Journal of Economic Behavior and Organization 238 (2025) 107236

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Research Paper

Individual performance and environment: Home advantage in ATP tennis

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ARTICLE INFO

JEL classification:
D91
M50
M54
L83
Z2

Keywords:
Tennis
Home advantage
Familiar environment
Athletes' performance
Behavioral factors
Cultural factors

ABSTRACT

We investigate the role of home advantage (HA) in ATP tennis (2000–2022). Our findings confirm the existence of HA with a heterogeneous effect shaped by a combination of individual player characteristics and situational contexts. Individual mechanisms reveal that less experienced players benefit more from HA, while talent does not show a significant interaction. Cultural background plays a role, with individualistic players exhibiting a stronger HA, unlike collectivistic ones. Among situational factors, the absence of spectators during COVID-19 indicates that while HA persists, crowd presence does not seem to be the primary driver. Opponent travel fatigue amplifies HA, whereas prior knowledge of the facilities has no substantial impact. These findings extend beyond sports, indicating that structured, familiar environments enhance performance and resilience in professional settings, though their effects vary based on experience and cultural background.

1. Introduction

The study of human performance in high-stakes environments offers a valuable perspective for exploring the confluence of individual and contextual factors that shape behavior. In many professional contexts, individuals are often required to make rapid, high-quality decisions, and their success depends on both skill and their ability to adapt to the environment in which they operate. However, in many organizational or corporate settings, detailed data on both individual inputs (such as motivation, experience, or skill) and outcomes (such as measurable achievements) are rarely publicly available, and workers' behaviors have mostly been tested in laboratory experiments, with some limitations (Luciano et al., 2018). As a result, identifying alternative laboratories where these dynamics can be observed at scale is important for advancing theories about individual and organizational behavior.

Sport provides such a setting. It offers an ideal context for observing how individuals and teams face challenges and make decisions

Notes: The dataset used for this study primarily originates from a public GitHub repository (Sackmann, 2023) that includes single-year data for ATP-level matches since 1968. We accessed this repository in 2023, downloading 23 CSV files covering 2000–2022. We complemented this dataset by including the tournament country and specifying crowd presence during the COVID-19 restrictions of 2020 and 2021. In particular, we gathered crowd information from diverse public sources, such as the ATP website's news section, tournaments' official websites and associated Wikipedia pages, online news, and YouTube footage of matches. Further details on the source and collection of data and our construction of the full dataset are included in Section 3.1 ("Data"). The paper uses the abbreviation "HA", standing for Home Advantage.

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https://doi.org/10.1016/j.jebo.2025.107236
Received 10 October 2024; Received in revised form 18 August 2025; Accepted 2 September 2025
Available online 12 September 2025
0167-2681/

in environments of fierce competition that require leveraging all possible resources to win (Kahn, 2000). Researchers using sports data have contributed to advancing literature in many streams, such as the resource-based view, status and reputation, network-related theory, rivalry, risk-taking, decision-making, leadership, unethical behavior, and motivation (Fonti et al., 2023). Sports settings are particularly well suited to understanding the relationship between input resources (such as individual motivation) and outcomes (such as prizes or achievements), because performance is both observable and quantifiable over repeated events, and the competitive context naturally varies across situations and locations.

One of the most directly transferable insights from professional sports to workplace settings is the understanding of how the context in which players operate can influence their behavior—mirroring how employees' performance may shift depending on the environment in which they work. In this context, since the seminal work of Schwartz and Barsky (1977), the economics literature has extensively investigated home advantage (HA) in sports competitions. HA describes the tendency for teams or athletes to perform better in their home environment than when competing away. This advantage is generally attributed to a combination of external factors—such as crowd support, travel fatigue, and familiarity with venues and facilities—and the way professionals respond to these external conditions, which in turn affects their performance and decision-making.

HA has been widely examined across a broad range of team sports, including basketball, hockey, baseball, football, soccer, rugby, volleyball, and handball (e.g., Bray et al., 2005; Caudill and Mixon, 2007; Marcelino et al., 2009; Pic, 2018; Pollard, 2006; Snyder and Purdy, 1985; Thomas et al., 2008). In contrast, research on HA in the domain of individual professional sports is relatively scarce and somewhat outdated. Jamieson (2010) identified a home-field advantage in athletics, while Balmer et al. (2005) revealed biased referee decisions in boxing.

Despite tennis being one of the most popular and widely played sports globally, the phenomenon of home advantage in this context has received little academic attention, with only a handful of studies exploring its presence (Nevill et al., 1997; Koning, 2011; Wunderlich et al., 2023). Given the individual nature of the sport and the absence of conventional team dynamics, analyzing HA in tennis offers a good opportunity to isolate the behavioral and contextual factors behind performance differences. In this study, we investigate HA in the ATP tennis setting on a comprehensive dataset comprising 59,963 matches played between 2000 and 2022, 14 % of which occurred in a player's home country (i.e. at home). By addressing this gap, our work contributes to a deeper understanding of how home advantage functions in an individual professional sport. Our findings reveal that, *ceteris paribus*, players competing in their home country have a 4 % higher probability of winning a match.

Our analysis goes beyond identifying the existence of HA by examining the potential underlying factors. We differentiate between player-specific mechanisms and situational channels. On the one hand, we assess how individual characteristics—such as talent, experience, and cultural background—moderate the extent of the advantage. On the other, we explore contextual factors like the role of specific high-skill tasks in channeling HA, travel fatigue, and familiarity with venues which may amplify or diminish the effect.

An additional novelty of our study is the investigation of the potential causal effect of home advantage specifically linked to the presence of a crowd. This is made possible by the experimental setting of matches played behind closed doors during the COVID-19 pandemic. Indeed, isolating the impact of crowd support on performance can provide insights into understanding the behavior of workers when supported (or not) by a crowd. In this regard, the pandemic led a surge of literature interest in approaching HA with a causal methodology, confirming the positive impact of crowd support on teams' success (e.g., Farnell et al., 2023; Losak and Sabel, 2021; Scoppa, 2021). However, none is known at an individual level, with the exception of Wunderlich et al. (2023), who explored home advantage in the German amateur, semi-professional, and professional tennis leagues. Our study addresses this literature gap by examining the role of crowd effects in HA at the international and professional level (ATP).

Interestingly, our results challenge some conventional assumptions. For instance, while home crowd support is often credited as a key driver of HA, our empirical analysis leveraging matches played without spectators during the COVID-19 pandemic reveals that HA persists even in the absence of a crowd. Yet this result is far from conclusive, since its size and significance vary with the model specification and with the sample. This suggests that psychological comfort, logistical ease, or other less visible factors may play a substantial role.

We also observe that less experienced players appear to benefit more from home conditions, perhaps due to reduced stress or enhanced confidence in domestic settings. Additionally, cultural orientation matters: players from more individualistic societies tend to leverage a stronger HA, potentially reflecting differences in how personal routines and motivation interact with supportive environments. While previous studies focused their attention on the mere detection of HA in tennis (e.g., Koning, 2011), our analyses investigate the rationales behind HA.

Finally, yet importantly, the dataset covers all professional men's matches from 2000 to 2022. This is a significant improvement over the one year covered by Nevill et al. (1997), the nine years by Koning (2011) and the four years by Wunderlich et al. (2023). A larger number of observations allows us to examine medium to long-term dynamics and avoid the risk of results being driven by specific time-related factors. Furthermore, our sample includes all international ATP professional tournaments played during the period, unlike Wunderlich et al. (2023), which focuses only on the German context, and Nevill et al. (1997), which is limited to four major tournaments.

Overall, this paper contributes to the existing literature on HA and yields insights into performance dynamics in other high-stakes domains, with relevance for contemporary professional settings characterized by high-skill demands. Our findings suggest that situational context can exert a significant influence on outcomes, particularly for individuals early in their career trajectories or originating from cultures prioritizing autonomy and self-determination.

The remainder of this paper is structured as follows. Section 2 presents the literature review on HA and the hypothesis. Section 3 describes our dataset and empirical strategy. Section 4 presents the main results and a battery of robustness tests. Section 5 and 6 explore the individual mechanisms and external situational channels underlying HA, respectively. Finally, Section 7 concludes and discusses some implications beyond sports.

2. Home advantage

2.1. Determinants of HA

HA has been extensively documented in sports, reflecting the tendency for athletes or teams to perform better in their home environment than when competing away (Schwartz and Barsky, 1977). Beyond establishing its existence, scholars have also investigated the underlying rationales behind HA, identifying a range of contributing factors—from crowd support and referee bias to travel fatigue and familiarity with playing conditions—that may help explain why teams tend to perform better at home. Broadly speaking, the rationales behind HA can be traced to two main categories of factors raising from the literature: player-specific mechanisms, which relate to intrinsic characteristics of athletes and how they moderate HA, and situational channels, which stem from external contextual conditions before or during the competition.

Player-specific mechanisms include, for instance, physiological responses, experience and age, and cultural background that have been usually assessed in team sports (see, e.g., Carré et al., 2006; Gelade, 2015; Staufenbiel et al., 2018). These individual-level factors contribute to shaping how much a player can capitalize on the home setting and help explain the variability in HA effects across different types of athletes.

Situational channels, by contrast, involve external match-related conditions that can influence outcomes. These include:

Presence of a crowd: The presence of supportive fans can significantly impact a team's morale and motivation. The cheering and encouragement of a home crowd can energize athletes, establishing a positive psychological atmosphere that can enhance performance (e.g., Boudreaux et al., 2017; Ponzo and Scoppa, 2018). On the other hand, visitors are discouraged by a negative attitude of local supporters such as booing or discriminatory chants (e.g., Greer, 1983; Magrath, 2018).

