Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Faculty of Business,
Economics and Social Sciences
Chair for Economic Policy

CARSTEN CREUTZBURG / WOLFGANG MAENNIG / STEFFEN Q. MUELLER

FROM BIAS TO BLISS: RACIAL PREFERENCES AND WORKER PRODUCTIVITY IN TENNIS

Urban
Transport
Media
Sports
Socio-
Regional
Real Estate
Architectural

HAMBURG CONTEMPORARY ECONOMIC DISCUSSIONS

NO. 75

Hamburg Contemporary Economic Discussions
University of Hamburg
Faculty of Business, Economics and Social Sciences
Chair for Economic Policy
Von-Melle-Park 5
20146 Hamburg | Germany
Tel +49 40 42838-4622
https://www.wiso.uni-hamburg.de/en/fachbereich-vwl/professuren/maennig/home.html
Editor: Wolfgang Maennig

Carsten Creutzburg
University of Hamburg
Faculty of Business, Economics and Social Sciences
Chair for Economic Policy
Von-Melle-Park 5
20146 Hamburg | Germany
Tel +49 40 42838-5572
Carsten.Creutzburg@uni-hamburg.de

Wolfgang Maennig
University of Hamburg
Faculty of Business, Economics and Social Sciences
Chair for Economic Policy
Von-Melle-Park 5
20146 Hamburg | Germany
Tel +49 40 42838-4622
Wolfgang.Maennig@uni-hamburg.de

Steffen Q. Mueller
University of Zurich
Department of Business Administration
Chair of Services & Operations Management
Plattenstrasse 14
8032 Zurich | Switzerland
Steffen.Mueller@uzh.ch

Photo Cover: wavebreakmedia/Shutterstock.com
Font: TheSans UHH by LucasFonts

ISSN 1865 - 2441 (Print)
ISSN 1865 - 7133 (Online)

ISBN 978-3-942820-64-6 (Print)
ISBN 978-3-942820-65-3 (Online)

Carsten Creutzburg, Wolfgang Maennig, Steffen Q. Mueller

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

Abstract: This study investigates 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 professional tennis from 2001 to 2020 (pre-COVID-19). We identify players' racial affiliation as one of five distinct race groups by combining clustering algorithms and facial recognition software. Our empirical design innovates by allowing 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.

Keywords*: Labor market discrimination, consumer discrimination, racial bias, productivity, home advantage*
JEL: *J15, J71, L83, Z22*

Version: *March 2024*

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, e.g., TV ratings (Kanazawa & Funk, 2001), ticket sales (Maennig & Mueller, 2022), and collectible purchases (Nardinelli & Simon, 1990). 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). Fans can motivate their favorite teams and players, demotivate opposing players, and influence

* We thank colleagues, seminar, and conference participants in Hamburg (University), Helsinki (ESEA), and Zurich (University) for helpful comments and suggestions and, in particular, Carlos Gómez González, Helmut Dietl, Jan van Ours, Katrin Scharfenkamp, Luis Aguiar, Marco Henriques Pereira, Martin Natter, Mark Wilson, Nicholas Watanabe, Pascal Meier, and Uschi Backes-Gellner.

referee decisions (Nevill & Holder, 1999). 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).

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 US 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 impact 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 performance.

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 & Younkin (2020) and Maennig & 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, 1967), 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 performance.

We contribute to the wide literature concerned with how consumer-driven discrimination relates to disparities in labor market outcomes (Bertrand & Mullainathan, 2004; Bond & Lehmann, 2018; Korenkiewicz & Maennig, 2023; Leonard et al., 2010; Principe & van Ours, 2022). Our study also connects to the literature concerned with 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 extent to which sport results are affected by fan support (Böheim et al., 2019; Caselli et al., 2023; Scoppa, 2021) and potentially biased referee decisions (Garicano et al., 2005; Parsons et al., 2011; Price & Wolfers, 2010).

2 Home advantage 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). The HA effect can be attributed to four factors: fans (e.g., motivation via fan support), familiarity with local conditions (e.g., stadium characteristics and climate), travel history (e.g., travel fatigue and jet lag), and 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). In particular, fans can impact 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). 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 they can otherwise consistently perform well, a phenomenon that is referred to as choking (Baumeister, 1984).

While some studies indicate that the HA increases with the number of attending fans (Smith & Groetzinger, 2010), other studies do not find any significant fan-driven HA effects or negative effects from the size of fan attendance on player performance that 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 instance, Cross & Uhrig (2023) find that without the presence of spectators, the HA effect is reduced by more than 50% across several European Football Leagues.

Early evidence of the presence of the HA effect in tennis is provided by Holder & 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 & 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% to 7%.

Among studies of the four factors contributing to the HA effect in tennis, none have investigated the effects of travel fatigue. Players travel from tournament to tournament, and thus, travel fatigue is argued to not vary much between players (Holder & Nevill, 1997; Koning, 2011). Second, regarding home-court familiarity with the home ground or stadium, the HA effect 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). Third, while no study has examined the direct impact of fans on the HA in tennis, this impact may be less pronounced than that in team sports, such as football or basketball, 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). Fourth, with the exception of the right of organizers to offer wild cards to local players who otherwise may not qualify for the tournament, no specific rules exist in tennis that give the home contestant a technical advantage.

Closely related to the same nationality or country-of-origin bias, it is commonly assumed that fans preferer players who are of similar a race as themselves (Parsons et al., 2011), and previous studies show that differences in racial preferences can affect various fan behaviors, such as attendance (Maennig & Mueller, 2022), TV consumption (Kanazawa & Funk, 2001), collectible purchases (Nardinelli & Simon, 1990), and all-star voting (Depken & Ford, 2006). However, to the best of our knowledge, Glamser (1990) and Caselli et al. (2023) are the only studies that investigate how potential differences in the racial preferences of fans can affect player performance. Examining referee decisions in English football, Glamser (1990) finds that Black players are cautioned significantly more often at away games than at home games. Analyzing Italian football games during the COVID-19 pandemic, Caselli et al. (2023) find that African players perform better when fans are prohibited from attending the stadium. Hence, depending on players' race, it seems reasonable to assume that fans behave differently in the ways they treat home (favorite) and visiting (opposing) team players.

While many studies on consumer discrimination identify instances of sport fans discriminating against minority players (Kahn, 1991; Nardinelli & Simon, 1990), there is also evidence of positive racial fan discrimination. For example, Gwartney & Haworth (1974) find a positive effect of employing Black players on home attendance in baseball in the period following the racial integration. Depken & Ford (2006) analyze all-star votes in baseball in 1990 and 2000 and find that fans preferred Black and Hispanic players, and the analysis of Kanazawa & Funk (2001) shows that basketball games with more White players increased TV ratings during the mid-1990s.

3 Data and empirical strategy

3.1 Data cleaning 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, i.e., before restrictions due to the COVID-19 pandemic were implemented.[1] We discard 1,542 matches with two home players and 1,905 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 player fixed effects in our regression analysis, we only consider players who competed in at least ten games, resulting in a final panel data size of 46,250 individual games played by 584 players.

[1] The data we use in this study are collected from https://www.atptour.com (tournament, match, and player characteristics), and https://www.ultimatetennisstatistics.com (tournament information).

To identify player race, 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; a small number of pictures were collected from other websites. Second, we use a facial recognition API (Kairos) to identify groups of players with similar racial appearance. The face recognition API gives percentage values for four race-ethnicity groups (Asian, Black, Hispanic, White, and Other). Assessing the player pictures and evaluating different combinations of cut-off values for the race-ethnicity-group predictions allows us to clearly identify Black (African-American), Asian (South Asian) and Indian players. However, race and ethnicity are ambiguous concepts, and while the players in our dataset who belong to one of these three race groups are clearly distinguishable, in general, it is unclear how many different race categories should be considered. In the third step, we approach this problem by determining the remaining race categories with a k-means clustering approach based on the API race-ethnicity predictions. Using the Bayesian Information Criterion (BIC) as the metric to determine the optimal number of clusters results in two additional race categories that we define as White and Southern (mostly players of south European and south and central American countries).[2] Last, using information from players' names and birthplaces, two researchers inspected each picture to correct for misclassifications; a few ambiguous cases were discussed with a third researcher until agreement on a classification was reached. The final mapping includes players from five mutually exclusive race categories: *White* (326, 55.82% of all players), *Southern* (210, 35.96%), *Asian* (29, 4.97%), *Black* (11, 1.88%), and *Indian* (8, 1.37%).

[2] We evaluate two to seven clusters and set the number of random centroids for initializing the k-means algorithm to 50. The BIC value for using two clusters is 68.25; the three next lowest BIC values result from computing three (75.26), four (92.69), and five (112.38) clusters.

