the context of sports, it is widely acknowledged that fan support is a major driving force behind the home advantage (HA) (Cross & Uhrig, 2023; Garicano et al., 2005). Depending on players' race, fans may behave differently in these areas; therefore, the HA effect may vary with respect to fans' racial preferences and the prevalence of discrimination in a sports league. Substantiating these considerations, empirical evidence shows that discriminatory fan behavior negatively affects the performance of black players in European Football (Caselli et al., 2023; Glamser, 1990).

Abbreviations: ATP, Association of Tennis Professionals; HA, home advantage; HR, higher-ranked; LR, lower-ranked.

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However, consumers and sport fans do not necessarily prefer same-race workers or athletes. For instance, previous studies find that the introduction of non-White players increased ticket sales in American professional sports following the period of racial integration in the 1950s (Gwartney & Haworth, 1974). Similarly, recent findings indicate that higher shares of Black actors have a positive effect on Hollywood film revenues (Kuppuswamy & Younkin, 2020). However, except for Glamser (1990) and Caselli et al. (2023), who analyze team sports (European football), previous studies do not account for the potential impact of differences in consumers' racial preferences on worker productivity.

This study investigates potential effects of consumer-driven racial discrimination on worker productivity in professional individual sports. We assess the extent to which player performance and the HA effect depend on players' racial background by predicting individual game outcomes using data on men's singles tennis from 2001 to 2020 (pre-COVID-19). In addition to various player- and match-specific variables, we control for other potentially relevant HA factors unrelated to the presence of fans.

To overcome the limited availability of information on the racial identities of players, earlier studies identify players' racial backgrounds by assessing individual pictures and names (Kahn, 1991). Following recent advances in discrimination studies, similar to Kuppuswamy and Younkin (2020) and Maennig and Mueller (2022), we combine web scraping and racial identification algorithms to reduce data collection costs and potential bias in manual race classification. We innovate by using a k-means clustering approach to identify groups of players with similar racial profiles.

As a central result, we provide evidence for social contexts in which minorities that are often negatively discriminated against are given favorable treatment and, in response, experience an increase in productivity. Black players benefit more strongly from fan support at home games than players of other races. Our findings indicate that both a direct effect of fan support on player performance and a fan-induced referee bias contribute to the differences in HA. A potential explanation for our results is provided by organizational aspects peculiar to tennis in combination with theories linked to event spectacle (Debord, 1970), group threat (Bonacich, 1972), and same-nationality and home bias (Hogg & Terry, 2000; Schneider, 1987). Furthermore, we find significant and economically relevant impacts of travel fatigue and surface familiarity on player productivity.

We contribute to the literature on discrimination and its effects on disparities in labor market outcomes (Bertrand & Mullainathan, 2004; Coates & Webber, 2023; Godtland et al., 2007; Groothuis & Hill, 2017; Gunderson, 2003; Korenkiewicz & Maennig, 2023). Our study also connects to the literature concerning home and same-nationality bias. Examples of such bias can be found in financial investment decisions (Hillberry & Hummels, 2003; Karlsson & Norden, 2007; Lau et al., 2010), Olympic judge ratings (Sandberg, 2018), and general consumption patterns (Balabanis & Diamantopoulos, 2004). Finally, we contribute to the literature investigating the effects of fan support on sporting results (Böheim et al., 2019; Caselli et al., 2023) and potentially biased referee decisions (Buraimo et al., 2012; Dawson & Dobson, 2010; Price & Wolfers, 2010).

2 | HA AND RACE-BASED FAN DISCRIMINATION IN SPORTS

HA is a widely acknowledged phenomenon in sports that describes the performance advantage of a player or team competing on home ground over those competing on neutral or away ground (Courneya & Carron, 1992). Early evidence of the presence of the HA effect in tennis is provided by Holder and Nevill (1997). Analyzing the four Grand Slam tournaments in 1993, they find evidence for an HA effect in the Wimbledon tournament but not for any of the other three tournaments. In contrast, using Association of Tennis Professionals (ATP) game data from 2000 to 2009, the results of Koning (2011) suggest the existence of an HA for men but not for women. Substantiating Koning's (2011) previous findings on male tennis players, Ovaska and Sumell (2014) examine male ATP games held between 2000 and 2009 and show that having an HA increases the probability of winning by approximately 4%–7%.

The HA effect can be attributed to factors such as (1) travel history (e.g., travel fatigue and jet lag), (2) familiarity with local conditions (e.g., stadium characteristics and climate), (3) fans (e.g., motivation via fan support), and (4) rule-specific advantages (e.g., first-mover advantage) (Nevill & Holder, 1999). Depending on the specific sport, the four general factors contribute to HA to different extents, but fan support is consistently suggested as a major driving force (Cross & Uhrig, 2023; Garicano et al., 2005).

With respect to the first factor, it is argued that tennis players travel from tournament to tournament; thus, travel fatigue does not vary much between players (Holder & Nevill, 1997; Koning, 2011).