Familiarity with facilities: Athletes are often more familiar with their home venue's facilities, playing surface, and general environment. This familiarity can provide a sense of comfort and confidence, contributing to improved performance (e.g., Loughead et al., 2003).[1]

Travel fatigue: Athletes playing away from home may experience the effects of travel, such as jet lag and disrupted routines. These factors can negatively affect physical and mental preparedness, potentially giving the home team an advantage (e.g., Oberhofer et al., 2010; Zak, 2021).

Referee bias: Referees or officials may have an unconscious bias toward the home team that is influenced by the reactions of the home crowd and may affect their decision-making during the match (Dawson and Dobson, 2010; Sutter and Kocher, 2004).

Psychological factors that could change the teams' behavior: The belief that HA exists may affect players' attitudes and performance. For example, the tendency for away teams to adopt more defensive tactics is likely to provide the home players with a territorial and psychological advantage, which may influence performance (González-Rodenas et al., 2020; Pollard, 1986). Moreover, the lack of pressure associated with playing in an unfamiliar environment can positively affect performance, and being in a familiar environment can reduce athletes' anxiety and stress (Carré et al., 2006). Lastly, athletes often engage in pre-match routines and rituals. Being in a familiar environment allows them to maintain these routines and contributes to a sense of normalcy and psychological comfort (Courneya and Carron, 1992).

2.2. Hypothesis development

Studies focusing on the behavior of athletes in team sports offer valuable insights into *group* dynamics, but their relevance to *individual* behavior is limited. In this regard, investigating individual sports can provide a more direct alternative perception of this phenomenon. With this in mind, we focus on ATP tennis, an ideal sport for measuring the interaction among psychological factors, individual performance, and behavior due to its one-on-one competitive structure. Moreover, frequent matchups, no draws outcome, high professionality (high rewards), and minimal referee bias are all positive features of the game of tennis for reducing heterogeneity.[2]

The suitability of the tennis setting is evidenced by the growing number of studies using it to test economic and psychological sports theories, such as performance under psychological pressure (Bühren and Steinberg, 2019), gender differences (Paserman, 2023; Wozniak, 2012), psychological momentum (Meier et al., 2020), loss aversion (Anbarci et al., 2018), and the superstar labor market (Grove et al., 2021).

As previous research in most sports has shown, home players leverage on home factors such as familiarity with the facilities and the

[1] This definition of familiarity, limited to prior knowledge of fields or arenas, is distinct from the broader notion of familiarity with a surrounding environment, which may also depend on factors such as cultural background or geographical proximity. In this paper, when we refer specifically to prior knowledge of facilities and venues, we use the term *familiarity with venues* or *familiarity with facilities*. By contrast, when referring to the broader concept, we adopt the expression *familiar environment*.

[2] The rules of tennis are straightforward: a player must win four points to secure a game, with sets typically won by the first to reach six games with at least a two-game lead. In cases where both players reach six games, a tiebreak is played to determine the winner of the set. Most tournaments follow a best-of-three-sets format, while prestigious events like the Grand Slam tournaments adopt a best-of-five structure.

presence of a crowd. Home teams' chances of winning increase across various sports, we aim to contribute to the existing literature, by confirming the HA in tennis.

We propose the following hypothesis to be tested:

Hypothesis—home advantage

All else being equal, the probability of winning a tennis match is higher when one player is performing in their own country.

We also explore player-specific mechanisms (*Individual Characteristics*) that could moderate HA in individual sports such as tennis. Subsequently, we identified the possible mechanism behind HA (*Home Advantage Channels*), as outlined in the literature.

Individual Characteristics

We analyze three individual dimensions—talent (ATP top 10), experience (age), and culture (individualism vs. collectivism). In competitive settings, personal traits might affect how athletes use resources like home advantage.

Home Advantage Channels

The second focus is on the mechanisms behind HA, analyzing pressure, travel fatigue, familiarity with the facilities, and especially crowd presence. Indeed, we estimate the crowd's effect on HA by leveraging the setting provided by the COVID-19 pandemic, which led to many matches being played without spectators.

3. Data and empirical strategy

3.1. Data

We collected a dataset combining several sources to investigate the HA in professional men's tennis and the underlying channels and mechanisms. The primary source is a public repository on GitHub called *ATP Tennis Rankings, Results, and Stats* (Sackmann, 2023), which includes single-year data for all ATP-level matches played since 1968. This data source has been used in previous works on tennis, such as Ishihara et al. (2022) and Tejkalova and Kristoufek (2021). In 2023, we accessed this repository and downloaded 23 CSV files covering 2000–2022. We chose 2000 as the starting point to cover a comprehensive period for contemporary tennis.

We complemented this dataset by adding the country in which the tournament was held, based on the city information that is available in the original database, which allowed us to determine whether a player was playing in their own country (at home) or abroad and against an opponent playing at home or not. Second, we included information regarding whether matches were played with or without a crowd during the COVID-19 restrictions of 2020 and 2021 (before 2020, tennis had never been subject to restrictions, and all players observed in the range 2000–2019 played in the presence of a crowd).

Concerning crowd control, each country imposed different rules to contain the pandemic, and the national tennis federations organizing the tournaments opted for heterogeneous solutions such as canceling, postponing, or confirming tournaments and allowing them to be played with or without a crowd. Therefore, we analyzed various public sources to determine whether a tournament allowed a crowd to be present for the match during the same period. The first information source was the ATP website's news section (https://www.atptour.com/en/news/). The second source was the tournaments' official websites (e.g., https://www.usopen.org/) and the Wikipedia page for each tournament (e.g., https://en.wikipedia.org/wiki/2020_US_Open_(tennis)). Online news about tournaments (e.g., https://www.nytimes.com/2020/09/13/sports/tennis/us-open-mens-final-zverev-thiem.html) was included as the third source. Our final resource to ascertain the presence of spectators in the stands was based on scrutinizing tournaments' footage that was published on YouTube (e.g., https://www.youtube.com/watch?v=Mac4XI3ka5I).

Our dataset also includes data on match and player characteristics. In particular, we include information about the winner of the match, the sets and final scores, the tournament in which the match was played, the type of court, the number of aces, double faults,

Table 1
Summary statistics. This table includes descriptive statistics (number of observations, median, mean, standard deviation, minimum and maximum values) of the variables used in the empirical analysis.

Variables	Obs.	Median	Mean	Standard Deviation	Min	Max
Win	59,963	0.000	0.497	0.500	0.000	1.000
Home	59,963	0.000	0.229	0.420	0.000	1.000
Age Difference	59,963	−0.100	−0.157	5.374	−21.700	25.900
Height Difference	59,400	0.000	0.141	9.471	−40.000	41.000
Rank Difference	59,754	−0.004	−0.013	0.131	−2.125	1.701
Points Difference	59,754	−0.041	−0.037	2.163	−16.641	16.070
Top-10-ATP	59,754	0.000	0.350	0.740	0.000	3.000
Individualist	59,181	0.000	0.283	0.451	0.000	1.000
Collectivist	59,181	0.000	0.207	0.405	0.000	1.000
Closed	59,963	0.000	0.042	0.200	0.000	1.000
Travel Fatigue	58,586	0.000	0.277	0.613	0.000	2.000
Familiarity	59,963	0.000	0.537	1.053	0.000	7.000
Aces Difference	59,440	0.000	0.119	6.451	−46.000	65.000
Ratio Games	59,905	1.000	1.232	0.994	0.056	18.000
Games Difference	59,963	0.00	0.011	5.738	−17.000	17.000
Double Faults	59,440	3.000	3.046	2.444	0.000	26.000
Nr. Saved Breakpoints	59,440	5.000	4.163	3.242	0.000	24.000

and breakpoints. Data about the players include nationality, age, height, ATP rankings, and number of ATP points as of the week of the match. We complement the information at the player level with national cultural attributes, such as individualism and collectivism, based on Hofstede (2011).

Overall, our dataset includes a total of 59,963 matches involving 1,488 athletes playing in 148 tournaments in 47 countries. Table 1 reports summary statistics for the key variables used in the analysis, including match outcomes, player characteristics, and match-level performance metrics, while all variable definitions, construction procedures, and data sources are reported in Table 2. The dataset is structured at the match level by defining a "reference player". If only one player is playing in their own country ("at home"), this athlete is considered the reference player in the dataset. If both players are at home or both are away, players are randomly assigned as reference players. This procedure avoids duplicate observations and allows for consistent estimation of the home advantage effect.

To better contextualize the structure and balance of the data, Appendix Table A1 presents a breakdown of match counts by host country, the share of matches featuring at least one home player, and the share of home victories. The number of matches hosted varies significantly across countries: the United States hosted 14,444 matches (24 % of the total), while France and Spain hosted 3,270 and 2,315 matches respectively. The incidence of home player participation also differs: in Spain, 29 % of matches involved at least one Spanish player, compared to just 11 % in France. To isolate the effect of crowd support, we exploit variation in the presence of spectators due to COVID-19 restrictions. In total, 2,490 matches were played without spectators. These occurred across a variety of settings, from ATP 250 tournaments to Grand Slams, and across different continents. For instance, 379 closed-door matches were played in France, 228 in Australia, and 209 in Italy.