Table 1 Player distribution by race and country

White			Southern			Asian			Black			Indian		
Country	N	%	Country	N	%	Country	N	%	Country	N	%	Country	N	%
USA	39	11.96	ESP	43	20.48	JPN	10	34.38	USA	4	36.36	IND	6	75.00
GER	38	11.66	ARG	38	18.10	CHN	5	17.24	FRA	2	18.18	PAK	1	12.50
FRA	33	10.12	ITA	27	12.86	USA	5	17.24	SWE	2	18.18	USA	1	12.50
AUS	23	7.06	FRA	16	7.62	KOR	3	10.34	BRA	1	9.09			
RUS	18	5.52	BRA	12	5.71	PHI	2	6.90	CAN	1	9.09			
CZE	16	4.91	USA	10	4.76	THA	2	6.90	GER	1	9.09			
AUT	13	3.99	CHI	7	3.33	NED	1	3.45						
NED	12	3.68	POT	5	2.38	PER	1	3.45						
SWE	11	3.37	AUS	4	1.90									
GBR	10	3.07	GBR	4	1.90									
Total	326			210			29			11			8	

Notes: This table shows the countries (max. 10) with the highest share of White, Southern, Asian, Black, and Indian players. The dataset covers 584 players who competed in ATP men's singles tournaments between 2001 and 2020 (pre-COVID-19).

Table 1 shows the distribution of players by race and country. In total, our data cover games from 584 players from 67 countries. In general, the racial distribution of players from popular tennis countries coincides with their population's racial mix; most White players come from countries where the population is predominantly White (e.g., USA, 39 players, 12% of all White players; Germany, 38, 12%; France, 33, 10%; Australia, 23, 7%) or Southern (e.g., Spain, 43, 20%; Argentina, 38, 18%; Italy, 27, 13%). Similarly, 75% of all players with an Indian racial appearance are from India, and most players with an Asian appearance are from East Asian countries (Japan, 10, 34%; China, 5, 17%; South Korea, 3, 10%). 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 392; considering players within the same race category, the average number of games is 388 for White, 410 for Southern, 245 for Asian, 402 for Black, and 81 for Indian players.

3.2 Model specification and variable descriptions

For our main analysis, consider the following empirical model:

$$HR\ won_{hlm} = \sum_{k}^{K} \gamma_k HA_{hm} \times Race_{hk} + \sum_{k}^{K} \theta_k HA_{lm} \times Race_{lk} + \varphi \boldsymbol{X}_{hlm} + \delta \boldsymbol{A}_{hlm} \tag{1}$$

$$+HR_{hm} + LR_{lm} + Y_m + \epsilon_{hlm}$$

$HR\ won_{hlm}$ 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. 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* (White, Southern, Asian, Black, or Indian). $\boldsymbol{X}_{hlm}$ captures HR and LR player- and match-specific characteristics, such as information on player ranks, type of tournament, and match conditions. $\boldsymbol{A}_{hlm}$ 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; $\gamma_k > 0$ [θ_k<0] indicates a positive fan-driven HA effect for HR [LR] players of race *k,* whereas $\gamma_k < 0$ [θ_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 $\boldsymbol{A}_{hlm}$). 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.[3] 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.[4]

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 HR and LR player levels (Cameron et al., 2011).

Table 2 shows descriptive statistics for our outcome and the explanatory variables considered in our main analysis. A comprehensive overview and summary statistics by HR player, LR player, and country are included in the Appendix, Section 2.

[3] We assume that the player travels from his home country to reach the first tournament location within a season. We further assume that a player travels back home if there is sufficient time (two 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.

[4] We extend the ATP data by including matches from the International Tennis Federation (ITF) Men's World Tennis Tour (entry-level to professional tennis; https://www.itftennis.com/en/) and the ATP Challenger Tour (second-lowest series; https://www.atptour.com/en/atp-challenger-tour) tournaments. The surface-to-country mapping covers all countries represented in at least one of these three divisions (N=122). The detailed mapping is included in the Appendix, Section 3, Table A5.

Table 2 Summary Statistics

	Mean	Sd	Min	Max
HR won	0.653		0	1
HR rank (ln)	3.115	1.121	0.000	6.494
Diff in LR and HR rank (ln)	1.164	0.947	0.006	6.983
Diff in LR and HR rank (ln)^2	2.252	3.553	0.000	48.760
Prize money (in Mil. Dollar)	2.868	3.798	0.251	19.822
Tourney: Grand Slam	0.141		0	1
Tourney: World Tour Finals	0.006		0	1
Tourney: ATP Masters	0.220		0	1
Tourney: ATP 250/500	0.583		0	1
Round: final	0.026		0	1
Round: semifinal	0.050		0	1
Round: quarterfinal	0.099		0	1
Condition: indoor	0.175		0	1
Surface: hard	0.546		0	1
Surface: clay	0.317		0	1
Surface: grass	0.112		0	1
Surface: carpet	0.025		0	1
HR time zones	3.164	4.134	0	19.500
LR time zones	2.855	3.838	0	19.500
HR time zones x HR east	1.506	3.128	0	19.500
LR time zones x LR east	1.419	2.995	0	19.500
HR surface match	0.464		0	1
LR surface match	0.494		0	1
HR home advantage	0.093		0	1
LR home advantage	0.131		0	1
HR HA x HR White	0.057		0	1
HR HA x HR Southern	0.032		0	1
HR HA x HR Asian	0.001		0	1
HR HA x HR Black	0.002		0	1
HR HA x HR Indian	0.000		0	1
LR HA x LR White	0.070		0	1
LR HA x LR Southern	0.054		0	1
LR HA x LR Asian	0.005		0	1
LR HA x LR Black	0.002		0	1
LR HA x LR Indian	0.000		0	1

Notes: Data include 46,250 games involving 584 players from ATP men's singles tournaments between 2001 and 2020 (pre-COVID-19). Each game features two players, a higher- (HR) and a lower-ranked (LR) player. Prize money is deflated using 2001 as base year.

The data include games from 1,271 tournaments in 43 countries; in descending order of importance: Grand Slams (19%), ATP World Tour Finals (0.61%), ATP World Tour Masters (22%), and ATP World Tour 500 and 250 (58%).[5] The largest share of tournaments is

[5] Prior to 2009, the "ATP Tour 250" events were known as the "ATP International Series", the "ATP Tour 500" events as the "ATP International Gold Series", the "ATP Tour Masters" as the "Tennis Masters Series" and "ATP Masters Series", and the "ATP Finals" as the "Tennis Masters Cup" and "ATP World Tour Finals".

played in countries with predominantly White and Southern 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 (3%). 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 (54.59%), and the predominant condition is outdoors (82.59%). In 35,871 (77.56%) of the matches, neither of the two players has a HA. Among the 10,379 (22.44%) remaining matches, one player has a HA. The relative share of HA games by race is distributed as follows: White, 61.19%; Southern, 31.55%; Asian, 2.73%; Black, 3.55%; and Indian, 0.98%.

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 3 Race-specific home advantage effects on higher-ranked players' game outcome

	(1)		(2)	
HR rank (ln)	0.022***	(0.008)	0.022***	(0.008)
Diff in LR and HR rank (ln)	0.105***	(0.010)	0.105***	(0.010)
Diff in LR and HR rank (ln)²	-0.011***	(0.002)	-0.011***	(0.002)
Prize money	0.005***	(0.001)	0.005***	(0.001)
Tourney: Grand Slam	-0.004	(0.011)	-0.004	(0.011)
Tourney: ATP Masters	-0.009	(0.007)	-0.009	(0.007)
Tourney: World Tour Finals	0.039	(0.030)	0.040	(0.030)
Round: final	0.012	(0.015)	0.012	(0.015)
Round: semifinal	-0.015	(0.009)	-0.015	(0.009)
Round: quarterfinal	0.010	(0.008)	0.010	(0.008)
Condition: indoor	-0.001	(0.008)	-0.001	(0.008)
Surface: clay	-0.008	(0.010)	-0.007	(0.010)
Surface: grass	-0.014	(0.012)	-0.013	(0.012)
Surface: carpet	-0.008	(0.018)	-0.007	(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 x HR east	0.001	(0.001)	0.001	(0.001)
LR time zones x LR east	0.002	(0.001)	0.002	(0.001)
HR surface match	0.057***	(0.007)	0.057***	(0.007)
LR surface match	-0.040***	(0.007)	-0.040***	(0.007)
HR home advantage	0.049***	(0.009)		
LR home advantage	-0.034***	(0.008)		
HR HA x HR White			0.048***	(0.012)
HR HA x HR Southern			0.047***	(0.012)
HR HA x HR Asian			0.051	(0.044)
HR HA x HR Black			0.090***	(0.007)
HR HA x HR Indian			0.124	(0.146)
LR HA x LR White			-0.025**	(0.010)
LR HA x LR Southern			-0.050***	(0.013)
LR HA x LR Asian			0.020	(0.039)
LR HA x LR Black			-0.082***	(0.026)
LR HA x LR Indian			-0.043	(0.066)
HR FE & LR FE	Yes		Yes	
Year FE	Yes		Yes	
R^2	0.695		0.695	

Notes: Dependent variable is the higher-ranked (HR) player's game outcome (y=1 for a win). Data include 46,250 games covering 584 players from ATP men's tournaments between 2001 and 2020 (pre-COVID-19). Each game features two players, a higher- and a lower-ranked (LR) player. Home advantage (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. * p < 0.1, ** p < 0.05, *** p < 0.01

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. Likewise, we find a significant positive impact 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 performance. 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 5.7 percentage point increase in the probability of winning, the HR-specific effect for surface familiarity is estimated to be approximately 30% 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. 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 5 [3.5] percentage points. The HA effect of the HR player is approximately 44% 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 White, Southern, 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 twice as large as the corresponding effects for White and Southern players, suggesting that Black players experience a greater increase in fan-driven performance than players of other races. Furthermore, the LR-specific HA effect for White players is approximately half the size of the Southern-specific effect.