With respect to the second factor (home-court familiarity with the home ground or stadium), the HA effect in tennis is likely affected by differences in the tournament surface and the type of surface to which a player is most accustomed.

As a result, not only can players be expected to have a surface advantage in home games, but they should also experience such an advantage in tournaments held in other countries if the court surface matches the surface used most often in their home country (Koning, 2011; Ovaska & Sumell, 2014).

For the third factor, fans can induce the HA effect via different mechanisms: by motivating their favorite (home) team and players, demotivating the opposing players, and biasing referee decisions (Nevill & Holder, 1999). To illustrate, Boudreaux et al. (2017) isolate a net crowd effect on the winning probability of a home-playing team of 21%–22.8% points. However, the presence of supporting fans does not necessarily increase player performance; fans can also create social pressure. This pressure can result in players failing at skill-based tasks that they can otherwise consistently perform well, a phenomenon that is referred to as choking (Baumeister, 1984; Cohen-Zada et al., 2017; Harb-Wu & Krumer, 2019).

To date, no study has examined the direct impact of fans on the HA in tennis. This impact may be different than that in team sports such as football or basketball. On the one hand, tennis is a sport that operates in a more intimate setting; in most matches, all attention is concentrated on two players. Consequently, the pressure experienced by players can be more intense. Unlike in team sports, where the action is distributed across multiple players, the singular action in tennis draws spectators into a more direct engagement with the players. On the other hand, the effect may be less pronounced because fans are required to meet certain behavioral standards for spectating during active game play. Moreover, in line with a general home and same-nationality (or country-of-origin) bias that has been frequently observed in various socioeconomic and political behaviors (Balabanis & Diamantopoulos, 2004; Sandberg, 2018), there is evidence that (neutral) tennis game spectators are biased toward watching games featuring players from the tournament country (Konjer et al., 2017).

In addition, while some studies indicate that the HA increases with the number of attending fans (Smith & Groetzing, 2010), other studies do not find any significant fan-driven HA effects or negative effects from the size of fan attendance on player productivity, which are presumably due to social pressure (Böheim et al., 2019). However, an analysis of “ghost games” in the course of the COVID-19 pandemic, during which fans were largely prohibited from attending live sporting events, shows that the HA effect can be assumed to largely depend on the physical presence of fans; for example, Cross and Uhrig (2023) find that without the presence of spectators, the HA effect is reduced by more than 50% across several European Football leagues.

It is commonly assumed that fans prefer players who are of a similar race as themselves (Parsons et al., 2011); Kahn (1991) and Nardinelli and Simon (1990) were among the first to identify instances of discrimination by sports fans. Caselli et al. (2023) find that African players performed better when fans were prohibited from attending the stadium during the COVID-19 pandemic. Racial preferences can affect various fan behaviors, such as attendance (Gwartney & Haworth, 1974; Maennig & Mueller, 2022), TV consumption (Kanazawa & Funk, 2001), and collectible purchases (Nardinelli & Simon, 1990). Depken and Ford (2006) analyze all-star votes in baseball in 1990 and 2000 and find that fans preferred Black and Hispanic players. Sur and Sasaki (2020) indicate an absence of racial bias in fan voting for cricket players; instead, their findings suggest a preference for popular foreign players.

Volz (2017) demonstrates that Black quarterbacks in the National Football League are more likely to be benched than their White counterparts are. Glamser (1990) finds that Black players are cautioned significantly more often in away games than in home games. Concerning wage discrimination, Johnson and Minuci (2020) present evidence of racial disparities in the salaries of Black players in the National Basketball Association (NBA). Similarly, Hindman and Paulsen (2024) identify persistent racial wage gaps in the spectator sports industry in the USA. However, Groothuis and Hill (2013) do not find consistent evidence for salary discrimination in the NBA.

Regarding the fourth factor, with the exception of the right of organizers to offer wild cards to local tennis players who otherwise may not qualify for the tournament, no specific rules exist in tennis that give the home contestant a technical advantage.

3 | DATA AND EMPIRICAL STRATEGY

3.1 | Data and racial identification

The original data for our main analysis cover 52,529 ATP men's singles tennis matches played from January 2001 to February 2020, that is, before restrictions due to the COVID-19 pandemic were implemented. The data we use in this study are collected from <https://www.atptour.com> (tournament, match, and player characteristics), and <https://www.>

[ultimatetennisstatistics.com](https://www.ultimatetennisstatistics.com) (tournament information). We discard 1542 matches with two home players and 1905 matches that did not have a regular finish due to retirement, disqualification, or a walkover, as well as 134 matches with missing player ranks. Last, as we include individual player fixed effects (FE) in our regression analysis, we only consider players who competed in at least two games (cf., Correia, 2015), resulting in a final panel data size of 48,574 individual games played by 975 players.