3.2. Empirical strategy

We first explore the validity of HA in tennis, estimating a fixed-effect regression to determine whether the players at home are more likely to win matches in contrast to away players. The model is structured as follows:

$$Y_{im} = \alpha + \beta Home_{im} + \lambda Controls_{im} + \phi_i + \phi_t + \epsilon_{im}, \tag{1}$$

where Y_{im} is a dichotomous indicator that takes the value of 1 if the reference player i won match m, and 0 if they lost. *Home* is our main variable of interest and is a binary indicator that takes the value of 1 for athletes competing in their home country against a non-local opponent, and 0 otherwise. We also include a vector of time-varying control variables (*Controls*) to account for players' different characteristics that may influence the probability of winning a match. Specifically, we consider the differences in relevant indicators between the two competing players that could also predict winning a match, including age (*Age Difference*), height (*Height Difference*), rank (*Rank Difference*), and the number of points (*Points Difference*) in the international ATP ranking. We also add a set of fixed effects at player ϕ_i and tournament date ϕ_t levels to account for potential unobserved variables that are not covered by control variables. Finally, ϵ_{im} is the error term, which is clustered at the player level. We are primarily interested in examining β, the estimated coefficient for *Home*. If this coefficient is positive and statistically significant, we can conclude that playing at home constitutes an advantage for tennis athletes, thereby supporting the HA hypothesis. In further estimations of Eq. (1), we enhance the models by including country and year fixed effects to account for unobserved regional and temporal heterogeneity. In our preferred specification, we additionally interact year and player fixed effects to capture individual players' evolving characteristics and attitudes toward the sport over time.

In the second step, we explore how a range of contextual and individual-level factors—such as travel fatigue, cultural proximity, experience, and social support—affect players' performance when competing at home versus away. Depending on the nature of the factor under investigation, we adopt a range of empirical strategies, combining fixed effects models and interaction terms, to examine how specific conditions relate to match outcomes. While many of these analyses are correlational in nature, they help uncover systematic patterns in how performance varies across different environments.

In one specific case, however, we can draw on a quasi-natural experiment that allows for a causal interpretation. To assess the impact of a supportive crowd, we leverage the unique setting created by the COVID-19 pandemic, which led to matches being played behind closed doors in a staggered fashion across countries and over time.[3] This setting enables a difference-in-differences (DiD) approach, where players competing at home constitute the treated group and those playing away form the control group. Specifically, we set up a DiD model based on the decisions made by countries and tournament organizers to hold matches without spectators. This exogenous shock permits us to compare the difference between tennis athletes' probability of winning when playing at home and away with an audience versus the same difference after the pandemic when matches did not have spectators. The model is estimated as follows:

$$Y_{im} = \alpha + \beta Home_{im} + \gamma Closed_m + \delta Home_{im} \times Closed_m + \lambda Controls + \phi_i + \phi_t + \epsilon_{im}, \tag{2}$$

where $Closed_m$ is a binary indicator that equals 1 for matches played behind closed doors during the COVID-19 pandemic and 0 otherwise. In this second case, we are particularly interested in examining the significance, sign, and magnitude of the DiD coefficient δ that indicates the differential effect of playing at home when behind closed doors with respect to β. In other terms, the linear

[3] All the matches played behind closed doors in our sample are due to restrictions related to COVID-19 pandemic. To the best of our knowledge, the only instance of a men's tennis match played behind closed doors prior to the COVID-19 pandemic occurred in 2009 during a Davis Cup match between Sweden and Israel in Malmö, due to political reasons (https://www.france24.com/en/20090306-empty-stadium-hosts-sweden-israel-tennis-match-). Since Davis Cup matches are not part of ATP tournaments, this does not affect our analysis.

Table 2

Variable description. This table includes the name, description, source, and measure of the variables used in the empirical analyses of this paper.

Variable	Description	Source	Measure
Win	Binary indicator equal to 1 if the reference player wins the match, and 0 if they lose.	*ATP Tennis Rankings, Results, and Stats*	Binary indicator
Home	Binary indicator equal to 1 if the athlete competes in their home country against a non-local opponent, 0 otherwise.	Authors' elaboration based on *ATP Tennis Rankings, Results, and Stats*	Binary indicator
Age Difference	Difference in age (years) between the reference player and the opponent at the beginning of the match.	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Height Difference	Difference in height (centimeters) between the reference player and the opponent.	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Rank Difference	Difference in the athletes' position (in thousands) in the ATP Rank between the opponent and the reference player at the beginning of the match.	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Points Difference	Difference in ATP points (in thousands) between the reference player and the opponent at the beginning of the match.	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Top-10-ATP	Categorical variable with four outcomes indicating whether the reference player and/or the opponent were ranked in the ATP Top 10 at the match start.	Authors' elaboration based on *ATP Tennis Rankings, Results, and Stats*	Categorical indicator
Individualist	Binary indicator equal to 1 if the reference player is from a country ranked in the top 25 % of Hofstede's Individualism Index, 0 otherwise.	Hofstede (2011)	Binary indicator
Collectivist	Binary indicator equal to 1 if the reference player is from a country ranked in the bottom 25 % of Hofstede's Individualism Index, 0 otherwise.	Hofstede (2011)	Binary indicator
Closed	Binary indicator equal to 1 if the match is played behind closed doors, 0 otherwise.	Different sources including ATP and tournaments' official websites	Binary indicator
Travel Fatigue	Categorical variable with three outcomes indicating whether only the reference player, only the opponent, both or neither competed in a different country within the last seven days.	Authors' elaboration based on *ATP Tennis Rankings, Results, and Stats*	Categorical indicator
Familiarity	Continuous indicator measuring the number of matches the reference player has played in the same tournament within the last year.	Authors' elaboration based on *ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Difference Aces	Difference in the number of aces between the reference player and their opponent.	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Ratio Games	Ratio between the number of wins and total games by the reference player.	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Games Difference	The difference between the number of games won by the reference player and the opponent.	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Double Faults	Number of double faults of the reference player (in natural logarithm).	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator
Saved Breakpoints	Ratio of saved breakpoints to total breakpoints faced by the reference player.	*ATP Tennis Rankings, Results, and Stats*	Continuous indicator

combination of $\beta + \delta$ indicates the difference in the probability of winning between athletes playing at home and away behind closed doors. If this linear combination is not aligned with the sign and significance of β, then we can conclude that the audience presence is influential in determining the winner of a tennis match.

Lastly, we also conduct several robustness checks to verify the stability of our results across different model specifications. This includes limiting the sample to matches with at least one player at home, incorporating additional match characteristics that could influence the outcomes, and excluding specific tournaments that might disproportionately impact the overall results.

4. Results

4.1. Baseline results

We first consider the results of the Eq. (1) estimations to investigate the presence of HA in tennis matches. Table 3 presents our findings, where we progressively introduce different sets of fixed effects in the specifications of the models. Specifically, Column 1 includes player and tournament date fixed effects, Column 2 introduces year fixed effects, Column 3 country fixed effects, and Column 4 shows the interaction between year and player fixed effects.

We find that the estimated coefficients for our main variable of interest, *Home*, is always positive and statistically significant across all the specifications, with a fairly stable magnitude ranging between 0.041 and 0.049. These results provide evidence for the presence of HA in tennis matches. The estimated coefficients for the control variables show the expected signs. In particular, on average, younger players (*Age Difference*) had fewer chances to win a match (−0.004), while taller players (*Height Difference*) had more chances (0.003). The recognized relative strength of the athletes (*Rank Difference* and *Point Difference*) had an important role, with higher-ranking players in a better position and more likely to win a match.[4]

Overall, these results confirm the hypothesis of existence of HA in tennis, similarly to findings from other individual or team sports (e.g., Farnell, 2023; Fischer and Haucap, 2021; Scoppa, 2021).[5]

4.2. Robustness tests

We conduct a series of robustness checks to assess the validity and stability of our baseline findings. These analyses are designed to test the sensitivity of our results to alternative definitions of treatment and control groups, the inclusion of additional match-level characteristics, and the exclusion of specific countries or tournaments that could disproportionately influence the results. All robustness results are reported in Section B of the Appendix.

First, in our baseline specification, we define the variable *Home* as equal to 1 when a player competes in their home country against an opponent who is not playing at home, thereby considering *Home* equal to 0 also when both players are at home. We begin by considering a broader definition of *Home*, setting it equal to 1 whenever a player is at home, regardless of the opponent's status. The results under this alternative definition (Table B1) are consistent with those of the baseline model.

Alternatively, we explore the potential bias arising from matches where both players are at home—though such matches constitute only 3 % of the sample—by excluding them entirely. The resulting estimates (Table B2) remain closely aligned with the baseline findings. We further examine the effect of matches in which neither player is at home by restricting the sample to only those matches involving at least one home player. Again, the results (Table B3) exhibit similar patterns in terms of coefficient sign and statistical significance, despite a reduction in the number of observations.

Second, we address the possibility that surface type or tournament category may confound the observed home advantage by including fixed effects for both variables. As shown in Table B4, the inclusion of these controls does not meaningfully alter our results.

Third, to test whether specific countries or tournaments disproportionately drive our findings, we conduct a leave-one-out analysis by iteratively excluding one country or tournament at a time. The estimated coefficients for home advantage remain positive, statistically significant, and consistent in magnitude (Fig. B1).

Fourth, we consider two alternative dependent variables as performance measures that, like our primary win/loss outcome, capture overall player performance but are less sensitive to the binary match outcome. These are: (i) the ratio of games won to total games played (*Ratio Games*), and (ii) the difference between games won and games lost by the player (*Difference Games*). The estimates based on these alternative metrics (Table B5) corroborate our main results.

Finally, although our baseline analysis uses a linear probability model due to its flexibility in incorporating multiple fixed effects,

[4] Given the inclusion of several control variables in the model, a potential concern could be the presence of high correlation and multicollinearity in the estimations. To address potential multicollinearity concerns, we examined pairwise correlations among the covariates, as reported in Table A2. The matrix combines Pearson correlations for pairs of continuous variables and polychoric correlations when at least one of the variables is binary or ordinal. All correlation coefficients are below 0.5, except for three pairwise correlations—*Ratio Games* vs. *Win, Games Difference* vs. *Win*, and *Ratio Games* vs. *Games Difference*—which fall between 0.5 and 0.75. This is not a concern, as these variables are never included in the same estimation. Additionally, we conducted a variance inflation factor (VIF) analysis to test for multicollinearity in the baseline models. The VIF values for individual variables, as well as the overall model, were consistently below the standard threshold of 5. These results provide reassurance about the validity of the model and the absence of multicollinearity in our estimates.