To test whether the differences in fan-driven HA effects across race clusters are statistically significant, Table 4 shows regression results using an alternative specification of Equation (1) by including a simple HR and LR HA effect and omitting the race-specific HA interaction terms for one race as a reference group.

Table 4 Differences in race-specific home advantage effects on higher-ranked players' game outcome

	(1) White	(2) Southern	(3) Asian	(4) Black	(5) Indian
HR home advantage	0.048***	0.047***	0.051	0.090***	0.124
	(0.012)	(0.012)	(0.044)	(0.007)	(0.146)
LR home advantage	-0.025**	-0.050***	0.020	-0.082***	-0.043
	(0.010)	(0.013)	(0.039)	(0.026)	(0.066)
HR HA x HR White		0.001	-0.004	-0.043***	-0.076
		(0.017)	(0.046)	(0.012)	(0.147)
HR HA x HR Southern	-0.001		-0.004	-0.043***	-0.077
	(0.017)		(0.045)	(0.013)	(0.146)
HR HA x HR Asian	0.004	0.004		-0.039	-0.073
	(0.046)	(0.045)		(0.051)	(0.150)
HR HA x HR Black	0.043***	0.043***	0.039		-0.034
	(0.012)	(0.013)	(0.051)		(0.146)
HR HA x HR Indian	0.076	0.077	0.073	0.034	
	(0.147)	(0.146)	(0.150)	(0.146)	
LR HA x LR White		0.024	-0.045	0.056**	0.018
		(0.016)	(0.041)	(0.028)	(0.067)
LR HA x LR Southern	-0.024		-0.070	0.032	-0.007
	(0.016)		(0.042)	(0.031)	(0.068)
LR HA x LR Asian	0.045	0.070		0.101**	0.063
	(0.041)	(0.042)		(0.048)	(0.076)
LR HA x LR Black	-0.056**	-0.032	-0.101**		-0.038
	(0.028)	(0.031)	(0.048)		(0.069)
LR HA x LR Indian	-0.018	0.007	-0.063	0.038	
	(0.067)	(0.068)	(0.076)	(0.069)	
Controls	Yes	Yes	Yes	Yes	Yes
HR FE & LR FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.695	0.695	0.695	0.695	0.695

Notes: Dependent variable is the higher-ranked (HR) player's game outcome (y=1 for a win). Data include 46,250 games covering 584 players from ATP men's tournaments between 2001 and 2020 (pre-COVID-19). Each game features two players, a higher- and a lower-ranked (LR) player. Home advantage (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. Robust standard errors (in parentheses) clustered on HR and LR player fixed effects. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 4 reaffirms that Black players benefit more from fan discrimination than White, Southern, or other non-Black minorities. We find a significant difference between the

HA effects of HR Black players and HR White and Southern players, as well as a significant difference between the HA effects of LR Black players and LR White and Asian players. The differences in race-specific HA effects between non-Black race-category combinations are all non-significant. Moreover, we perform several robustness checks to evaluate whether our findings are sensitive to different model specifications and subsamples of the data. 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, excluding same-race matches only marginally affects regression coefficient estimates and standard errors. Second, spectators may behave differently toward superstars as well as their match opponents. While the three tennis superstars Rafael Nadal, Novak Djokovic, and Roger Federer compete in a relatively large fraction of games (3,241), excluding matches from these three extraordinary players does not change our results. Third, we control for tournament country fixed effects; the results remain the same. For brevity, the corresponding results are relegated to the Appendix, Section 4.

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, 1967). Second, the vast majority of tournaments are hosted by countries with primarily White populations, and on average, Black players are lower ranked and less successful than White players. In line with group threat theory (Bonacich, 1972), White fans should be less inclined to discriminate against Black players because they do not pose a threat to the dominance of White players in the ATP rankings. Third, unlike for 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 pro-diversity character. Hence, congruent with spectacle and group threat theory, virtue signaling (Flory et al., 2023), and a predisposition of neutral fans toward the home player, Black tennis players may benefit more strongly from fans' support in home games than players of other races.

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 White populations (for details, see Appendix, Section 2).

4.2 Surface peculiarities and referee bias

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 by adding to Equation (1) an interaction term that captures potential differences in the HA effects between clay and non-clay surfaces; the corresponding results are reported in Table 5.

Table 5 The impact of clay courts on home advantage effects

	(1)		(2)	
Surface: clay	-0.003	(0.011)	-0.003	(0.011)
HR home advantage	0.064***	(0.010)		
LR home advantage	-0.033***	(0.011)		
HR HA x Surface: clay	-0.040**	(0.017)		
LR HA x Surface: clay	-0.005	(0.014)		
HR HA x HR White			0.065***	(0.014)
HR HA x HR Southern			0.054***	(0.012)
HR HA x HR Asian			0.059	(0.043)
HR HA x HR Black			0.115***	(0.018)
HR HA x HR Indian			0.126	(0.147)
LR HA x LR White			-0.030**	(0.013)
LR HA x LR Southern			-0.045*	(0.025)
LR HA x LR Asian			0.018	(0.040)
LR HA x LR Black			-0.068**	(0.027)
LR HA x LR Indian			-0.043	(0.066)
HR HA x HR White x Surface: clay			-0.063**	(0.028)
HR HA x HR Southern x Surface: clay			-0.013	(0.017)
HR HA x HR Asian x Surface: clay			-0.083	(0.131)
HR HA x HR Black x Surface: clay			-0.083***	(0.020)
HR HA x HR Indian x Surface: clay			0.000	(.)
LR HA x LR White x Surface: clay			0.016	(0.019)
LR HA x LR Southern x Surface: clay			-0.010	(0.029)
LR HA x LR Asian x Surface: clay			0.159	(0.130)
LR HA x LR Black x Surface: clay			-0.044	(0.048)
LR HA x LR Indian x Surface: clay			0.000	(.)
Controls	Yes		Yes	
HR FE & LR FE	Yes		Yes	
Year FE	Yes		Yes	
R^2	0.695		0.695	

Notes: Data include 46,250 games covering 584 players from ATP men's tournaments between 2001 and 2020 (pre-COVID-19). Each game features two players, a higher- (HR) and a lower-ranked (LR) player. Dependent variable is the HR player's game outcome. Home advantage (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. Clay-specific HA effects for Indian players are not included because of an insufficient number of observations. Standard errors (in parentheses) clustered on HR and LR player fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5, Model (1) shows that the HA effect for HR players on non-clay surfaces is approximately twice as high as on clay surfaces, indicating a roughly equal contribution of a direct impact of fans and biased referee line calls on player performance. The effect for LR players, however, is insignificant and of small magnitude. In line with our base results, HR players may have a stronger fan-induced HA effect because, on average, they have more supportive fans than LR players. Moreover, while we control for surface familiarity effects, there may exist an additional effect contributing to HR players' increased advantage on non-clay courts. HR players can be assumed to have better skills than LR players, which may include playing close-line balls that are more likely to result in favorable referee decisions. The advantage arising from close-line balls may therefore also diminish more strongly for HR players on clay courts due to differences in their skills from those of LR players. However, our results show that clay courts do not significantly increase HR players' chances of winning independently of having a HA. The increased effect on HR players' winning probability on non-clay courts can be attributed to both a direct impact of fans and biased referee decisions.

Table 5, Model (2) indicates that the race-specific HA effects for White and Black HR players significantly decrease for matches on clay, all other race-specific HA effects are not significantly different from zero. Furthermore, we highlight that our data feature 14,668 matches on clay surfaces, of which 3,384 are HA games, distributed among the five race groups as follows: 1,540 HA games for White, 1,741 for Southern, 9 for Asian, and 94 for Black players. The data do not include any Indian player home games on clay; hence, clay-specific HA effects for Indian players are not estimable.

Exploiting the peculiar characteristics of clay courts indicates that both a direct impact of fans and a referee bias equally contribute to the HA effect in tennis. Moreover, a potential home bias from referees is unlikely playing a role in tennis because referees are usually not from the same country as the country hosting the tournament (Koning, 2011). However, we cannot rule out the possibility that the observed referee bias may further be attributable to a bias arising from differences in referees' own racial preferences.