To identify player races, this study combines web scraping, clustering, and automated race classification with manual hand coding to reduce data collection costs and mitigate subjective bias in human race classification (Kuppuswamy & Younkin, 2020; Maennig & Mueller, 2022). First, we scraped all male player pictures that were available on [ATP.com](https://www.atp.com); a small number of pictures were collected from other websites. Second, we use an application programming interface (API) for facial recognition (Kairos) to identify groups of players with similar racial appearance. Kairos assesses the player pictures and gives percentage values for five race-ethnicity groups (*Asian, Black, Hispanic, White, and Other*) that sum to 100%. To classify players into mutually exclusive race-ethnicity groups, we evaluate different combinations of cutoff percentage values for the predictions. For every combination, Kairos assigns a unique set of players only to the *Black, Asian*, and *Other* race-ethnicity group, as they receive sufficiently high percentage values in one of these three groups compared with the other race categories. Players with African American appearance are grouped into the *Black* race-ethnicity category, players with Southeast and East Asian appearances are classified under the *Asian* race-ethnicity group, and those with Indian appearance are assigned to the *Other* race ethnicity group.

In contrast, the Kairos classification of the remaining players, such as those with a Caucasian appearance, is ambiguous, as the percentage values returned by the API are often similar across multiple categories, preventing mutually exclusive assignment.

In the third step, we approach this problem by determining the remaining race categories via a k-means clustering approach that is based on the API race-ethnicity predictions of the players who have not been classified as *Black, Asian*, or *Indian*. Using the Bayesian information criterion (BIC) as the metric to determine the optimal number of clusters, we evaluate two to five additional clusters and set the number of random centroids for initializing the k-means algorithm to 50. The BIC value for using two additional clusters is 68.25; the three next lowest BIC values result from computing three (75.26), four (92.69), and five (112.38) additional clusters. The results suggest that we should classify the remaining players in two additional race categories—the BIC value for using two clusters is the lowest. By evaluating different threshold percentages, Kairos places players with a Northern White racial appearance (mostly players of Northern European countries) first and players with a Southern White appearance (mostly players of Southern European and South and Central American countries) in a second group; we label the two race-ethnicity groups *Northern White* and *Southern White*.

Fourth, not all player photos were taken under uniform lighting conditions and from the same angle. This discrepancy may introduce challenges in the automated processing of these images. Two researchers inspected each picture to correct for misclassifications, using information on player names, birth places, Wikipedia entries, and additional pictures; a few ambiguous cases were discussed with a third researcher until an agreement on a classification was reached. The final mapping includes players from five mutually exclusive race categories: *Northern White* (519, 53.23% of all players), *Southern White* (351, 36%), *Asian* (63, 6.46%), *Black* (26, 2.67%), and *Indian* (16, 1.64%).

Manual labeling of race, and thus training data for facial recognition algorithms, can introduce biases (Birhane et al., 2023; Maennig & Mueller, 2022; Zou & Schiebinger, 2018). However, racial discrimination is typically not based on an individual's "official" race or genomic characteristics but rather on how one's race is perceived by others in real-world interactions. To mitigate potential bias in the training data, the facial recognition models used in this study were trained on a large, diverse database of facial images from across the globe, with no restrictions on athletes. A standard feature of such diverse facial image databases is that manual race classification is performed by people from different cultural and racial backgrounds. As described by Kairos, they curated a database representing a wide range of ethnicities, age groups, and genders, and they explicitly monitored and tracked the composition of their training, tuning, validation, and testing datasets to minimize sampling bias. In addition, Kairos uses a hybrid approach that combines real and synthetic facial data to expand diversity in their training set (Kairos, 2018). These diverse training inputs support broader inclusivity and reduced bias in automatic race classification than models trained on narrower datasets do. However, as mentioned above, we supplemented the algorithmic classifications with manual hand coding, enabling us to review and, when necessary, correct ambiguous cases. While no method of racial classification can fully exclude social and systemic biases, our twofold approach allows us to leverage both the consistency of machine classification and the contextual advantages of human evaluation.

TABLE 1 Player distribution by race and country.

Northern White			Southern White			Asian			Black			Indian		
Country	N	%	Country	N	%	Country	N	%	Country	N	%	Country	N	%
USA	60	11.56	ESP	65	18.52	CHN	20	31.75	USA	9	34.62	IND	14	87.5
GER	55	10.60	ARG	49	13.96	JPN	18	28.57	FRAU	5	19.23	PAK	1	6.25
FRA	47	9.06	ITA	49	13.96	USA	8	12.70	QAT	3	11.54	USA	1	6.25
AUS	41	7.90	FRA	25	7.12	KOR	7	11.11	SWE	2	7.69			
RUS	28	5.39	BRA	20	5.70	THA	3	4.76	AUS	1	3.85			
CZE	27	5.2	USA	15	4.27	PHI	2	3.17	BAR	1	3.85			
GBR	25	4.82	CHI	12	3.42	AUS	1	1.59	BRA	1	3.85			
AUT	20	3.85	COL	9	2.56	FRA	1	1.59	CAN	1	3.85			
CRO	18	3.47	MEX	9	2.56	NED	1	1.59	GBR	1	3.85			
NED	18	3.47	POR	9	2.56	PER	1	1.59	GER	1	3.85			
Total	519			351			63			26			16	

Note: This table shows the countries (max. 10) with the highest share of Northern White, Southern White, Asian, Black, and Indian players. The dataset covers 975 players who competed in ATP men's singles tournaments between 2001 and 2020 (pre-COVID-19).