[5] For the sake of robustness, we replicated these estimations limiting the analysis to a more recent sample (2012–2022). The results align with our baseline findings and are available upon request.

Table 3
Baseline Results. The analysis covers the time span from 2000 to 2022 and 1488 players. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. The table reports coefficient estimates followed by standard errors, clustered at the player level, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Win			
Dependent Variable	(1)	(2)	(3)	(4)
Home	0.043***	0.049***	0.043***	0.041***
	(0.006)	(0.005)	(0.006)	(0.006)
Age Difference	−0.004***	−0.004***	−0.004***	−0.004***
	(0.001)	(0.000)	(0.001)	(0.001)
Height Difference	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Rank Difference	0.558***	0.564***	0.556***	0.620***
	(0.027)	(0.028)	(0.027)	(0.033)
Points Difference	0.053***	0.054***	0.053***	0.061***
	(0.003)	(0.003)	(0.003)	(0.002)
Observations	59,067	59,067	59,067	59,067
Adjusted R-squared	0.139	0.143	0.139	0.137
Player Fixed Effects	Yes	Yes	Yes	Yes
Tournament-date Fixed Effects	Yes	No	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes
Country Fixed Effects	No	No	Yes	Yes
Player × Year Fixed Effects	No	No	No	Yes

we also estimate nonlinear specifications using Probit (Column 1, Table B6) and Logit (Column 2, Table B6) models, including only year and country fixed effects due to convergence constraints. The marginal effects reported in Panel B of Table B6 indicate a home advantage of around 3.5 percentage points, consistent with the magnitude obtained from the baseline analysis.

Together, these robustness checks confirm that our findings are not sensitive to model specification, sample selection, or contextual variation, thereby reinforcing the credibility of our main results.

5. Investigating the mechanisms behind home advantage

After having shown that, in professional tennis, home players consistently have a higher probability of winning a match, this section explores how individual player characteristics may influence the home advantage. This setting offers a distinctive advantage, as tennis being an individual sport allows us to directly observe player-specific characteristics—whereas most studies on HA focus on team sports and, when considering individual factors, analyze them at the group level or as averages across players, which inevitably requires certain assumptions and approximations.[6]

First, we analyze whether talent and experience play a role, considering that more talented or experienced athletes may rely more on internal resources than on the greater familiarity with the home environment to achieve a match victory. Along the same lines, we investigate whether the player's cultural background—and thus their greater or lesser tendency toward individualism or collectivism (according to Hofstede, 2011)—might lead them to fully or only partially exploit the advantages of playing at home.[7]

5.1. Talent and experience

We explore how players' talent and experience influence the extent of their home advantage. Highly talented players often have more experience in high-pressure situations, enabling them to capitalize on familiar conditions more effectively. They may also possess

[6] For example, in team sports, team quality is often proxied by past results, such as performance in latest matches (Scoppa, 2021) or in previous seasons (Ferraresi and Gucciardi, 2023). These measures are useful indicators of overall team strength, but they naturally provide less detail at the individual level, since rosters and lineups change and aggregate results reflect collective rather than individual, player-specific contributions.

[7] A potential concern of this kind of analysis is self-selection: *ex ante*, some of the dimensions along which we test heterogeneity (e.g., experience, talent) could be subject to the risk that certain types of players are disproportionately represented at home. Several features of our setting reduce this risk. Our specification includes rich fixed effects and controls (ATP ranking/points, age) that absorb talent and age differences at the match level, where identification relies on opponent differentials rather than levels. Moreover, ATP participation rules limit strategic sorting into home events: "Commitment Players" (top-30) must enter all Masters 1,000 and a set of ATP 500 tournaments, and once accepted into a mandatory event, a withdrawal without valid reason yields a zero-point result that counts toward the ranking; for others, rankings are computed on the best-18 results and unjustified withdrawals likewise incur zero-point penalties (see the ATP Official Rulebook at https://www.atptour.com/en/corporate/rulebook). Finally, patterns such as home wild cards for younger players or the fact that more talented and successful players accumulate more matches reflect tournament structure and performance rather than selective home participation. While residual self-selection cannot be fully excluded, the institutional features of the ATP tour and our modeling choices substantially reduce its threat to identification.

greater psychological resilience, allowing them to perform at high level in a setting that is more familiar. However, the expectations placed on top athletes can sometimes introduce added pressure, making them more susceptible to performance fluctuations if they feel the need to meet high standards and expectations.

Performance in sports also depend on player's experience (Staufenbiel et al., 2018). Less experienced players may derive greater benefits from competing at home compared to their seasoned counterparts. Familiar surroundings can boost their confidence and help them manage the challenges of competition. However, while they may gain confidence, less experienced players might struggle to effectively leverage it if they become overwhelmed by key moments. Difficulties in maintaining focus and composure could prevent potential advantages from translating into improved performance.

To test for this, we augment the baseline model by introducing interaction terms between *Home* and two alternative indicators: *Top-10 ATP* and *Age Difference*. *Top-10 ATP* is a proxy for player talent, defined as a categorical variable with four possible outcomes based on whether the player and/or the opponent were ranked within the ATP Top 10 at the start of the match. This allows us to distinguish between matches where neither, one, or both players were highly ranked, thereby assessing whether home advantage varies with player quality. *Age Difference* is the same variable previously included as a control, which captures the age difference between the focal player and their opponent. This indicator serves as a proxy for relative experience and may influence the extent to which players benefit from home conditions.

Table 4 reports the results, showing that HA appears to be similarly relevant for both top-ranked and lower-ranked players (Column 1). Specifically, the interaction terms between *Home* and *Top-10 ATP* or *non-Top-10 ATP* status are not statistically significant, suggesting that the effect of playing at home does not differ systematically with player ranking. In contrast, the analysis of experience

Table 4

Mechanisms – Players' individual factors. The analysis covers the time-span from 2000 to 2022 and 1,488 players. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Top-10-ATP* is a categorical indicator with four outcomes depending on the position in the ATP ranking before the match of both the player and the opponent. *Individualist* and *Collectivist* are binary indicators set to 1 if a player is from a country ranked in the top 25 % of individualistic or collectivist cultures, respectively, according to Hofstede (2011). *Controls* is a vector of variables, including: *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. The table reports coefficient estimates followed by standard errors, clustered at the player level, in parentheses. The linear combination of *Home* and interaction terms is reported only when the coefficients of the interaction terms are statistically significant. The main effects for *Individualist* and *Collectivist* are subsumed by the fixed effects and therefore not separately reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

		Win		
Dependent Variable		(1)	(2)	(3)
Home	(A)	0.043***	0.041***	0.026***
		(0.007)	(0.006)	(0.008)
Top-10 vs *non-Top-10*		−0.095***		
		(0.016)		
non-Top-10 vs *Top-10*		−0.135***		
		(0.010)		
Top-10 vs *Top-10*		−0.161***		
		(0.029)		
Home × *Top-10* vs *non-Top-10*		0.011		
		(0.017)		
Home × *non-Top-10* vs *Top-10*		−0.014		
		(0.017)		
Home × *Top-10* vs *Top-10*		−0.048		
		(0.034)		
Age Difference			−0.004***	
			(0.001)	
Home × *Age Difference*	(B)		−0.002**	
			(0.001)	
Home × *Individualist*	(C)			0.035**
				(0.014)
Home × *Collectivist*				0.000
				(0.023)
Linear Combination	(A) + (B)		0.041***	
	(A) + (C)			0.061***
Observations		59,067	59,067	59,067
Adjusted R-squared		0.141	0.137	0.138
Controls		Yes	Yes (No Age Diff.)	Yes
Player FEs		Yes	Yes	Yes
Tournament-edition FEs		Yes	Yes	Yes
Year FEs		Yes	Yes	Yes
Country FEs		Yes	Yes	Yes
Player × Year FEs		Yes	Yes	Yes

(Column 2) supports the hypothesis that less experienced players derive greater benefit from playing at home. The interaction term *Home* × *Age Difference* is negative and statistically significant, indicating that the HA diminishes as the age (and presumably experience) gap increases. However, the magnitude of this interaction effect remains modest. Overall, these findings suggest that experience plays a more relevant role than talent in shaping home advantage.

5.2. Cultural factors

We are interested in examining how cultural characteristics, particularly those tied to nationality, may influence the effect of HA. Cultural differences shape how athletes perceive and respond to external support (Galli and Vealey, 2008). Drawing on Hofstede's (2011) cultural dimension of individualism versus collectivism, we investigate whether players from more individualistic cultures—where personal achievement, independence, and self-reliance are emphasized—derive greater benefits from home conditions. The underlying rationale is that individualistic players, who tend to rely on internal motivation and personal resources, may find the home environment particularly performance-enhancing.

To test this, we interact the *Home* variable with binary indicators for individualism and collectivism. A player is classified as *Individualist* if they are from a country in the top 25 % of Hofstede's Individualism Index, and *Collectivist* if they are from a country in the bottom 25 %. Results are reported in Column 3 of Table 4. The coefficient for *Home* remains positive and significant. Notably, the interaction between *Home* and *Top-25 % Individualist* is positive and statistically significant, while the interaction between *Home* and *Top-25 % Collectivist* is close to zero and not significant. This suggests that the HA effect is stronger for players from individualistic cultures.

Overall, these findings indicate that individualism moderates the impact of home advantage. Players from individualistic cultures appear to benefit more from home conditions, likely due to their greater reliance on personal motivation and internal psychological resources. In contrast, collectivist players—whose strengths may be more rooted in group dynamics and shared identity—do not show a comparable enhancement in performance when playing at home.