5 Conclusion

This paper investigates 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 team sports, which are frequently characterized by emotionally invested and often aggressive fans, singles matches in tennis do not indicate the presence of a negative discrimination against minority players from fans; conversely, we find that Black players benefit more strongly from fan support than players of other racial appearances.

Our central contribution is to provide evidence for social environments in which minorities are subject to preferential treatment, resulting in a performance increase. 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 theory pose reasonable explanations for the observed differences in race-specific HA effects. Tennis is typically perceived as a “White” sport, and fans only rarely have the chance to attend home games of Black players, potentially making these games more attractive to them. 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.

Finally, the concepts of race and ethnicity are ambiguous and difficult to quantify, and how individuals perceive someone's racial appearance depends on various factors, including name, mother or native language, and nationality. Taking into account these limitations, we provide new insights into possible ramifications of positive racial discrimination on work performance. In addition, our findings may help to further our understanding of how social environments can affect competitiveness and thus potentially have implications for general questions of labor productivity. Concerning future research, a natural extension of this study is to analyze the relationships among consumer-driven racial attitudes, workplace dynamics, and performance outcomes in other industries. Understanding the mechanisms of preferential treatment and performance enhancements can help develop strategies to foster inclusive environments and optimize productivity across diverse domains.

References

Balabanis, G., & Diamantopoulos, A. (2004). Domestic Country Bias, Country-of-Origin Effects, and Consumer Ethnocentrism: A Multidimensional Unfolding Approach. *Journal of the Academy of Marketing Science*, *32*(1), 80–95.

Baumeister, R. F. (1984). Choking under pressure: Self-consciousness and paradoxical effects of incentives on skillful performance. *Journal of Personality and Social Psychology*, *46*(3), 610–620.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *American Economic Review*, *94*(4), 991–1013.

Böheim, R., Grübl, D., & Lackner, M. (2019). Choking under pressure – Evidence of the causal effect of audience size on performance. *Journal of Economic Behavior and Organization*, *168*, 76–93.

Bonacich, E. (1972). A Theory of Ethnic Antagonism: The Split Labor Market. *American Sociological Review*, *37*(5), 547–559.

Bond, T. N., & Lehmann, J. Y. K. (2018). Prejudice and racial matches in employment. *Labour Economics*, *51*, 271–293.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust Inference With Multiway Clustering. *Journal of Business and Economic Statistics*, *29*(2), 238–249.

Caselli, M., Falco, P., & Mattera, G. (2023). When the Stadium Goes Silent: How Crowds Affect the Performance of Discriminated Groups. *Journal of Labor Economics*, *41*(2), 431–451.

Combes, P. P., Decreuse, B., Laouénan, M., & Trannoy, A. (2016). Customer Discrimination and Employment Outcomes: Theory and Evidence from the French Labor Market. *Journal of Labor Economics*, *34*(1), 107–160.

Courneya, K. S., & Carron, A. V. (1992). The Home Advantage in Sport Competitions: A Literature Review. *Journal of Sport and Exercise Psychology*, *14*(1), 13–27.

Cross, J., & Uhrig, R. (2023). Do Fans Impact Sports Outcomes? A COVID-19 Natural Experiment. *Journal of Sports Economics*, *24*(1), 3–27.

Debord, G. (1967). *Society of the spectacle*. Detroit: Black and Red.

Depken, C. A., & Ford, J. M. (2006). Customer-based discrimination against major league baseball players: Additional evidence from All-star ballots. *Journal of Socio-Economics*, *35*(6), 1061–1077.

Flory, J. A., Leibbrandt, A., Rott, C., & Stoddard, O. (2023). Leader Signals and "Growth Mindset": A Natural Field Experiment in Attracting Minorities to High-Profile Positions. *Management Science*.

Garicano, L., Palacios-Huerta, I., & Prendergast, C. (2005). Favoritism under social pressure. *Review of Economics and Statistics*, *87*(2), 208–216.

Glamser, F. D. (1990). Contest Location, Player Misconduct, and Race: A Case from English Soccer. *Journal of Sport Behavior*, *13*(1), 41–49.

Gwartney, J., & Haworth, C. (1974). Employer Costs and Discrimination: The Case of Baseball. *Journal of Political Economy*, *82*(4), 873–881.

Hillberry, R., & Hummels, D. (2003). Intranational home bias: Some explanations. *Review of Economics and Statistics*, *85*(4), 1089–1092.

Hogg, M. A., & Terry, D. J. (2000). Social Identity and Self-Categorization Processes in Organizational Contexts. *Academy of Management Review*, *25*(1), 121–140.

Holder, R. L., & Nevill, A. M. (1997). Modelling performance at international tennis and golf tournaments: Is there a home advantage? *Journal of the Royal Statistical Society Series D: The Statistician*, *46*(4), 551–559.

Kahn, L. M. (1991). Discrimination in Professional Sports: A Survey of the Literature. *Industrial and Labor Relations Review*, *44*(3), 395–418.

Kanazawa, M. T., & Funk, J. P. (2001). Racial discrimination in professional basketball: Evidence from Nielsen ratings. *Economic Inquiry*, *39*(4), 599–608.

Karlsson, A., & Norden, L. L. (2007). Home sweet home: Home bias and international diversification among individual investors. *Journal of Banking and Finance*, *32*(2), 317–333.

Koning, R. H. (2011). Home advantage in professional tennis. *Journal of Sports Sciences*, *29*(1), 19–27.

Konjer, M., Meier, H. E., & Wedeking, K. (2017). Consumer Demand for Telecasts of Tennis Matches in Germany. *Journal of Sports Economics*, *18*(4), 351–375.

Korenkiewicz, D., & Maennig, W. (2023). Women on a Corporate Board of Directors and Consumer Satisfaction. *Journal of the Knowledge Economy*, *14*(4), 3904–3928.

Kuppuswamy, V., & Younkin, P. (2020). Testing the Theory of Consumer Discrimination as an Explanation for the Lack of Minority Hiring in Hollywood Films. *Management Science*, *66*(3), 1227–1247.

Laouénan, M. (2017). 'Hate at First Sight': Evidence of consumer discrimination against African-Americans in the US. *Labour Economics*, *46*, 94–109.

Lau, S. T., Ng, L., & Zhang, B. (2010). The world price of home bias. *Journal of Financial Economics*, *97*(2), 191–217.

Leonard, J. S., Levine, D. I., & Giuliano, L. (2010). Customer Discrimination. *Review of Economics and Statistics*, *92*(3), 670–678.

Maennig, W., & Mueller, S. Q. (2022). Consumer and employer discrimination in professional sports markets new evidence from Major League Baseball. *International Journal of Sport Finance*, *17*(4), 230–244.

Nardinelli, C., & Simon, C. (1990). Customer Racial Discrimination in the Market for Memorabilia: The Case of Baseball. *Quarterly Journal of Economics*, *105*(3), 575–595.

Nevill, A. M., & Holder, R. L. (1999). Home Advantage in Sport. *Sports Medicine*, *28*(4), 221–236.

Ovaska, T., & Sumell, A. J. (2014). Who Has The Advantage? An Economic Exploration of Winning in Men's Professional Tennis. *American Economist*, *59*(1), 34–51.

Parsons, C. A., Sulaeman, J., Yates, M. C., & Hamermesh, D. S. (2011). Strike Three: Discrimination, Incentives, and Evaluation. *American Economic Review*, *101*(4), 1410–1435.

Price, J., & Wolfers, J. (2010). Racial discrimination among NBA referees. *Quarterly Journal of Economics*, *125*(4), 1859–1887.

Principe, F., & van Ours, J. C. (2022). Racial bias in newspaper ratings of professional football players. *European Economic Review*, *141*, 103980.

Recht, L. D., Lew, R. A., & Schwartz, W. J. (1995). Baseball teams beaten by jet lag. *Nature*, *377*, 583–583.

Sandberg, A. (2018). Competing Identities: A Field Study of In-group Bias Among Professional Evaluators. *Economic Journal*, *128*(613), 2131–2159.

Schneider, B. (1987). The people make the place. *Personnel Psychology*, *40*(3), 437–453.

Scoppa, V. (2021). Social pressure in the stadiums: Do agents change behavior without crowd support? *Journal of Economic Psychology*, *82*, 102344.

Smith, E. E., & Groetzinger, J. D. (2010). Do Fans Matter? The Effect of Attendance on the Outcomes of Major League Baseball Games. *Journal of Quantitative Analysis in Sports*, *6*(1), 4.

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

Appendix

1 Introduction

This Appendix includes the descriptive statistics, details on the country-to-surface mapping, and the results of the robustness tests that we omitted from the main text for brevity.

2 Descriptive statistics

This Section presents additional descriptive statistics: Table A1 shows the distribution of players by country and race (White, Southern, Asian, Black, and Indian). Table A2 displays summary statistics for the number of matches played by race across all players as well as for higher-ranked (HR) and lower-ranked (LR) players. Table A3 depicts the same statistics as Table A2 but restricts the sample to matches featuring one player with a home advantage. Table A5 displays the number of matches played between HR and LR players by race.