Abbreviation: ATP, Association of Tennis Professionals.

Table 1 shows the distribution of players by race and country. In total, our data cover games from 975 players from 75 countries. In general, the racial distribution of players from popular tennis countries coincides with their population's racial mix; most Northern White players come from countries where the population is predominantly Northern White (e.g., USA, 60 players, 12% of all Northern White players; Germany, 55, 11%; France, 47, 9%; Australia, 41, 8%) and most Southern White players come from countries where the population is predominantly Southern White (e.g., Spain, 65, 19%; Argentina, 49, 14%; Italy, 49, 14%). Similarly, 88% of all players with an Indian racial appearance are from India, and most players with an Asian appearance are from East Asian countries (China, 20, 32%; Japan, 18, 29%; South Korea, 7, 11%). The country with the most diverse racial composition is the USA, with players of all five race groups, followed by Canada, France, and Germany, with players of three race groups. The remaining countries feature players from either two different races or exclusively same-race players. The average number of included games per player is 387; considering players within the same race category, the average number of games is 383 for Northern White, 407 for Southern White, 233 for Asian, 381 for Black, and 78 for Indian players.

3.2 | Model specification and variable descriptions

For our main analysis, consider the following empirical model:

$$\text{HR won}_{hlm} = \sum_k^K \gamma_k \text{HA}_{hm} \times \text{Race}_{hk} + \sum_k^K \theta_k \text{HA}_{lm} \times \text{Race}_{lk} + \varphi \mathbf{X}_{hlm} + \delta \mathbf{A}_{hlm} + \text{HR}_{hm} + \text{LR}_{lm} + Y_m + \epsilon_{hlm}. \quad (1)$$

HR won_{hlm} is the binary game outcome (1 = won) of the higher-ranked (HR) player h competing against the lower-ranked (LR) player l in match m ; the actual rank number of the HR player is always smaller (better) than that of the LR player, with the best player having a rank of 1. HA_{hm} [HA_{lm}] is a binary variable that equals one if the HR [LR] player has an HA in match m ; a player is defined as having an HA when playing a match in a tournament hosted by his home country. Race_{hk} [Race_{lk}] is a binary variable that indicates whether the HR [LR] player is of race k (Northern White, Southern White, Asian, Black, or Indian). $\mathbf{X}_{hlm}$ captures HR and LR player- and match-specific characteristics, such as information on player ranks, type of tournament, and match conditions. $\mathbf{A}_{hlm}$ controls for relevant HA factors unrelated to fan-driven effects. HR_{hm} and LR_{lm} are fixed effects to control for time-invariant player-specific effects, Y_m is a year fixed effect to account for player-invariant season-specific effects, and ϵ_{hlm} is an idiosyncratic error term.

We are primarily interested in the estimates of the race-specific HA effects, γ_k and θ_k , which can be attributed to the crowd factor; $\gamma_k > 0$ [$\theta_k < 0$] indicates a positive fan-driven HA effect for HR [LR] players of race k , whereas $\gamma_k < 0$ [$\theta_k > 0$] suggests a negative effect. Specifically, we distinguish between fan-driven effects and the impact of HA factors linked to travel fatigue and home-court familiarity (contained in A_{hlm}). First, we include the number of time zones passed through by the HR and LR players. Second, in addition to a common travel fatigue effect, flying eastwards requires more recovery time than flying westwards (Recht et al., 1995). We consider the additional impact of jet lag by specifying an interaction term between the number of time zones passed through and a binary variable indicating whether the HR [LR] player traveled east. We assume that the player travels from his home country to reach the first tournament location of a season. We further assume that a player travels back home if there is sufficient time (2 months or more) between two tournaments. For all remaining games, we compute the difference of time zones between consecutive tournaments in which the HR [LR] player competed. Furthermore, if a player's home country covers several time zones, we use the average. Third, this study controls for home-court familiarity by including two binary variables to indicate whether the HR and LR players compete on a surface that matches the surface (carpet, clay, grass, or hard) used predominantly in their home countries. To construct the country-to-surface mapping, we extend our dataset by including ATP entry-level tournaments (see Supporting Information S2: Section 3, Table A5).

With respect to the error term structure in the regression analysis of tennis game outcomes, it is important to acknowledge that match results are primarily determined by the two players competing against each other—disturbance terms are likely correlated within matches of both the HR and the LR player. As a consequence, we allow for arbitrary error term correlations between observations of the same players by computing heteroscedasticity-robust two-way clustered standard errors at the individual HR and LR player levels (Cameron et al., 2011).