6. Home advantage channels

We now investigate the situational channels that may underlie the HA. Situational channels stem from external contextual conditions before or during the competition. These factors are important because they can shape the conditions under which HA emerges, influencing player's performance in ways that may favor the home competitor. As already noted in the introduction, the literature identifies several potential drivers of home advantage, mainly attributable to (i) crowd presence, (ii) travel fatigue, and (iii) familiarity with the facilities.[8]

In addition to these traditional factors, we also examine performance in specific high-pressure moments—such as aces, double faults, or saved break points—as potential situational channels. These match events, while reflecting player skill, occur in specific contexts that are shaped by the environment and the competitive situation, including pressure, momentum shifts, and audience influence. For this reason, they may be considered components of the situational dynamics that can amplify or mitigate HA.

6.1. Audience presence

As noted earlier, HA can arise from multiple situational factors that often occur together. Under normal conditions, separating these factors can be challenging, as they tend to co-occur. However, the opportunity presented by the COVID-19 pandemic, which led to many matches being played behind closed doors without fans, allowed us to isolate the specific effect of the presence or absence of supporters, although it does not allow us to isolate other potential channels. Hence, we investigated the influence of an audience on explaining tennis players' performance when playing at home compared with playing away in a DID setting.[9]

The result of the DID estimations based on Eq. (2) is presented in Column 1 Table 5, confirming the HA effect when matches were

[8] Another factor, that of referees, may play a significant role in various sports but is excluded from our analysis. In the case of tennis, referees play a more limited role, as they intervene in a relatively small number of situations and, in the event of disputes, such disputes are often resolved through the use of objective tools such as Hawk-Eye.

[9] A fundamental assumption of the DID application is the presence of parallel trends in the dependent variables before the treatment between the treated and control groups. In our case, this implies that the probability of winning a match played at home should follow a similar pattern to those played away in the period before the pandemic when all matches were played with spectators. We conduct a parallel trends test following the approach of Gertler et al. (2016), verifying that changes in the probability of winning a match evolved similarly for players competing at home and away prior to the onset of the pandemic and the implementation of audience restrictions. Specifically, the test compares the average growth rates of the dependent variable across the two groups before the pandemic restrictions. The results reported in Table B7 in the Appendix indicate no significant differences in these pre-treatment trends between home and away matches, supporting the validity of the parallel trends assumption. While the parallel trends assumption is supported by the Gertler test, we cannot fully exclude that some differential COVID-related shocks—such as training restrictions or quarantines—might have affected groups differently, which should be considered when interpreting the results. Last, to address concerns about potential self-selection bias regarding the quality gap between treatment and control groups under closed-door conditions, we conducted t-tests comparing player rankings across groups. These tests showed no statistically significant differences in player quality between home and away players in either closed-door or open-door matches, indicating that the quality distribution remained stable (detailed results available upon request).

played in the presence of an audience. Indeed, we document positive and statistically significant coefficients for *Home*, with coefficient (0.043) similar in magnitude to those of Table 3. We also find a negative, though insignificant, estimated coefficient of the DID indicator *Home* × *Closed*, with the linear combination of the coefficients for *Home* and *Home* × *Closed* being close to zero and not significant based on the model's specifications.

As a validity check, we run a placebo test by artificially coding all matches in 2019 as closed-door. The results (Table B.8 Column 1 in the Appendix) show no significant effect, consistent with the main analysis and suggesting that the DiD design does not spuriously detect an effect when no treatment occurred.

In a further analysis, we exclude from the estimations open-door matches played during the 2020–2022 period to address the concern that audience behavior may have changed following the pandemic outbreak. While this changes the composition of the control group relative to the baseline DiD setup, it may help reduce concerns about potential confounding effects from changes in audience behavior and other pandemic-related factors, allowing for a cleaner comparison between pre-pandemic matches (with full crowd presence) and those held without spectators. Results from this restricted sample (Table B.8 Column 2 in the Appendix) continue to show a significant HA in the presence of fans, and provide modest evidence that the absence of spectators may attenuate this effect: the interaction *Home* × *Closed* is negative and marginally significant at the 10 % level, while the linear combination of *Home* and *Home* × *Closed* remains indistinguishable from zero.

6.2. Travel fatigue

The role of travel fatigue in influencing HA in sports has received attention, as athletes often face significant challenges when competing in away games, particularly when long distances and jet lag are involved (see, e.g., Manfredini et al., 1998; Oberhofer et al., 2010; Wunderlich et al., 2023; Zak, 2021). Given its potential relevance to match outcomes, it is important to measure this factor explicitly. Hence, we operationalize travel fatigue by constructing a proxy variable, *Travel Fatigue*, based on the players' travel patterns between tournaments. Specifically, for each player (and opponent), we considered them to be travel-fatigued (*Travel Fatigue* equal to 1) if they competed in their previous match in a different country than the current one, in the previous week.[10] If either condition was not met — i.e., the player remained in the same country or had a rest period longer than a week — they were coded as not travel-fatigued (*Travel Fatigue* equal to zero). This binary indicator was created separately for both the reference player and their opponent. We then combined these into a categorical variable capturing relative fatigue conditions, distinguishing cases where only the opponent was fatigued, only the player was fatigued, or both/neither were fatigued.

Column (2) of Table 5 presents the results of the analysis incorporating an interaction term between *Home* and *Travel Fatigue*, allowing us to examine how travel fatigue relates both to the opponent's and the player's performances. Our results show that the interaction term for *Home* × *Travel Fatigue (opponent)* is positive and marginally statistically significant (10 % level), indicating a potential increase in HA when the opponent experiences higher levels of travel fatigue. Conversely, we find that travel fatigue for the home player does not significantly diminish the HA, as indicated by the small and statistically insignificant coefficient for *Home* × *Travel Fatigue (player)*. This suggests that the effect of travel fatigue is more pronounced for the visiting player, supporting the notion that the relative strain on the opponent enhances the home player's chances of winning. The results suggest that HA may partly reflect the influence of players' prior accumulated travel fatigue.

6.3. Familiarity with venues and facilities

While familiarity with a venue or its facilities is often considered an important aspect of HA, as athletes may perform better when comfortable with local conditions (see, e.g., Loughead et al., 2003), its role is less clear in sports like tennis, where players frequently compete at different venues across countries due to the highly international nature of the ATP tour. Familiarity with facilities remains relevant for HA, however, as repeated exposure to the same tournament may confer subtle advantages in anticipation, preparation, or psychological comfort. To account for this, we constructed a continuous variable, *Familiarity*, measuring the number of matches a player had competed in at the same tournament during the previous year. This variable captures recent exposure to the tournament setting and allows us to test whether prior participation provides an advantage in performance at home.

Column (3) of Table 5 introduces an interaction term for *Home* × *Familiarity* to examine whether familiarity with the tournaments' facilities amplifies HA. The estimated coefficient is small in magnitude and statistically not significant, suggesting that, in this context, familiarity with the venue does not meaningfully affect match outcomes. Overall, our findings offer little support for familiarity with facilities as a key driver of HA.

6.4. High-pressure tasks

We now examine whether the higher probability of home players winning can be linked to their performance in specific high-pressure moments—such as aces, double faults, or saved break points. These actions, often decisive in determining match outcomes, occur under intense pressure and within contexts influenced by factors such as momentum shifts, audience presence, and other situational conditions. Such high-pressure, context-dependent moments can provide insights into how HA is reflected in observable on-

[10] Due to data availability, we cannot use a daily measure of travel fatigue, as the original database provides information by week rather than the exact match date.

court behavior.

To explore this, we focus on three key performance indicators: the difference in the number of aces (*Difference Aces*) between players and the number of double faults (*Double Faults*), which capture aspects of precision, focus, and mental control under pressure; and the ratio between saved vs total breakpoints (*Saved Breakpoints*), which reflects a player's resilience and ability to perform in critical, high-stakes moments during a match.

The results, reported in Table 5, show that players competing at home produce a higher relative number of aces and save more breakpoints compared to their opponents (columns 4 and 6), while committing fewer double faults despite this effect being slightly below the significance threshold (column 5). These patterns suggest that home players are not only performing better, but are also demonstrating greater psychological composure and decision-making in key situations. In other words, HA appears to strengthen a player's ability to manage pressure, maintain technical precision, and elevate their game when it matters most.

7. Conclusions and implications

Human behavior in sports offers a valuable perspective for exploring how individuals and teams cope with challenges and make decisions in environments of fierce competition that require using all possible resources to win. In this paper, we focus on Home Advantage, a well-studied psychological phenomenon that reveals that athletes playing at home show some advantages with respect to those away which in the end increase their chance to perform better and ultimately win a match.

While previous research has primarily focused on team sports, our study shifts the focus to individual sports, specifically men's tennis, which offers an ideal setting to test this phenomenon. Key factors such as regular matchups, the absence of draws, strong motivation to win, and the use of technology to limit referee bias make it particularly suitable. We use a comprehensive dataset of ATP-

Table 5

Channels. The analysis covers the time span from 2000 to 2022 and 1,488 players. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. Column 1 reports results from the estimation of a DiD model, while the remaining columns present estimates from fixed-effects regressions. The table reports coefficient estimates followed by standard errors, clustered at the player level, in parentheses. The linear combination of *Home* and interaction terms is reported only when the coefficients of the interaction terms are statistically significant. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

		Win			Difference Aces	Double Faults	Saved Breakpoints
Dependent Variable		(1) – Audience Presence (DiD)	(2) – Travel Fatigue	(3) - Familiarity	(4)	(5)	(6)
Home	(A)	0.043***	0.037***	0.037***	0.435***	−0.013	0.008***
		(0.006)	(0.007)	(0.008)	(0.067)	(0.008)	(0.003)
Closed		0.023					
		(0.046)					
Home × *Closed*		−0.036					
		(0.028)					
Travel Fatigue (player)			0.043***				
			(0.009)				
Travel Fatigue (opponent)			−0.016*				
			(0.010)				
Home × *Travel Fatigue (player)*			0.003				
			(0.016)				
Home × *Travel Fatigue (opponent)*	(B)		0.039*				
			(0.021)				
Familiarity				0.004			
				(0.003)			
Home × *Familiarity*				0.003			
				(0.004)			
Linear Combination	$A + B$		0.076***				
Observations		59,067	59,067	55,020	57,325	57,325	54,531
Adjusted R-squared		0.137	0.137	0.139	0.377	0.236	0.025
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Player Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Tournament-edition Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Player × Year Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes

level tournaments covering an extensive and recent period (2000–2022) to investigate the presence of HA in tennis. Our findings indicate that players competing at home have approximately a 4-percentage-point higher probability of winning a match compared to those playing away, supporting the HA hypothesis.