Table A1 Player distribution by race and country

White			Southern			Asian			Black			Indian		
Country	N	%	Country	N	%	Country	N	%	Country	N	%	Country	N	%
USA	39	11.96	ESP	43	20.48	JPN	10	34.38	USA	4	36.36	IND	6	75.00
GER	38	11.66	ARG	38	18.1	CHN	5	17.24	FRA	2	18.18	PAK	1	12.50
FRA	33	10.12	ITA	27	12.86	USA	5	17.24	SWE	2	18.18	USA	1	12.50
AUS	23	7.06	FRA	16	7.62	KOR	3	10.34	BRA	1	9.09			
RUS	18	5.52	BRA	12	5.71	PHI	2	6.90	CAN	1	9.09			
CZE	16	4.91	USA	10	4.76	THA	2	6.90	GER	1	9.09			
AUT	13	3.99	CHI	7	3.33	NED	1	3.45						
NED	12	3.68	POR	5	2.38	PER	1	3.45						
SWE	11	3.37	AUS	4	1.9									
GBR	10	3.07	GBR	4	1.9									
CRO	10	3.07	SRB	4	1.9									
BEL	9	2.76	COL	3	1.43									
CAN	9	2.76	CRO	3	1.43									
SUI	9	2.76	CZE	3	1.43									
SVK	9	2.76	MAR	3	1.43									
SRB	7	2.15	ECU	2	0.95									
KAZ	6	1.84	GER	2	0.95									
ROU	6	1.84	RSA	2	0.95									
RSA	5	1.53	SUI	2	0.95									
SLO	5	1.53	TUR	2	0.95									
UKR	5	1.53	ALG	1	0.48									
BLR	4	1.23	ARM	1	0.48									
POL	4	1.23	BIH	1	0.48									
BIH	2	0.61	BOL	1	0.48									
DEN	2	0.61	CAN	1	0.48									
FIN	2	0.61	CRC	1	0.48									
HUN	2	0.61	CYP	1	0.48									
ISR	2	0.61	DOM	1	0.48									
ZIM	2	0.61	GEO	1	0.48									
BUL	1	0.31	GRE	1	0.48									
ESP	1	0.31	HUN	1	0.48									
EST	1	0.31	ISR	1	0.48									
GEO	1	0.31	MON	1	0.48									
ITA	1	0.31	PAR	1	0.48									
LAT	1	0.31	PER	1	0.48									
LTU	1	0.31	ROU	1	0.48									
LUX	1	0.31	RUS	1	0.48									
MDA	1	0.31	URU	1	0.48									
MON	1	0.31												
NOR	1	0.31												
TUN	1	0.31												
UZB	1	0.31												
Total	326			210			29			11			8	

Notes: This table shows the distribution of players by country and race (White, Southern, Asian, Black, and Indian). The data set covers 584 players who competed in ATP men's singles tournaments between 2001 and 2020 (pre-COVID-19).

Table A2 Summary statistics for the number of matches played by race

	Matches	Mean	Sd	Min	Max
All players:					
White	50,559	387.50	283.06	10	1,320
Southern	37,579	410.18	267.73	10	1067
Asian	2,642	244.57	174.77	11	524
Black	1,380	401.72	268.38	10	671
Indian	340	80.85	43.91	13	117
Total	92,500	391.72	275.66	10	1,320
Higher-ranked players:					
White	24,764	324.72	289.86	10	1,229
Southern	19,736	314.75	237.72	10	969
Asian	1,086	205.62	138.05	10	373
Black	611	330.51	175.97	22	440
Indian	53	26.96	3.50	23	30
Total	46,250	317.41	265.29	10	1,229
Lower-ranked players:					
White	25,795	140.26	79.47	10	323
Southern	17,843	149.82	86.38	10	353
Asian	1,556	94.72	55.62	11	191
Black	769	141.14	76.89	10	231
Indian	287	59.15	32.20	13	87
Total	46,250	141.96	82.17	10	353

Notes: This table shows summary statistics for matches played by race (White, Southern, Asian, Black, and Indian) across all players as well as for HR and LR players. The data set includes 46,250 games covering 584 players who competed in ATP men's singles tournaments between 2001 and 2020 (pre-COVID-19).

Table A3 Summary statistics for the number of home-advantage matches played by race

	Matches	Mean	Sd	Min	Max
All players:					
White	6,351	85.24	87.05	1	302
Southern	3,275	65.34	68.45	1	248
Asian	283	24.40	16.20	1	54
Black	368	87.30	47.11	2	132
Indian	102	38.92	25.35	7	60
Total	10,379	76.92	79.91	1	302
Higher-ranked players:					
White	2,635	79.14	80.27	1	264
Southern	1,500	52.37	44.03	1	133
Asian	64	13.16	6.01	1	20
Black	107	42.59	17.63	2	58
Indian	15	11.53	3.87	2	13
Total	4,321	67.73	69.58	1	264
Lower-ranked players:					
White	3,716	32.13	25.18	1	102
Southern	1,775	27.11	30.00	1	115
Asian	219	18.59	11.40	1	39
Black	261	56.57	38.42	2	102
Indian	87	29.14	19.49	7	47
Total	6,058	31.18	27.66	1	115

Notes: This table shows summary statistics for home-advantage matches by race (White, Southern, Asian, Black, and Indian) across all players as well as for HR and LR players. The data set includes 10,379 games in which one player (n = 462) competed in his home country (either the HR or LR player) in ATP men's singles tournaments between 2001 and 2020 (pre-COVID-19).

Table A4 Cross tabulation of matches between higher- and lower-ranked players by race

	LR player's race					
HR player's race	White	Southern	Asian	Black	Indian	Total
White	14,349	8,929	896	430	160	24,764
Southern	10,397	8,341	591	296	111	19,736
Asian	656	342	46	30	12	1,086
Black	357	218	20	12	4	611
Indian	36	13	3	1	0	53
Total	25,795	17,843	1,556	796	287	46,250

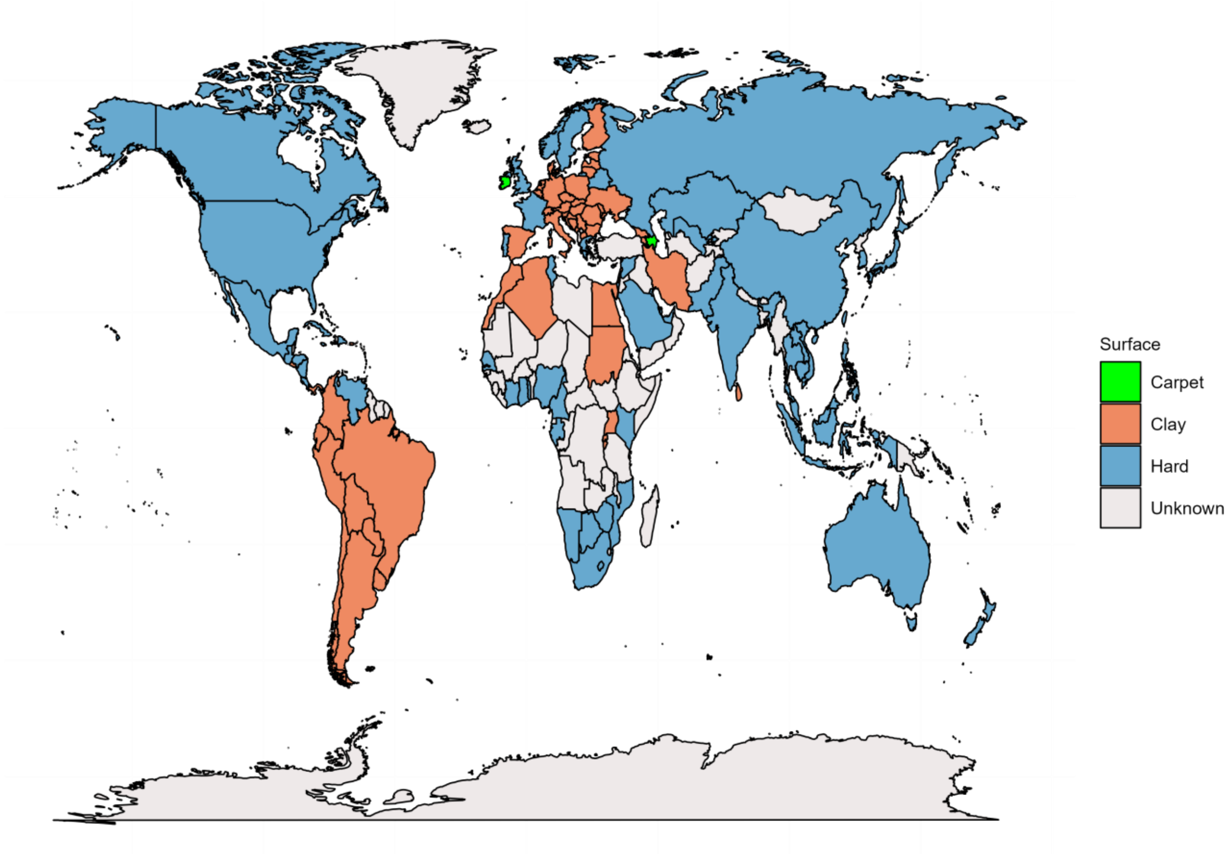
Notes: This table shows the total number of matches between higher-ranked (HR) and lower-ranked (LR) White, Southern, Asian, Black, and Indian players. The data set includes 46,250 games covering 584 players who competed in ATP men's singles tournaments between 2001 and 2020 (pre-COVID-19).