Descriptive statistics for the variables considered in our main analysis are displayed in Table 2. The data include 48,573 ATP men's singles games in 43 countries with 975 players.

The HR player wins in 65.5% of the matches against his LR opponent while maintaining an average world ranking position of 24. To account for potential nonlinear effects in ability levels between the HR and LR players, in addition to the natural logarithm of the HR player's world rank, we include the natural logarithm of the rank difference between the LR and HR player and its square. The mean number of time zones traversed prior to the tournament by the HR player is 3.2, whereas the mean number of time zones traversed prior to the tournament by the LR opponent is 2.8. On average, an HR player competes in his home country in 9% of matches in the dataset, while playing matches on his country's most common surface in 47% of cases. In contrast, an LR player has an HA in 14% of matches in the dataset and competes on his home country's most common surface in every second match, on average. A comparison of different racial groups reveals that Northern White HR and LR players demonstrate the highest propensity for competition on home turf, with 5.7% and 8.6% of matches taking place on their respective home turf surfaces, respectively.

The data include games from 1259 tournaments in descending order of importance: Grand Slams (14%), ATP World Tour Finals (0.6%), ATP World Tour Masters (21%), and ATP World Tour 500 and 250 (59%). On average, tournaments offer a total prize money of 2.8 million U.S. dollars (deflated using 2001 as the base year). The largest share of tournaments is played in countries with predominantly Northern White and Southern White populations: the US (24% of all games), France (10%), Great Britain (8%), Australia (7%), Germany (5%), Spain (4%), Italy (3%), Austria (3%), the Netherlands (3%), and Switzerland (2.5%). Intuitively, the countries hosting the major share of tournaments largely intersect with the countries featuring the highest share of professional tennis players (cf., Table 1). Furthermore, the largest share of games are played on hard courts (54.3%) and outdoors (82.7%). In 37,127 (76.43%) of the matches, neither of the two players has an HA. Among the 11,447 (23.57%) remaining matches, one player has an HA. The relative share of HA games by race is distributed as follows: Northern White: 61.41%; Southern White: 31.27%; Asian: 3.41%; Black: 3.73%; and Indian: 1.18%. A comprehensive overview and summary statistics by HR player, LR player, and country are included in Supporting Information S2: Section 2.

4 | RESULTS

4.1 | Baseline estimates

In Table 3, we present the fixed effects regression results based on the empirical model described in Equation (1), with and without including race-specific HA effects.

TABLE 2 Summary statistics.

	Description	Mean	SD	Min	Max
Dependent variable					
HR won	HR player won the match	0.655		0	1
Independent variables					
HR rank (ln)	Log of HR player's rank	3.166	1.133	0	6.494
Diff in LR and HR rank (ln)	Log of HR player rank minus LR player rank	1.172	0.952	0.005	7.223
Diff in LR and HR rank (ln) ²	Log of HR player rank minus LR player rank squared	2.278	3.589	0	52.165
Prize money (in Mil. Dollar)	Total tournament prize money	2.840	3.811	0.251	19.822
Tourney: Grand Slam	Tournament is Grand Slam	0.140		0	1
Tourney: World Tour finals	Tournament is world Tour final	0.006		0	1
Tourney: ATP Masters	Tournament is ATP Master	0.212		0	1
Tourney: ATP 250/500	Tournament is ATP 250/500	0.592		0	1
Round: Final	Match is final	0.024		0	1
Round: Semifinal	Match is semifinal	0.048		0	1
Round: Quarterfinal	Match is quarterfinal	0.095		0	1
Condition: Indoor	Tournament is indoor	0.827		0	1
Surface: Hard	Tournament surface is hard	0.543		0	1
Surface: Clay	Tournament surface is clay	0.320		0	1
Surface: Grass	Tournament surface is grass	0.113		0	1
Surface: Carpet	Tournament surface is carpet	0.025		0	1
HR time zones	No. of time zones crossed by HR player before tournament	3.196	4.154	0	19.500
LR time zones	No. of time zones crossed by LR player before tournament	2.848	3.842	0	19.500
HR time zones $\times$ HR east	No. of time zones crossed by HR player to the east	1.521	3.149	0	19.500
LR time zones $\times$ LR east	No. of time zones crossed by LR player to the east	1.410	2.989	0	19.500
HR surface match	Tournament surface matches HR's home surface	0.466		0	1
LR surface match	Tournament surface matches LR's home surface	0.500		0	1
HR home advantage	HR player has a home advantage	0.093		0	1
LR home advantage	LR player has a home advantage	0.143		0	1
HR HA $\times$ HR Northern White	HR is Northern White and has a home advantage	0.057		0	1
HR HA $\times$ HR Southern White	HR is Southern White and has a home advantage	0.032		0	1
HR HA $\times$ HR Asian	HR is Asian and has a home advantage	0.002		0	1
HR HA $\times$ HR Black	HR is Black and has a home advantage	0.002		0	1
HR HA $\times$ HR Indian	HR is Indian and has a home advantage	0.000		0	1
LR HA $\times$ LR Northern White	LR is Northern White and has a home advantage	0.086		0	1
LR HA $\times$ LR Southern White	LR is Southern White and has a home advantage	0.042		0	1
LR HA $\times$ LR Asian	LR is Asian and has a home advantage	0.007		0	1
LR HA $\times$ LR Black	LR is Black and has a home advantage	0.006		0	1
LR HA $\times$ LR Indian	LR is Indian and has a home advantage	0.002		0	1

Note: Data include 48,574 games involving 975 players from ATP men's singles tournaments between 2001 and 2020 (pre-COVID-19). Each game features two players, a HR and a LR player. Prize money is deflated using 2001 as base year.