However, the HA is not uniform and depends on several factors. To better understand the origins of this advantage, we distinguish between two main groups of factors: individual mechanisms, which refer to how specific player characteristics influence HA, and situational channels, which are contextual factors that either amplify or attenuate the advantage.

Individual mechanisms relate to how intrinsic player characteristics, such as talent, experience, and cultural background, affect the impact of the home advantage. While talent does not seem to influence HA, we observed that less experienced players derive greater benefit from home conditions, suggesting that the advantage diminishes as the experience gap increases between the player and the opponent. Additionally, cultural background plays a significant role: athletes from individualistic cultures show a stronger HA, likely because they rely on personal routines and intrinsic motivation, which are reinforced in a familiar environment. In contrast, players from collectivist cultures do not exhibit the same enhancement in HA. These results are consistent with prior evidence showing that individual-level attributes, such as age, experience, and cultural background, influence how much an athlete benefits from the home setting (Carré et al., 2006; Gelade, 2015; Staufenbiel et al., 2018).

Situational channels, on the other hand, refer to external factors that can create or amplify HA, regardless of player characteristics. To isolate the effect of crowd support, we took advantage of the COVID-19 pandemic, which led to matches being played behind closed doors. The results of this analysis suggest that, even in the absence of an audience, HA persists despite a lower magnitude. While the presence of a crowd could be one contributing factor to HA, it is unclear whether it plays a primary role, or whether other factors also significantly influence HA. Another situational factor we explored was travel fatigue, finding that HA increases when the opponent is more fatigued from travel, while the fatigue of the home player does not have a significant role. This supports the idea that the HA is also linked to reduced travel stress. Finally, we examined the role of familiarity with facilities, with the results not suggesting that prior knowledge of the tournament or venue has a substantial effect. This implies that, while a familiar environment may seem like an intuitive advantage, its actual impact is limited.

In general, our results confirm that HA is the result of a combination of both intrinsic and contextual factors. While crowd support is a commonly cited explanation for HA, our study suggests that its impact is not decisive. Factors such as psychological comfort, reduced travel fatigue, and the interplay between the environment and player characteristics like experience and culture seem to play just as, if not more, significant a role in determining the HA.

Despite focusing on a specific context, our findings have broader implications for workplace incentive design and performance assessment. Just as athletes perform better in a familiar environment, employees working in consistent and well-structured settings—where they can rely on established routines and maintain a sense of personal control—may experience enhanced performance. Our analysis of the mechanisms behind HA underscores the importance of familiarity in boosting concentration and resilience, particularly during high-skill and high-pressure tasks. Moreover, the moderating role of experience on the benefits of a supportive environment suggests that less experienced employees may require additional encouragement and resources to perform at their best. Tailoring organizational support to account for varying levels of experience could help maximize productivity and well-being across the workforce.

Cultural background also shapes how individuals respond to their environment. Employees from more individualistic cultures may benefit disproportionately from familiar and empowering settings. In such cultures, where individuals are often motivated by personal goals and self-determination, a positive and enabling atmosphere can be especially effective in enhancing performance—particularly when individuals feel aligned with their environment and autonomous in their role. These findings align with prior research indicating that employee engagement (Saks, 2006) and a supportive atmosphere (Luthans et al., 2008) are critical for improving outcomes such as organizational commitment and job satisfaction.

Additionally, while external observation—such as the presence of an audience or supervisor—has been found to influence teams' performance (e.g., Fischer and Haucap, 2021, Scoppa, 2021), our findings suggest that its role may be less significant in individual context. In our analysis, the removal of the crowd during the COVID-19 period did not significantly reduce the home advantage. This indicates that familiarity with one's surroundings, rather than external observation alone, is a more powerful driver of performance.

In today's post-COVID-19 work environment, where remote work has become common, these insights carry particular relevance. Employees who lack a familiar or structured work context may underperform—not because they are unseen, but because they are disconnected from an environment that supports focus and routine. This may partially explain why some organizations are encouraging a return to in-person work: not purely for oversight, but to reintroduce environmental consistency, social embeddedness, and routines specific to the professional setting—factors that, while distinct from the general physical familiarity of one's home, may better replicate the conditions under which task-specific skills are practiced and refined.

In conclusion, our findings confirm that a familiar environment enhances individual performance—even in individualistic and high-pressure domains such as professional tennis. However, several limitations offer avenues for future research. First, this study focuses exclusively on male tennis players to ensure consistency in match format and tournament structure. Future work could explore whether these dynamics apply similarly to women's tennis. Second, due to a lack of detailed attendance data in tennis, alternative measures to proxy crowd support could be adopted (e.g., social media sentiment). Finally, while our analysis centers on singles matches, doubles tennis presents a promising opportunity to study small-group dynamics. Future research could also explore how team composition—such as gender mix, nationality, cultural background, and experience level—interacts with contextual factors to shape performance and home advantage.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Variables and sample description

Table A1
Distribution of matches and home player win percentage by country. This table shows the distribution of matches by country, including home and away attributes (i.e., whether at least one player is playing at home or both are away), open-doors/closed-doors attributes, and the home player win percentage for both the full sample and closed-doors matches only.

Country	Matches					Home player win percentage	
	Total	o/w Home	o/w Away	o/w Open-doors	o/w Closed-doors	Total	Closed-doors
Argentina	746	438	308	692	54	54 %	61 %
Australia	4,836	781	4,055	4,608	228	45 %	44 %
Austria	1,669	346	1,323	1,615	54	46 %	44 %
Belgium	184	26	158	158	26	38 %	25 %
Brazil	821	191	630	821	0	40 %	–
Bulgaria	185	23	162	132	53	26 %	17 %
Canada	1,215	145	1,070	1,169	46	35 %	0 %
Chile	520	123	397	493	27	50 %	57 %
China	1,570	112	1,458	1,570	0	18 %	–
Colombia	141	34	107	141	0	41 %	–
Croatia	887	219	668	861	26	50 %	33 %
Denmark	121	10	111	121	0	30 %	–
United Arab Emirates	698	0	698	655	43	–	–
Ecuador	106	9	97	106	0	22 %	–
Spain	2,669	1,308	1,361	2,519	150	54 %	58 %
France	5,979	2,211	3,768	5,600	379	49 %	33 %
United Kingdom	4,654	626	4,028	4,466	188	49 %	55 %
Germany	3,516	1,188	2,328	3,328	188	47 %	46 %
Greece	62	1	61	62	0	0 %	–
Hong Kong	91	2	89	91	0	0 %	–
Hungary	79	9	70	79	0	33 %	–
India	682	91	591	682	0	22 %	–
Israel	26	2	24	26	0	50 %	–
Italy	1,897	405	1,492	1,712	185	41 %	50 %
Japan	860	0	860	796	64	–	–
Kazakhstan	83	14	69	30	53	36 %	40 %
Korea	24	4	20	24	0	0 %	–
Morocco	596	67	529	596	0	42 %	–
Malaysia	181	2	179	181	0	0 %	–
Mexico	837	48	789	782	55	4 %	0 %
Monaco	1,228	22	1,206	1,176	52	23 %	0 %
Netherlands	1,555	302	1,253	1,524	31	44 %	0 %
Poland	235	26	209	235	0	15 %	–
Portugal	621	91	530	596	25	36 %	33 %
Qatar	683	21	662	658	25	0 %	0 %
Romania	485	98	387	485	0	41 %	–
South Africa	93	30	63	93	0	53 %	–
Russia	1,184	468	716	1,100	84	53 %	53 %
Singapore	27	0	27	0	27	–	–
Serbia	183	63	120	156	27	52 %	38 %
Switzerland	1,430	299	1,131	1,404	26	50 %	40 %
Sweden	1,221	302	919	1,195	26	48 %	33 %
Thailand	310	34	276	310	0	38 %	–
Turkiye	211	18	193	184	27	11 %	25 %
United States of America	14,444	5,233	9,211	14,123	321	51 %	49 %
Uzbekistan	89	5	84	89	0	20 %	–
Vietnam	29	1	28	29	0	0 %	–
Total	**59,963**	**15,448**	**44,515**	**57,473**	**2,490**	**48 %**	**46 %**

Table A2

Correlation Matrix. The table reports the pairwise Pearson correlation when both the variables are continuous and the Polychoric correlation when at least one is binary/categorical (see Table 2 - Column "Measure").