3 Surface-to-country mapping

We construct the surface-to-country mapping by accumulating the matches played per surface by country. Specifically, we consider the court surface on which most matches in a given country were played as its predominant surface. To this end, we extend the original Association of Tennis Professionals (ATP) World Tour data (56,115 matches) by data for the two lower professional tennis tiers, the ATP Challenger Tour (111,944 matches), and the International Tennis Federation (ITF) Men's World Tennis Tour (331,753 matches); the corresponding data relate to all matches from the three divisions held from 2001 to 2021. However, the data include players from Moldova and the Bahamas, but no professional tennis matches in the three aforementioned divisions were played in both countries. Based on neighboring countries, we assume the most common surface in Moldova and the Bahamas to be clay and hard court, respectively. Similarly, in Luxembourg, the number of professional games played on clay and hard court is the same (124 matches each). As two of Luxembourg's three neighboring countries' predominant surface is clay (Germany and Belgium), we define clay as Luxembourg's most common surface.

Figure A1 and Table A5 show the resulting surface-to-country mapping. As a remark, the mapping is based on 122 player countries, i.e., all player countries included in the matches from the three divisions. The mapping features two countries with carpet, 54 countries with clay, and 66 with hard court as predominantly used surface. The cleaned dataset of ATP matches that we analyze in this study includes 67 out of the 122 player countries (39 with clay and 28 with hard court as most common surface).

Figure A1 Surface-to-country mapping



Notes: Tis figure shows the distribution of countries' predominantly used surface by geographic location. The mapping includes 122 countries and is based on 499,812 matches from the ATP World Tour (56,115 matches), the ATP Challenger Tour (111,944 matches), and the ITF Men's World Tennis Tour (331,753 matches) held between 2001 and 2021. The court surface on which most matches (per country) are played is considered the country's predominant surface.

Table A5 Surface-to-country mapping

Country	Surface	Country	Surface	Country	Surface
AZE	Carpet	PER	Clay	INA	Hard
IRL	Carpet	POL	Clay	IND	Hard
ALG	Clay	PUR	Clay	ISR	Hard
ARG	Clay	ROU	Clay	JAM	Hard
ARM	Clay	RWA	Clay	JAP	Hard
AUT	Clay	SLO	Clay	KAZ	Hard
BDI	Clay	SMR	Clay	KEN	Hard
BEL	Clay	SRB	Clay	KOR	Hard
BER	Clay	SRI	Clay	KSA	Hard
BIH	Clay	SUD	Clay	KUW	Hard
BOL	Clay	SUI	Clay	LAO	Hard
BRA	Clay	SVK	Clay	MAS	Hard
BUL	Clay	UGA	Clay	MEX	Hard
CHI	Clay	UKR	Clay	MOZ	Hard
COL	Clay	URU	Clay	MRI	Hard
CRO	Clay	AND	Hard	NAM	Hard
CZE	Clay	ARU	Hard	NCA	Hard
DEN	Clay	AUS	Hard	NIG	Hard
ECU	Clay	BAH	Hard	NOR	Hard
EGY	Clay	BAR	Hard	NZL	Hard
ESA	Clay	BLR	Hard	PAK	Hard
ESP	Clay	BOT	Hard	PHI	Hard
EST	Clay	BRN	Hard	POR	Hard
FIN	Clay	CAM	Hard	QAT	Hard
GEO	Clay	CAN	Hard	RSA	Hard
GER	Clay	CHN	Hard	RUS	Hard
HUN	Clay	CIV	Hard	SEN	Hard
IRI	Clay	CMR	Hard	SGP	Hard
ITA	Clay	CRC	Hard	SWE	Hard
LAT	Clay	CUB	Hard	SYR	Hard
LBN	Clay	CUW	Hard	THA	Hard
LTU	Clay	CYP	Hard	TOG	Hard
LUX	Clay	DOM	Hard	TUN	Hard
MAR	Clay	FRA	Hard	TUR	Hard
MDA	Clay	GAB	Hard	UAE	Hard
MKD	Clay	GBR	Hard	USA	Hard
MNE	Clay	GHA	Hard	UZB	Hard
MON	Clay	GRE	Hard	VEN	Hard
NED	Clay	GUA	Hard	VIE	Hard
PAN	Clay	GUM	Hard	ZIM	Hard
PAR	Clay	HON	Hard		

Notes: Tis table shows countries' predominantly used court surface. The mapping includes 122 countries and is based on 499,812 matches from the ATP World Tour (56,115 matches), the ATP Challenger Tour (111,944 matches), and the ITF Men's World Tennis Tour (331,753 matches) held between 2001 and 2021. The court surface on which most matches (per country) are played is considered the country's predominant surface.

4 Robustness tests

4.1 Excluding same-race players

Minorities of the same race only face each other in a very limited number of games; however, fans may behave differently when same-race players are competing against each other. Consequently, as a robustness check, we exclude matches featuring same-race players.

Table A6 Race-specific home advantage effects on higher-ranked player's game outcome, excluding same-race games

	(1)	(2)	(3)
HR home advantage	0.043***		0.085***
	(0.013)		(0.019)
LR home advantage	-0.037***		-0.077***
	(0.012)		(0.030)
HR HA x HR White		0.037**	-0.048**
		(0.018)	(0.023)
HR HA x HR Southern		0.044**	-0.040
		(0.019)	(0.025)
HR HA x HR Asian		0.032	-0.052
		(0.051)	(0.059)
HR HA x HR Black		0.085***	
		(0.019)	
HR HA x HR Indian		0.090	0.005
		(0.131)	(0.133)
LR HA x LR White		-0.011	0.067**
		(0.018)	(0.033)
LR HA x LR Southern		-0.079***	-0.002
		(0.017)	(0.033)
LR HA x LR Asian		0.012	0.089*
		(0.039)	(0.050)
LR HA x LR Black		-0.077***	
		(0.030)	
LR HA x LR Indian		-0.037	0.040
		(0.060)	(0.064)
Controls	Yes	Yes	Yes
HR FE & LR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	23,502	23,502	23,502
R^2	0.704	0.704	0.704

Notes: Dependent variable is the higher-ranked (HR) player's game outcome (y=1 for a win). Data include 23,502 games covering 584 players from ATP singles men tournaments between 2001 and 2020 (pre-COVID-19). Each game features a higher- and a lower-ranked (LR) player, all matches between players of the same race are excluded. Home advantage (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 a HA. Robust standard errors (in parentheses) clustered on HR and LR player fixed effects. * p < 0.1, ** p < 0.05, *** p < 0.01

The regression results presented in Table A6 are based on the same model specifications as the results reported in Table 3 and Table 4 (column 4) in the main text, but excluding games in which two players of the same racial affiliation compete against each other. Comparing Model (1) from Table 3 (main text) to Table A6 shows that the results only differ marginally from each other. Based on the full sample (Table 3), the HR player's winning probability increases by 4.9 percentage points if he has a HA. Excluding same race players (Table A6) results in a corresponding increase of 4.3 percentage points. The corresponding HA effects for the LR player are 3.4 (Table 3) and 3.7 (Table A6) percentage points.

Similarly, comparing Model (2) from Table 3 and Table A6 shows that there only exist marginal differences regarding the race-specific HR player's HA effect across model specifications: Table A6 shows that the HA effect is positive and significant for White, Southern, and Black HR players, with Black HR players showing the largest HA effect; the effects' magnitudes are very similar to the ones reported in Table 3. Comparing the race-specific LR player's HA effect suggests some minor differences: Excluding same-race players results in an insignificant HA effect for White LR players, the HA effect for Southern LR players increases by 2.9 percentage points, and the HA effect for Black LR players decreases by 0.5 percentage points.

Table A6 Model (3) corresponds to Table 4 Model (4) in the main text. Despite discarding all same-race games, we can reaffirm that black players benefit more from fan discrimination than other races. While the difference between Black and Southern HR players becomes insignificant when excluding same-race players from the sample, the difference between the HA effects of HR Black players and HR White players as well as a difference between the HA effects of Black LR players and LR White and Asian players remain significant.

4.2 Excluding superstars

Spectators may behave differently toward superstars as well as their match opponents. To investigate this issue, we exclude the three tennis superstars Rafael Nadal, Novak

Djokovic, and Roger Federer. The corresponding regression results are presented in Table A7, they are based on the same model specifications as the results reported in Table 3 and Table 4 (column 4) in the main text.