Abbreviations: ATP, Association of Tennis Professionals; HA, home advantage; HR, higher-ranked; LR, lower-ranked.

TABLE 3 Race-specific home advantage effects on HR players' game outcome.

	(1)	(2)
HR rank (ln)	0.021** (0.008)	0.021** (0.008)
Diff in LR and HR rank (ln)	0.106*** (0.009)	0.106*** (0.009)
Diff in LR and HR rank (ln) ²	−0.012*** (0.001)	−0.012*** (0.001)
Prize money	0.005*** (0.001)	0.005*** (0.001)
Tourney: Grand Slam	−0.005 (0.010)	−0.005 (0.010)
Tourney: ATP Masters	−0.010 (0.007)	−0.010 (0.007)
Tourney: World Tour finals	0.040 (0.030)	0.040 (0.030)
Round: Final	0.012 (0.015)	0.012 (0.015)
Round: Semifinal	−0.014 (0.009)	−0.015 (0.009)
Round: Quarterfinal	0.011 (0.008)	0.011 (0.008)
Condition: Indoor	0.000 (0.008)	−0.000 (0.008)
Surface: Clay	−0.009 (0.010)	−0.008 (0.010)
Surface: Grass	−0.013 (0.012)	−0.012 (0.012)
Surface: Carpet	−0.010 (0.018)	−0.009 (0.018)
HR time zones	−0.002** (0.001)	−0.002** (0.001)
LR time zones	0.003*** (0.001)	0.003*** (0.001)
HR time zones × HR east	0.000 (0.001)	0.000 (0.001)
LR time zones × LR east	0.001 (0.001)	0.001 (0.001)
HR surface match	0.056*** (0.007)	0.056*** (0.007)
LR surface match	−0.039*** (0.007)	−0.039*** (0.007)
HR home advantage	0.047*** (0.008)	
LR home advantage	−0.032*** (0.008)	
HR HA × HR Northern White		0.046*** (0.012)
HR HA × HR Southern White		0.045*** (0.012)
HR HA × HR Asian		0.061 (0.045)
HR HA × HR Black		0.067*** (0.023)
HR HA × HR Indian		0.094 (0.120)
LR HA × LR Northern White		−0.025** (0.010)
LR HA × LR Southern White		−0.046*** (0.013)
LR HA × LR Asian		0.011 (0.036)
LR HA × LR Black		−0.071*** (0.023)
LR HA × LR Indian		−0.014 (0.068)
HR FE & LR FE	Yes	Yes
Year FE	Yes	Yes
R ²	0.701	.701

Note: Dependent variable is the HR player's game outcome ($y = 1$ if HR won). Data include 48,574 games covering 975 players from ATP men's tournaments between 2001 and 2020 (pre-COVID-19). Each game features two players, a HR and a LR player. HA is a binary value that equals one if the corresponding player competes in a match within a tournament hosted by his home country. Data include matches with either one or no player having an HA. Prize money is deflated using 2001 as base year. Robust standard errors (in parentheses) clustered on HR and LR player fixed effects.

Abbreviations: ATP, Association of Tennis Professionals; HA, home advantage; HR, higher-ranked; LR, lower-ranked.

* $p < .1$, ** $p < .05$, *** $p < .01$.

The results presented in Table 3 confirm previous findings regarding the impact of differences in player ranks on the HR player's winning probability; a better (lower) rank of the HR player improves his winning probability, whereas a better LR player rank decreases it. Similarly, we find a significant positive effect of tournament prize money. Considering HA factors unrelated to fans, the number of time zones passed through by the HR [LR] player significantly decreases [increases] the HR player's winning chances, indicating that travel fatigue decreases productivity, confirming, for example, Cardazzi et al. (2024). However, while we do not find evidence for a significant additional jet lag effect associated with flying eastward, we find significant and large surface familiarity effects. With a 5.6% point increase in the probability of winning, the HR-specific effect for surface familiarity is estimated to be approximately 44% greater than the corresponding LR effect. This difference in surface familiarity effects is in line with HR players, on average, having more playing experience than LR players do. The other player- and match-specific control variables are not significantly different from zero.