	Win	Home	Age Difference	Height Difference	Rank Difference	Points Difference	Top-10-ATP	Individualist	Collectivist	Closed	Travel Fatigue	Familiarity	Difference Aces	Ratio Games	Games Difference	Double Faults	Saved Breakpoints
Win	1.000																
Home	−0.023	1.000															
Age Difference	−0.032	−0.065	1.000														
Height Difference	0.081	0.031	−0.087	1.000													
Rank Difference	0.393	−0.229	0.086	0.034	1.000												
Points Difference	0.487	−0.068	0.019	0.043	0.323	1.000											
Top-10-ATP	−0.053	−0.070	0.036	−0.022	0.005	−0.090	1.000										
Individualist	−0.028	0.422	−0.090	0.071	−0.066	−0.072	−0.044	1.000									
Collectivist	0.004	−0.293	−0.064	0.062	−0.003	0.054	0.020	−0.32	1.000								
Closed	−0.006	0.006	−0.013	0.015	0.000	−0.006	−0.031	0.094	0.037	1.000							
Travel Fatigue	−0.023	−0.068	−0.005	0.001	−0.020	−0.007	−0.105	−0.042	−0.001	0.080	1.000						
Familiarity	0.138	0.340	0.049	0.022	0.121	0.163	0.215	0.075	−0.044	−0.424	−0.078	1.000					
Difference Aces	0.358	0.047	−0.035	0.474	0.122	0.123	−0.018	0.070	0.036	−0.007	−0.002	0.061	1.000				
Ratio Games	0.674	0.005	−0.032	0.042	0.117	0.198	−0.014	−0.036	0.009	−0.008	−0.011	0.042	0.156	1.000			
Games Difference	0.754	−0.001	−0.032	0.057	0.180	0.286	−0.048	−0.024	0.010	0.001	−0.016	0.070	0.240	0.728	1.000		
Double Faults	−0.196	−0.010	−0.007	0.056	−0.055	−0.063	−0.060	0.059	−0.040	−0.012	−0.032	−0.018	0.040	−0.156	−0.129	1.000	
Saved Breakpoints	0.367	0.002	−0.002	0.029	0.083	0.098	0.007	0.015	−0.007	−0.009	−0.021	0.032	0.125	0.216	0.272	0.013	1.000

Appendix B. Robustness tests

Table B1
Robustness: Home advantage (alternative definition of Home). The analysis covers the time-span from 2000 to 2022 and 1,488 players. *Home* is a binary indicator equal to 1 when the player is competing at home, and 0 otherwise. *Controls* is a vector of variables, including: *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. The table reports coefficient estimates followed by standard errors, clustered at the player level, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Win			
Dependent Variable	(1)	(2)	(3)	(4)
Home	0.035***	0.043***	0.035***	0.032***
	(0.005)	(0.005)	(0.006)	(0.006)
Observations	59,067	59,067	59,067	59,067
Adjusted R-squared	0.138	0.143	0.138	0.137
Controls	Yes	Yes	Yes	Yes
Player Fixed Effects	Yes	Yes	Yes	Yes
Tournament-date Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes
Country Fixed Effects	No	No	Yes	Yes
Player × Year Fixed Effects	No	No	No	Yes

Table B2
Robustness: Home advantage (excluding matches where both players are at home). The analysis covers the time-span from 2000 to 2022 and 1,488 players. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Controls* is a vector of variables, including: *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. The table reports coefficient estimates followed by standard errors, clustered at the player level, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Win			
Dependent Variable	(1)	(2)	(3)	(4)
Home	0.040***	0.047***	0.039***	0.038***
	(0.006)	(0.005)	(0.006)	(0.006)
Observations	57,389	57,389	57,389	57,389
Adjusted R-squared	0.138	0.142	0.138	0.136
Matches with both at home excluded	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Player Fixed Effects	Yes	Yes	Yes	Yes
Tournament-date Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes
Country Fixed Effects	No	No	Yes	Yes
Player × Year Fixed Effects	No	No	No	Yes

Table B3

Robustness: Home advantage (excluding matches where none of players are at home). The analysis covers the time-span from 2000 to 2022 and 1,488 players. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Controls* is a vector of variables, including: *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. The table reports coefficient estimates followed by standard errors, clustered at the player level, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Win			
Dependent Variable	(1)	(2)	(3)	(4)
Home	0.071***	0.053***	0.071***	0.081***
	(0.012)	(0.011)	(0.012)	(0.014)
Observations	14,879	14,879	14,879	14,879
Adjusted R-squared	0.159	0.162	0.157	0.108
Matches with none at home excluded	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Player Fixed Effects	Yes	Yes	Yes	Yes
Tournament-date Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes
Country Fixed Effects	No	No	Yes	Yes
Player × Year Fixed Effects	No	No	No	Yes

Table B4

Robustness: Match characteristics. The analysis covers the time-span from 2000 to 2022 and 1,488 players. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Controls* is a vector of variables, including: *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. The table reports coefficient estimates followed by standard errors, clustered at the tournament and player level, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Win	
Dependent Variable	Surface (1)	Tournament (2)
Home	0.042***	0.040***
	(0.006)	(0.006)
Observations	59,067	59,067
Adjusted R-squared	0.137	0.137
Player Fixed Effects	Yes	Yes
Tournament-date Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Player × Year Fixed Effects	Yes	Yes
Surface Fixed Effects	Yes	No
Tournament Fixed Effects	No	Yes

Table B5

Robustness: Alternative dependent variables. The analysis covers the time-span from 2000 to 2022 and 1,488 players. *Ratio Games* represents the proportion of games won by the reference player relative to the total games played. *Difference Games* refers to the difference between the number of games won and games lost by the reference player. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Controls* is a vector of variables, including: *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. The table reports coefficient estimates followed by standard errors, clustered at the tournament and player level, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable	Ratio Games (1)	Difference Games (2)
Home	0.032**	0.200**
	(0.013)	(0.079)
Observations	57,789	57,847
Adjusted R-squared	0.065	0.118
Controls	Yes	Yes
Player Fixed Effects	Yes	Yes
Tournament-date Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Player × Year Fixed Effects	Yes	Yes

Table B6

Robustness: Alternative model (Probit and Logit). The analysis covers the time-span from 2000 to 2022 and 1,488 players. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Controls* is a vector of variables, including: *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. Panel A reports the estimates from Probit (Column 1) and Logit (Column 2) regressions, while Panel B presents the corresponding marginal effects. The table reports coefficient estimates followed by standard errors, clustered at the player level, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A – Probit / Logit estimations		
	Win	
Dependent Variable	(1)	(2)
Home	0.100***	0.170***
	(0.020)	(0.032)
Observations	59,234	59,234
Pseudo R-squared	0.104	0.106
Model	Probit	Logit
Controls	Yes	Yes
Player Fixed Effects	No	No
Tournament-date Fixed Effects	No	No
Year Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Player × Year Fixed Effects	No	No
Panel B – Marginal effects		
	Win	
Dependent Variable	(1)	(2)
Home	0.036***	0.037***
	(0.007)	(0.007)
Observations	59,234	59,234
Pseudo R-squared	0.104	0.106
Model	Probit	Logit
Controls	Yes	Yes
Player Fixed Effects	No	No
Tournament-date Fixed Effects	No	No
Year Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Player × Year Fixed Effects	No	No

Table B7

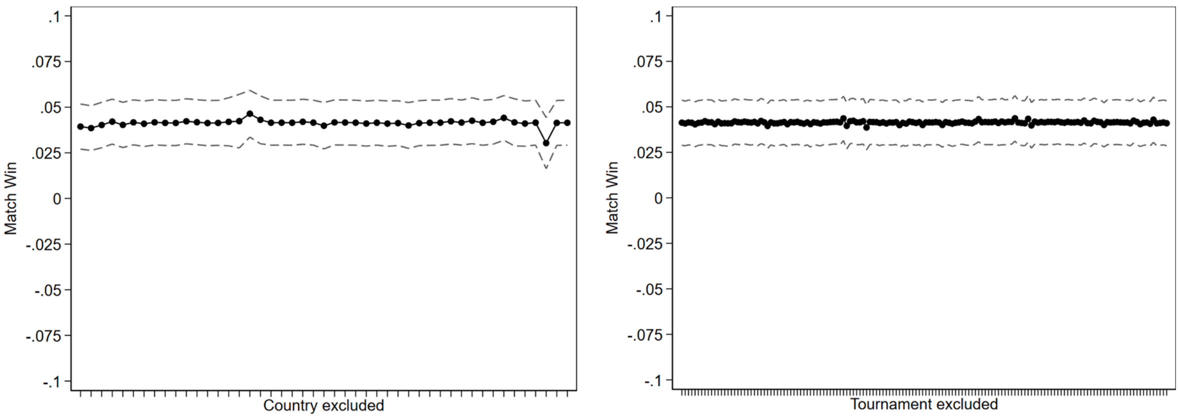
Parallel trend assumption. This analysis follows Gertler et al. (2016) tests by comparing the average growth rate of the dependent variable between treated and untreated groups in the pre-treatment periods. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Treated	Untreated	Difference	P-value
Win	0.001 (0.010)	−0.000 (0.005)	−0.001 (0.005)	0.893

Table B8

Robustness: Crowd support. The analysis covers the time-span from 2000 to 2022 and 1,488 players. *Home* is a binary indicator equal to 1 when the player is competing at home and the opponent is playing away, and 0 otherwise. *Placebo Closed* is a binary indicator equal to 1 for all 2019 matches, and 0 otherwise. *Controls* is a vector of variables, including: *Age Difference* is a continuous indicator built as the difference between the observed player's and their opponent's age. *Age Difference* is a continuous indicator built as the difference between the reference player's and the opponent's age. *Height Difference* is a continuous indicator built as the difference between the reference player's and the opponent's height. *Rank Difference* is a continuous indicator built as the difference between the opponent's and the reference player's ATP rank. *Points Difference* is a continuous indicator built as the difference between the reference player's and the opponent's ATP score. Estimations reported in Column 2 are performed on a subsample excluding open matches played from 2020 to 2022. In these estimations, the main terms for *Placebo Closed* and *Closed* are subsumed by the fixed effects. The table reports coefficient estimates followed by standard errors, clustered at the player level, in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

		Win	
Dependent Variable		(1)	(2)
Home	(A)	0.042*** (0.006)	0.045*** (0.007)
Home × *Placebo Closed*		−0.014 (0.030)	
Home × *Closed*	(B)		−0.052* (0.030)
Linear Combination	(A) + (B)		−0.007
Observations		59,067	55,394
Adjusted R-squared		0.137	0.139
Exclusion from the sample		–	20–22 open matches
Controls		Yes	Yes
Player FEs		Yes	Yes
Tournament-date FEs		Yes	Yes
Year FEs		Yes	Yes
Country FEs		Yes	Yes
Player × Year FEs		Yes	Yes



Panel A Panel B

Fig. B1. Exclusion of one country (Panel A) and tournament (Panel B) at a time. The figure includes the coefficient estimates (bold dots) and their 5 % confidence intervals (grey dashed lines) for different estimations, each excluding one country (Panel A) or tournament (Panel B) at a time.