As with excluding same-race players (Table A6), comparing Model (1) from Table 3 (main text) and Table A7 shows that the results only differ marginally from each other when excluding superstars. If the HR player has a HA, his winning probability decreases by 0.1 percentage points compared to including superstars (4.9 vs. 4.8 percentage points). Likewise, if the LR player has a HA, the winning probability of the HR decreases by 0.1 percentage points in comparison to including superstars (-3.4 vs. -3.5 percentage points).

Table A7 Race-specific home advantage effects on higher-ranked player's game outcome, excluding superstars

	(1)	(2)	(3)
HR home advantage	0.048***		0.092***
	(0.009)		(0.009)
LR home advantage	-0.035***		-0.083***
	(0.008)		(0.028)
HR HA x HR White		0.047***	-0.045***
		(0.013)	(0.014)
HR HA x HR Southern		0.046***	-0.046***
		(0.013)	(0.015)
HR HA x HR Asian		0.053	-0.039
		(0.044)	(0.051)
HR HA x HR Black		0.092***	
		(0.009)	
HR HA x HR Indian		0.123	0.031
		(0.148)	(0.148)
LR HA x LR White		-0.024**	0.058*
		(0.011)	(0.030)
LR HA x LR Southern		-0.054***	0.028
		(0.013)	(0.032)
LR HA x LR Asian		0.021	0.103**
		(0.041)	(0.051)
LR HA x LR Black		-0.083***	
		(0.028)	
LR HA x LR Indian		-0.044	0.039
		(0.067)	(0.070)
Controls	Yes	Yes	Yes
HR FE & LR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	43,009	43,009	43,009
R^2	0.679	0.679	0.679

Notes: Dependent variable is the higher-ranked (HR) player's game outcome (y=1 for a win). Data include 43,009 games covering 581 players from ATP singles men tournaments between 2001 and 2020 (pre-COVID-19). Each game features two players, a higher- and a lower-ranked (LR) player. All matches involving Roger Federer, Rafael Nadal, or Novak Djokovic are excluded. Home advantage (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 a HA. Robust standard errors (in parentheses) clustered on HR and LR player fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Concerning race-specific HA effect across model specifications, when excluding superstars from the sample, the HA effect for White, Southern, and Black HR and LR players keep their statistical significance and remain of almost the same magnitude; most coefficient estimates only change by 0.1 to 0.2 percentage points. The HA effect for Asian and Indian HR and LR players remains insignificant.

As with Model (2), comparing Model (3) in Table A7 with Model (4) in Table 4 in the main text shows that discarding superstar games does not change our results and reaffirms that Black players benefit more from a fan-support induced HA than White, Southern, or other non-Black minority players. Coefficient estimates' significance and magnitude only changes marginally. What stands out most is that the significance level of the difference in the LR player's HA effect between Black and White players drops from the 5% to 10%.

4.3 Including tournament fixed effects

As a further robustness test, we estimate our baseline model specification, Table 3 and Table 4 Model (4) in the main text, including tournament fixed effects. The corresponding regression results are presented in Table A8. In brief, Table A8 shows that including tournament country fixed effects does not change our results; the differences in the coefficient estimates' magnitude and statistical significance are marginal when compared to our base-line results.

Table A8 Race-specific home advantage effects on higher-ranked player's game outcome, including tournament country fixed effects

	(1)	(2)	(3)
HR home advantage	0.051***		0.085***
	(0.009)		(0.009)
LR home advantage	-0.032***		-0.082***
	(0.008)		(0.028)
HR HA x HR White		0.051***	-0.034**
		(0.012)	(0.014)
HR HA x HR Southern		0.046***	-0.039***
		(0.013)	(0.013)
HR HA x HR Asian		0.069	-0.017
		(0.045)	(0.052)
HR HA x HR Black		0.085***	
		(0.009)	
HR HA x HR Indian		0.145	0.060
		(0.156)	(0.156)
LR HA x LR White		-0.022**	0.061**
		(0.011)	(0.030)
LR HA x LR Southern		-0.052***	0.031
		(0.014)	(0.033)
LR HA x LR Asian		0.043	0.126***
		(0.038)	(0.047)
LR HA x LR Black		-0.082***	
		(0.028)	
LR HA x LR Indian		-0.052	0.030
		(0.060)	(0.064)
Controls	Yes	Yes	Yes
HR FE & LR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Tournament country FE	Yes	Yes	Yes
N	46,250	46,250	46,250
R^2	0.696	0.696	0.696

Notes: Dependent variable is the higher-ranked (HR) player's game outcome (y=1 for a win). Data include 46,250 games covering 584 players from ATP men tournaments between 2001 and 2020 (pre-COVID-19). Each game features two players, a higher- and a lower-ranked (LR) player. Home advantage (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 a HA. Prize money is deflated using 2001 as base year. Robust standard errors (in parentheses) clustered on HR and LR player fixed effects. * p < 0.1, ** p < 0.05, *** p < 0.01

75 CREUTZBURG, C. / MAENNIG, W. / MUELLER, S. Q.: From bias to bliss: Racial preferences and worker productivity in tennis, 2024.

74 MAENNIG, W. / WILHELM, S.: Crime Prevention Effects of Data Retention Policies, 2023.

73 MAENNIG, W.: Centralization in national high-performance sports systems: Reasons, processes, dimensions, characteristics, and open questions, 2023.

72 MAENNIG, W. / WILHELM, S.: News and noise in crime politics: The role of announcements and risk attitudes, 2022.

71 MAENNIG, W.: Auch in Peking 2022: Relativ schwache Medaillenausbeute der SportsoldatInnen, 2022.

70 MAENNIG, W. / MUELLER, S. Q.: Heterogeneous consumer preferences for product quality and uncertainty, 2021.

69 MAENNIG, W. / MUELLER, S. Q.: Consumer and employer discrimination in professional sports markets – New evidence from Major League Baseball, 2021.

68 ECKERT, A. / MAENNIG, W.: Pharma-Innovationen: Überragende Position der USA und Schwächen der deutschen universitären und außeruniversitären Forschung, 2021.

67 MUELLER, S. Q. / RING, P. / FISCHER, M.: Excited and aroused: The predictive importance of simple choice process metrics, 2020.

66 MUELLER, S. Q. / RING, P. / SCHMIDT, M.: Forecasting economic decisions under risk: The predictive importance of choice-process data, 2019.

65 MUELLER, S. Q.: Pre- and within-season attendance forecasting in Major League Baseball: A random forest approach, 2018.

64 KRUSE, F. K. / MAENNIG, W.: Suspension by choice – determinants and asymmetries, 2018.

63 GROTHE, H. / MAENNIG, W.: A 100-million-dollar fine for Russia's doping policy? A billion-dollar penalty would be more correct! Millionenstrafe für Russlands Doping-Politik? Eine Milliarden-Strafe wäre richtiger! 2017.

62 MAENNIG, W., / SATTARHOFF, C. / STAHLECKER, P.: Interpretation und mögliche Ursachen statistisch insignikanter Testergebnisse - eine Fallstudie zu den Beschäftigungseffekten der Fußball-Weltmeisterschaft 2006, 2017.

61 KRUSE, F. K. / MAENNIG, W.: The future development of world records, 2017.

60 MAENNIG, W.: Governance in Sports Organizations, 2017.

59 AHLFELDT, G. M. / MAENNIG, W. / FELIX J. RICHTER: Zoning in reunified Berlin, 2017.

58 MAENNIG, W.: Major Sports Events: Economic Impact, 2017.

57 MAENNIG, W.: Public Referenda and Public Opinion on Olympic Games, 2017.

56 MAENNIG, W. / WELLBROCK, C.: Rio 2016: Sozioökonomische Projektion des Olympischen Medaillenrankings, 2016.

55 MAENNIG, W. / VIERHAUS, C.: Which countries bid for the Olympic Games? Economic, political, and social factors and chances of winning, 2016.

54 AHLFELDT, G. M. / MAENNIG, W. / STEENBECK, M.: Après nous le déluge? Direct democracy and intergenerational conflicts in aging societies, 2016.

53 LANGER, V. C. E.: Good news about news shocks, 2015.

52 LANGER, V. C. E. / MAENNIG, W. / RICHTER, F. J.: News Shocks in the Data: Olympic Games and their Macroeconomic Effects – Reply, 2015.

51 MAENNIG, W.: Ensuring Good Governance and Preventing Corruption in the Planning of Major Sporting Events – Open Issues, 2015.

50 MAENNIG, W. / VIERHAUS, C.: Who Wins Olympic Bids? 2015 (3rd version).

49 AHLFELDT, G. M. / MAENNIG, W. / RICHTER, F.: Urban Renewal after the Berlin Wall, 2013.

48 BRANDT, S. / MAENNIG, W. / RICHTER, F.: Do Places of Worship Affect Housing Prices? Evidence from Germany, 2013.

47 ARAGÃO, T. / MAENNIG, W.: Mega Sporting Events, Real Estate, and Urban Social Economics – The Case of Brazil 2014/2016, 2013.