Considering our main variables of interest, Model (1) shows the existence of a positive fan-driven HA effect in tennis; an HA for the HR [LR] player increases [decreases] the HR player's winning probability by 4.7 [3.2] percentage points. The HA effect of the HR player is approximately 47% greater than the LR player's effect. As a reasonable explanation for this difference, HR players, on average, have been professional tennis players for a longer time and are more successful than LR players; thus, they can be assumed to be more popular and have more fans. As a result, HR players should benefit more strongly from competing within tournaments hosted by their home country because they are likely to draw more fans to support them than LR players.

Model (2) reveals substantial differences in the variation in HA effects across player races. First, the HR- and LR-specific HA effects are significantly positive for Northern White, Southern White, and Black players; the corresponding effects for Asian and Indian players are not significant. Thus, we do not find any evidence of negative fan discrimination against Black or other minority players. Second, the estimated HA effect for Black players is approximately 46% greater than the corresponding effects for Northern White and Southern White players, suggesting that Black players experience a greater increase in fan-driven productivity than players of other races do. Furthermore, the LR-specific HA effect for Northern White players is approximately half the size of the Southern White-specific effect.

The increased HA effect for Black players is likely rooted in different causes. First, the consistently low number of Black athletes in professional tennis offers only limited opportunities to see Black players compete, which, according to spectacle theory, should make these games more attractive to fans (Debord, 1970). Second, the vast majority of tournaments are hosted by countries with primarily Northern White populations, and on average, Black players are LR and less successful than Northern White players are. In line with group threat theory (Bonacich, 1972), Northern White fans should be less inclined to discriminate against Black players because they do not pose a threat to the dominance of Northern White players in the ATP rankings. Third, unlike matches in team sports, tennis fans usually purchase day tickets for specific tournaments, providing access to all games during the day. While we do not have any information on the number of fans supportive of the home player in any particular game, it can be expected that each game features a relatively large number of neutral fans from the country hosting the tournament. In line with theories of similarity attraction (Schneider, 1987), social identification, and social categorization (Hogg & Terry, 2000), tennis game spectators from the tournament country are likely biased toward supporting their home players (Konjer et al., 2017). "Virtue signaling" is another potentially contributing factor, as fans may also show stronger support for minority players in an attempt to demonstrate their pro-diversity character. Hence, congruent with spectacle and group threat theory, virtue signaling (Flory et al., 2023), and a predisposition of neutral fans toward home players, Black tennis players may benefit more strongly from fans' support in home games than players of other races. In addition, our results do not support the idea that Black players face greater discrimination in away games than other race-ethnicity groups do (see Supporting Information S2: Section 5, Table A7).

The race-specific HA effects for Asian and Indian players do not indicate a significant fan-driven HA effect. As Asians and Indians also pose minorities, home games of these players should also increase the HA effect according to spectacle theory and group threat theory. However, all Indian players except one are from either India or Pakistan, and likewise, the vast majority of Asian players are from East Asian countries. Hence, we only have a very limited number of home games played by players of Asian and Indian racial appearance linked to countries with predominantly Northern White populations (for details, see Supporting Information S2: Section 2).

Complementing our analysis, we inspect the mechanisms behind fan-driven HA effects in more detail. In tennis, referee line calls directly translate to points; thus, biased referee decisions can theoretically have a large impact on game outcomes. Clay courts have the peculiar characteristic of retaining an imprint of a ball that bounces off, allowing the referee to check the imprint for verifying whether a ball was in or out. Clay courts should therefore substantially

decrease the HA effect because they leave no room for biased line calls. We test this hypothesis and provide evidence of referee bias contributing to the HA effect in tennis. The corresponding results are reported in Supporting Information S2: Section 4.

4.2 | Robustness checks

We perform several robustness checks; for brevity, all corresponding results are relegated to Supporting Information S2: Section 5.

First, while minorities of the same race only face each other in a very limited number of games, fans may behave differently when same-race players are competing against each other. However, Black, Southern White, and Northern White HR players all show a positive and significant HA effect when same-race matches are excluded (see Table A8), with Black HR players showing the largest HA effect; the HA effect for Black LR players decreases by 0.4% points compared with Table 3.

Second, superstar players may have the capacity to increase attendance (Hausman & Leonard, 1997; Humphreys & Johnson, 2020) and increase media coverage (Gooding & Stephenson, 2017). Recent findings also indicate that consumers are willing to pay more for game tickets when superstar athletes are involved (Kaplan, 2022), suggesting that superstars influence consumer behavior. In particular, spectators may behave differently toward superstars and their match opponents, possibly due to the perceived prestige of witnessing such high-level talent or the anticipation of watching extraordinary performances. While the three tennis superstars Rafael Nadal, Novak Djokovic, and Roger Federer compete in a relatively large number of games (3266), excluding matches from these three extraordinary players does not change our results (see Table A9). Furthermore, evidence is provided that competing against an HR superstar player does not affect the HA effect on the LR competitor's winning probability (see Table A10).

Third, top-performing players are likely to participate in a greater number of matches than lower-level players are, which could lead to an oversampling of skilled players relative to others. Hence, we exclude final rounds from our analysis; the results remain unchanged (see Table A11).