Data availability

Data will be made available on request.

References

Anbarci, N., Arin, K.P., Kuhlenkasper, T., Zenker, C., 2018. Revisiting loss aversion: evidence from professional tennis. J. Econ. Behav. Organ. 153, 1–18.
Balmer, N.J., Nevill, A.M., Lane, A.M., 2005. Do judges enhance home advantage in European championship boxing? J. Sports Sci. 23 (4), 409–416.
Boudreaux, C.J., Sanders, S.D., Walia, B., 2017. A natural experiment to determine the crowd effect upon home court advantage. J. Sports Econom. 18 (7), 737–749.
Bray, S.R., Obara, J., Kwan, M., 2005. Batting last as a home advantage factor in men's NCAA tournament baseball. J. Sports Sci. 23 (7), 681–686.
Bühren, C., Steinberg, P.J., 2019. The impact of psychological traits on performance in sequential tournaments: evidence from a tennis field experiment. J. Econ. Psychol. 72, 12–29.
Carré, J., Muir, C., Belanger, J., Putnam, S.K., 2006. Pre-competition hormonal and psychological levels of elite hockey players: relationship to the 'home advantage'. Physiol. Behav. 89 (3), 392–398.
Caudill, S.B., Mixon, F.G.J., 2007. Stadium size, ticket allotments and home field advantage in college football. Soc. Sci. J. 44 (4), 751–759.
Courneya, K.S., Carron, A.V., 1992. The home advantage in sport competitions: a literature review. J. Sport Exerc. Psychol. 14 (1).
Dawson, P., Dobson, S., 2010. The influence of social pressure and nationality on individual decisions: evidence from the behaviour of referees. J. Econ. Psychol. 31 (2), 181–191.
Farnell, A., 2023. False start? An analysis of NFL penalties with and without crowds. J. Sports Econom. 15270025221148997.
Ferraresi, M., Gucciardi, G., 2023. Team performance and the perception of being observed: experimental evidence from top-level professional football. Ger. Econ. Rev. 24 (1), 1–31.
Fischer, K., Haucap, J., 2021. Does crowd support drive the home advantage in professional football? Evidence from German ghost games during the COVID-19 pandemic. J. Sports Econom. 22 (8), 982–1008.
Fonti, F., Ross, J.M., Aversa, P., 2023. Using sports data to advance management research: a review and a guide for future studies. J. Manage 49 (1), 325–362.
Galli, N., Vealey, R.S., 2008. Bouncing back" from adversity: athletes' experiences of resilience. Sport Psychol. 22 (3), 316–335.
Gelade, G.A., 2015. National culture and home advantage in football. Cross-Cult. Res. 49 (3), 281–296.
Gertler, P.J., Martinez, S., Premand, P., Rawlings, L.B., Vermeersch, C.M., 2016. Impact Evaluation in Practice. World Bank Publications.
González-Rodenas, J., Aranda-Malaves, R., Tudela-Desantes, A., Nieto, F., Usó, F., Aranda, R., 2020. Playing tactics, contextual variables and offensive effectiveness in English Premier League soccer matches. A multilevel analysis. PLoS. One 15 (2), e0226978.
Greer, D.L., 1983. Spectator booing and the home advantage: a study of social influence in the basketball arena. Soc. Psychol. Q. 252–261.
Grove, W.A., Jetter, M., Papps, K.L., 2021. Career lotto? Labor supply in a superstar market. J. Econ. Behav. Organ. 183, 362–376.
Hofstede, G., 2011. Dimensionalizing cultures: the hofstede model in context. Online Read. Psychol. Cult. 2 (1). https://doi.org/10.9707/2307-0919.1014.
Ishihara, T., Robin, N., Naito, T., Murata, M., Crespo, M., 2022. Effects of the COVID-19 pandemic on professional tennis players' match statistics: a large-scale population-based study. Scand. J. Med. Sci. Sports 32 (10), 1516–1518.
Jamieson, J.P., 2010. The home field advantage in athletics: a meta-analysis. J. Appl. Soc. Psychol. 40 (7), 1819–1848.
Kahn, L.M., 2000. The sports business as a labor market laboratory. J. Econ. Perspect. 14 (3), 75–94.
Koning, R.H., 2011. Home advantage in professional tennis. J. Sports Sci. 29 (1), 19–27.
Losak, J.M., Sabel, J., 2021. Baseball home field advantage without fans in the stands. Int. J. Sport Finance 16 (3).
Loughead, T.M., Carron, A.V., Bray, S.R., Kim, A.J., 2003. Facility familiarity and the home advantage in professional sports. Int. J. Sport Exerc. Psychol. 1 (3), 264–274.
Luciano, M.M., Mathieu, J.E., Park, S., Tannenbaum, S.I., 2018. A fitting approach to construct and measurement alignment: the role of big data in advancing dynamic theories. Organ. Res. Methods 21 (3), 592–632.
Luthans, F., Norman, S.M., Avolio, B.J., Avey, J.B., 2008. The mediating role of psychological capital in the supportive organizational climate-employee performance relationship. J. Organ. Behav. 29 (2), 219–238.
Magrath, R., 2018. To try and gain an advantage for my team': homophobic and homosexually themed chanting among English football fans. Sociology. 52 (4), 709–726.
Manfredini, R., Manfredini, F., Fersini, C., Conconi, F., 1998. Circadian rhythms, athletic performance, and jet lag. Br. J. Sports Med. 32 (2), 101–106.
Marcelino, R., Mesquita, I., Andrés, J.M.P., Sampaio, J., 2009. Home advantage in high-level volleyball varies according to set number. J. Sports Sci. Med. 8 (3), 352.

Meier, P., Flepp, R., Ruedisser, M., Franck, E., 2020. Separating psychological momentum from strategic momentum: evidence from men's professional tennis. J. Econ. Psychol. 78, 102269.
Nevill, A.M., Holder, R.L., Bardsley, A., Calvert, H., Jones, S., 1997. Identifying home advantage in international tennis and golf tournaments. J. Sports Sci. 15 (4), 437–443.
Oberhofer, H., Philippovich, T., Winner, H., 2010. Distance matters in away games: evidence from the German football league. J. Econ. Psychol. 31 (2), 200–211.
Paserman, M.D., 2023. Gender differences in performance in competitive environments? Evidence from professional tennis players. J. Econ. Behav. Organ. 212, 590–609.
Pic, M., 2018. Performance and home advantage in handball. J. Hum. Kinet. 63, 61.
Pollard, R., 1986. Home advantage in soccer: a retrospective analysis. J. Sports Sci. 4 (3), 237–248.
Pollard, R., 2006. Home advantage in soccer: variations in its magnitude and a literature review of the inter-related factors associated with its existence. J. Sport Behav. 29 (2), 169.
Ponzo, M., Scoppa, V., 2018. Does the home advantage depend on crowd support? Evidence from same-stadium derbies. J Sports Econ. 19 (4), 562–582.
[Dataset] Sackmann, J., 2023. ATP Tennis Rankings, Results, and Stats. GitHub. https://github.com/JeffSackmann/tennis_atp.
Saks, A.M., 2006. Antecedents and consequences of employee engagement. J. Manag. Psychol. 21 (7), 600–619.
Schwartz, B., Barsky, S.F., 1977. The home advantage. Soc. Forces 55 (3), 641–661.
Scoppa, V., 2021. Social pressure in the stadiums: do agents change behavior without crowd support? J. Econ. Psychol. 82, 102344.
Snyder, E.E., Purdy, D.A., 1985. The home advantage in collegiate basketball. Sociol. Sport J. 2 (4), 352–356.
Staufenbiel, K., Riedl, D., Strauss, B., 2018. Learning to be advantaged: the development of home advantage in high-level youth soccer. Int. J. Sport Exerc. Psychol. 16 (1), 36–50.
Sutter, M., Kocher, M.G., 2004. Favoritism of agents–the case of referees' home bias. J. Econ. Psychol. 25 (4), 461–469.
Tejkalova, A.N., Kristoufek, L., 2021. Anything can happen in women's tennis, or can it? An empirical investigation into bias in sports journalism. Commun. Sport 9 (5), 742–760.
Thomas, S., Reeves, C., Bell, A., 2008. Home advantage in the six nations rugby union tournament. Percept. Mot. Skills. 106 (1), 113–116.
Wozniak, D., 2012. Gender differences in a market with relative performance feedback: professional tennis players. J. Econ. Behav. Organ. 83 (1), 158–171.
Wunderlich, F., Corten, C., Furley, P., Memmert, D., 2023. Home advantage in tennis exists independent of competition level, gender and COVID-19 restrictions: evidence from German team tennis competitions. Int. J. Sport Exerc. Psychol. 22 (7), 1759–1775.
Zak, U., 2021. The performance advantage of traveling. J. Econ. Psychol. 87, 102431.