46 MAENNIG, W. / STEENBECK, M. / WILHELM, M.: Rhythms and Cycles in Happiness, 2013.

45 RICHTER, F. / STEENBECK, M. / WILHELM, M.: The Fukushima Accident and Policy Implications: Notes on Public Perception in Germany, 2014 (2nd version).

44	MAENNIG, W.: London 2012 – das Ende des Mythos vom erfolgreichen Sportsoldaten, 2012.
43	MAENNIG, W. / WELLBROCK, C.: London 2012 – Medal Projection – Medaillenvorausberechnung, 2012.
42	MAENNIG, W. / RICHTER, F.: Exports and Olympic Games: Is there a Signal Effect? 2012.
41	MAENNIG, W. / WILHELM, M.: Becoming (Un)employed and Life Satisfaction: Asymmetric Effects and Potential Omitted Variable Bias in Empirical Happiness Studies, 2011.
40	MAENNIG, W.: Monument Protection and Zoning in Germany: Regulations and Public Support from an International Perspective, 2011.
39	BRANDT, S. / MAENNIG, W.: Perceived Externalities of Cell Phone Base Stations – The Case of Property Prices in Hamburg, Germany, 2011.
38	MAENNIG, W. / STOBERNACK, M.: Do Men Slow Down Faster than Women? 2010.
37	DU PLESSIS, S. A. / MAENNIG, W.: The 2010 World Cup High-frequency Data Economics: Effects on International Awareness and (Self-defeating) Tourism, 2010.
36	BISCHOFF, O.: Explaining Regional Variation in Equilibrium Real Estate Prices and Income, 2010.
35	FEDDERSEN, A. / MAENNIG, W.: Mega-Events and Sectoral Employment: The Case of the 1996 Olympic Games, 2010.
34	FISCHER, J.A.V. / SOUSA-POZA, A.: The Impact of Institutions on Firms Rejuvenation Policies: Early Retirement with Severance Pay versus Simple Lay-Off. A Cross-European Analysis, 2010.
33	FEDDERSEN, A. / MAENNIG, W.: Sectoral Labor Market Effects of the 2006 FIFA World Cup, 2010.
32	AHLFELDT, G.: Blessing or Curse? Appreciation, Amenities, and Resistance

around the Berlin “Mediaspree”, 2010.

31 FALCH, T. / FISCHER, J.A.V.: Public Sector Decentralization and School Performance: International Evidence, 2010.

30 AHLFELDT, G. / MAENNIG, W. / ÖLSCHLÄGER, M.: Lifestyles and Preferences for (Public) Goods: Professional Football in Munich, 2009.

29 FEDDERSEN, A. / JACOBSEN, S. / MAENNIG, W.: Sports Heroes and Mass Sports Participation – The (Double) Paradox of the “German Tennis Boom”, 2009.

28 AHLFELDT, G. / MAENNIG, W. / OSTERHEIDER, T.: Regional and Sectoral Effects of a Common Monetary Policy: Evidence from Euro Referenda in Denmark and Sweden, 2009.

27 BJØRNSKOV, C. / DREHER, A. / FISCHER, J.A.V. / SCHNELLENBACH, J.: On the Relation Between Income Inequality and Happiness: Do Fairness Perceptions Matter? 2009.

26 AHLFELDT, G. / MAENNIG, W.: Impact of Non-Smoking Ordinances on Hospitality Revenues: The Case of Germany, 2009.

25 FEDDERSEN, A. / MAENNIG, W.: Wage and Employment Effects of the Olympic Games in Atlanta 1996 Reconsidered, 2009.

24 AHLFELDT, G. / FRANKE, B. / MAENNIG, W.: Terrorism and the Regional and Religious Risk Perception of Foreigners: The Case of German Tourists, 2009.

23 AHLFELDT, G. / WENDLAND, N.: Fifty Years of Urban Accessibility: The Impact of Urban Railway Network on the Land Gradient in Industrializing Berlin, 2008.

22 AHLFELDT, G. / FEDDERSEN, A.: Determinants of Spatial Weights in Spatial Wage Equations: A Sensitivity Analysis, 2008.

21 MAENNIG, W. / ALLMERS, S.: South Africa 2010: Economic Scope and Limits, 2008.

20 MAENNIG, W. / WELLBROCK, C.-M.: Sozio-ökonomische Schätzungen Olympischer Medaillengewinne: Analyse-, Prognose- und Benchmarkmöglichkeiten, 2008.

19	AHLFELDT, G.: The Train has Left the Station: Real Estate Price Effects of Mainline Realignment in Berlin, 2008.
18	MAENNIG, W. / PORSCHE, M.: The Feel-good Effect at Mega Sport Events – Recommendations for Public and Private Administration Informed by the Experience of the FIFA World Cup 2006, 2008.
17	AHLFELDT, G. / MAENNIG, W.: Monumental Protection: Internal and External Price Effects, 2008.
16	FEDDERSEN, A. / GRÖTZINGER, A. / MAENNIG, W.: New Stadia and Regional Economic Development – Evidence from FIFA World Cup 2006 Stadia, 2008.
15	AHLFELDT, G. / FEDDERSEN, A.: Geography of a Sports Metropolis, 2007.
14	FEDDERSEN, A. / MAENNIG, W.: Arenas vs. Multifunctional Stadia – Which Do Spectators Prefer? 2007.
13	AHLFELDT, G.: A New Central Station for a Unified City: Predicting Impact on Property Prices for Urban Railway Network Extension, 2007.
12	AHLFELDT, G.: If Alonso was Right: Accessibility as Determinant for Attractiveness of Urban Location, 2007.
11	AHLFELDT, G., MAENNIG, W.: Assessing External Effects of City Airports: Land Values in Berlin, 2007.
10	MAENNIG, W.: One Year Later: A Re-Appraisal of the Economics of the 2006 Soccer World Cup, 2007.
09	HAGN, F. / MAENNIG, W.: Employment Effects of the World Cup 1974 in Germany.
08	HAGN, F. / MAENNIG W.: Labour Market Effects of the 2006 Soccer World Cup in Germany, 2007.
07	JASMAND, S. / MAENNIG, W.: Regional Income and Employment Effects of the 1972 Munich Olympic Summer Games, 2007.
06	DUST, L. / MAENNIG, W.: Shrinking and Growing Metropolitan Areas – Asymmetric Real Estate Price Reactions? The Case of German Single-family Houses, 2007.
05	HEYNE, M. / MAENNIG, W. / SUESSMUTH, B.: Mega-sporting Events as

Experience Goods, 2007.

04 DU PLESSIS, S. / MAENNIG, W.: World Cup 2010: South African Economic Perspectives and Policy Challenges Informed by the Experience of Germany 2006, 2007.

03 AHLFELDT, G. / MAENNIG, W.: The Impact of Sports Arenas on Land Values: Evidence from Berlin, 2007.

02 FEDDERSEN, A. / MAENNIG, W. / ZIMMERMANN, P.: How to Win the Olympic Games – The Empirics of Key Success Factors of Olympic Bids, 2007.

01 AHLFELDT, G. / MAENNIG, W.: The Role of Architecture on Urban Revitalization: The Case of "Olympic Arenas" in Berlin-Prenzlauer Berg, 2007.

04/2006 MAENNIG, W. / SCHWARTHOFF, F.: Stadium Architecture and Regional Economic Development: International Experience and the Plans of Durban, October 2006.

03/2006 FEDDERSEN, A. / VÖPEL, H.: Staatliche Hilfen für Profifußballclubs in finanziellen Notlagen? – Die Kommunen im Konflikt zwischen Imageeffekten und Moral-Hazard-Problemen, September 2006.

02/2006 FEDDERSEN, A.: Measuring Between-season Competitive Balance with Markov Chains, July 2006.

01/2006 FEDDERSEN, A.: Economic Consequences of the UEFA Champions League for National Championships – The Case of Germany, May 2006.

04/2005 BUETTNER, N. / MAENNIG, W. / MENSSEN, M.: Zur Ableitung einfacher Multiplikatoren für die Planung von Infrastrukturkosten anhand der Aufwendungen für Sportstätten – eine Untersuchung anhand der Fußball-WM 2006, May 2005.

03/2005 SIEVERS, T.: A Vector-based Approach to Modeling Knowledge in Economics, February 2005.

02/2005 SIEVERS, T.: Information-driven Clustering – An Alternative to the Knowledge Spillover Story, February 2005.

Hamburg Contemporary Economic Discussions

(Download: https://www.wiso.uni-hamburg.de/en/fachbereich-vwl/professuren/maennig/research/hceds.html)

01/2005 FEDDERSEN, A. / MAENNIG, W.: Trends in Competitive Balance: Is there Evidence for Growing Imbalance in Professional Sport Leagues? January 2005.

Hamburg

Contemporary Economic Discussions

HCED NO. 75

ISSN 1865-2441 (PRINT)
ISSN 1865-7133 (ONLINE)

ISBN 978-3-942820-64-6(PRINT)
ISBN 978-3-942820-65-3 (ONLINE)