Fourth, we include tournament fixed effects to control for time-invariant tournament characteristics beyond the tournament variables included in Equation (1); the results remain the same (see Table A12). In addition, we estimate the baseline model specification but include additional interactions to control for heterogeneity in how players are treated by fans across countries. An inclusion of binary variables for all hosting countries would lead to over-parameterization. We thus augmented our standard interaction between HA and race with a binary variable indicating whether the tournament is hosted in the United States, which hosts the largest share of games. Our results suggest that fans may treat players differently based on country. While the HA effect is positive for LR black players, it is smaller when the tournament is played in the U.S. (see Table A13).

Fifth, some players may have the financial resources to travel home easily; conversely, other players may lack the financial resources to remain away from home for 2 months. Moreover, some athletes may be reluctant to remain in a foreign country for the purpose of training or awaiting the next tournament. Therefore, we relax our assumption that players travel back home if there is sufficient time (2 months or more) between two tournaments. In contrast, we assume that players return home when there are at least 2 weeks between tournaments (see Table A14) and, in addition, control for the number of days between the last match of a player in a previous tournament and the first match in the next tournament (see Table A15). In both cases, the estimates of the regression coefficients and the standard errors are subject to only minimal changes compared with our baseline results in Table 3.

Sixth, European players from Spain, Italy, Portugal, and Greece may be perceived differently from their counterparts from Central and South America. To address this issue, we divide the Southern White group and categorize players from Central and South America into a distinct sixth racial cluster. Our results suggest that for both HR and LR players, the magnitude of the HA effects is similar, and the coefficients are not significantly different for European players and players from the Americas (see Table A16).

Seventh, in instances of relatively unknown players, the fans may exhibit a relatively neutral stance toward them, and the advantage may vanish. Hence, we discard all matches involving a player ranked outside of the top 100; the results remain broadly unchanged (see Table A17). Furthermore, we limit our dataset by including only players who competed in at least five and 10 matches. The results remain unchanged and are available upon request.

5 | CONCLUSION

This paper investigates the potential effects of consumer-driven racial discrimination on worker productivity. Using men's professional tennis data, we assess the extent to which player performance and the HA effect depend on players' racial profiles. In contrast to well-studied team sports, which are frequently characterized by emotionally invested and sometimes offensive fans, singles matches in tennis operate in a more intimate setting, and fans are required to meet certain behavioral standards for spectating during active game play. In contrast to the majority of studies on team sports, which indicate the presence of negative discrimination against minority players from fans, we find that Black players benefit more strongly from fan support than players of other races do.

Our central contribution is to provide evidence for social environments in which minorities are subject to preferential treatment, resulting in increased productivity. The increased HA effect is independent of effects from travel fatigue and home-court familiarity and can be attributed to both a direct fan impact on player performance and a referee bias in favor of the home player. Spectacle and group threat theories pose reasonable explanations for the observed differences in race-specific HA effects: Tennis is typically perceived as a "White" sport. At first glance, this perception may indicate that Black players in the sport are subject to a higher level of discrimination. In addition, it could create a perceived entry barrier, discouraging participation. However, the limited frequency of home games featuring Black players could make these games more attractive to fans. In addition, neutral fans can be assumed to be biased toward home players, and fans might support Black players more strongly for reasons linked to virtue signaling. The interplay between these factors results in an environment where minorities that otherwise often experience discrimination are treated favorably.

Owing to the specific context in our study, the results may be more relevant to areas of other individual sports, where athletes compete one-on-one, face similar psychological demands, and are subject to (potentially biased) referee calls. We also note that the concepts of race and ethnicity are to a certain extent ambiguous and difficult to quantify and that how individuals perceive a person's racial appearance depends on various factors, including name, mother or native language, and nationality. Given these limitations, our results may serve as a foundation for understanding the potential ramification of positive racial discrimination on work performance. With respect to future research, a natural extension of this study is to analyze the relationships among consumer-driven racial attitudes, workplace dynamics, and productivity outcomes in other industries. Understanding the mechanisms of preferential treatment and productivity enhancements can help develop strategies to foster inclusive environments and optimize productivity across diverse domains.

ACKNOWLEDGMENTS

We thank colleagues, seminar, and conference participants in Hamburg (University), Helsinki (ESEA), and Zurich (University) for helpful comments and suggestions and, in particular, Carlos Gomez Gonzalez, Helmut Dietl, Jan van Ours, Katrin Scharfenkamp, Luis Aguiar, Marco Henriques Pereira, Martin Natter, Mark Wilson, Nicholas Watanabe, Pascal Meier, and Uschi Backes-Gellner. We also thank three anonymous referees for their constructive and helpful reviews. Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Creutzburg, C., Maennig, W. & Mueller, S.Q. (2026) From bias to bliss: racial preferences and worker productivity in tennis. *Contemporary Economic Policy*, 44(2), 380–393. Available from: <https://doi.org/10.1111/coep.70004>