Behavioral Home Bias in a Real Market Setting: Evidence from Online Sports Betting*

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Abstract

We study the home bias using individual-level data from an online sports-betting market. Contrary to other markets where home bias is confounded by institutional and information frictions, our market's experimental-like features enable us to test cleanly whether the psychological drivers of the home bias are strong enough to survive significant welfare costs. We find that individuals exhibit a bias toward home teams, which does not yield superior performance but distorts portfolios, generating welfare costs of similar magnitude as in the stock market. Our findings help solidify the foundation of the behavioral explanation of the home bias in other real markets.

Keywords: Individual Decision-making, Behavioral Bias, Local Bias, Home Bias, Sentiment, Information

JEL Classification: D91, G41, D12, D81, G11, G14, G50

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1 Introduction

A large literature in economics and finance has established that individuals exhibit a "home bias" in a wide range of contexts. For instance, investors tilt their portfolios toward securities of their home country or local area, employees invest their retirement savings in their own-company stock, consumers prefer domestic or locally-produced products over foreign-made ones, and trade among individuals is more likely to occur within (rather than across) countries or geographic areas.[1] Many explanations have been put forward in the literature to explain the home bias phenomenon. Some of them appeal to an inherent behavioral bias—possibly due to loyalty, optimism, and/or familiarity—that leads to suboptimal decisions and substantial welfare costs. Others argue that superior information about home markets, hedging motives against real exchange rate and other risks, and transaction costs are the most important factors. In this paper, we contribute to this literature by examining a rich dataset of individual activity in an online sports betting market. Our setting is especially interesting not only because it constitutes a large and fast-growing digital consumer market, but also because it provides a frictionless test bed to examine whether the psychological motives that give rise to the observed home bias can be strong enough to persist in market settings and in the face of substantial welfare costs.

Sports betting is a very common and economically important activity, with "half of America's population and over two-thirds of Britain's [placing a] bet on something" per year (*The Economist*, 8 July 2010) and with $1 trillion wagered on sports, globally, per year (2013 H2 Gambling Capital report). *Online* sports betting in particular is becoming ever more popular.[2] Besides its popularity and economic value, the sports betting market possesses some unique, experimental-like features that render it an attractive environment for the study of the home bias. First, sports

[1] For evidence on investors' portfolios, see, e.g., French and Poterba (1991) and Coval and Moskowitz (1999). For evidence on employees' retirement savings behavior, see Benartzi (2001). For evidence on consumers' choice of products see Shimp and Sharma (1987), and for individuals' choice of trading partners, see Hortaçsu, Martínez-Jerez and Douglas (2009).

[2] The Covid-19 pandemic has catalyzed the digitization of the sports betting market, has expanded its customer base, and has unleashed pent-up demand for gambling services. In a survey of over 2,000 US sports bettors in December 2020, 68% reported that they are now more comfortable making online sports wagers, 65% are planning to do all their sports wagering online in the future, and 61% plan to bet more frequently in 2021 than in 2020.

wagers bear no systematic risk. This implies that, contrary to traditional financial markets, tests of individuals' betting performance are not affected by a potentially misspecified asset pricing model. Second, sports wagers have an observable terminal value which is exogenously determined and revealed by match outcomes. This implies that there is no mispricing at termination, therefore we can disentangle whether a preference towards home teams is driven by an inherent behavioral bias or a local informational advantage. Third, sports bettors do not face frictions that may force them to prefer home assets, e.g., due to transaction costs, limited market integration, or moral hazard. Fourth, individuals have strong monetary incentives as they risk their own money on wagers that involve significant losses and gains. Interestingly, sports bettors also earn emotional rewards from their home team winning. Hence, according to standard utility models, we would expect that bettors would prefer to place monetary bets *against* their home team so that the monetary gains earned if the bets win reduce the emotional disappointment induced by the home team's defeat.

Our data set contains approximately 100,000 wagers on various soccer events placed by about 500 individuals at an online sportsbook over a period of five years. We start by examining whether individuals exhibit the home bias, by testing whether they overweight in their betting portfolios teams that are "close" to them. Proximity is defined at three progressively more inclusive levels: (i) teams that are located in the individual's area of residence (*local teams*), (ii) teams that are located in the individual's country of residence (*domestic teams*), and (iii) teams with players whose country of origin is the same as the individual's country of residence (*domestic-player teams*). Throughout the paper, we collectively refer to teams in these three groups as "home" teams. First, we test whether individuals disproportionately bet on their home teams. We find that individuals overweight their home teams in their weekly portfolios relative to a contemporaneous "market" portfolio that invests equally in all available teams. Specifically, local teams make up 5.4% of the average individual portfolio but only 1.3% of the market portfolio; domestic teams make up 14.5% of the average individual portfolio but only 5.6% of the market portfolio; and domestic-player teams make up 16.6% of the average individual portfolio but only 6.9% of the market portfolio. That is, depending on the home-team definition, individuals on average overweight home teams by 150% to 300%. This is comparable to the 150% overweighting for stocks of locally-headquartered firms found in finance studies (e.g., Ivkovic and Weisbenner, 2005). That the magnitude of the home bias is similar in these two markets is not surprising in view of recent survey evidence (2018 UK Gambling Commission report) which shows that, similar to stock market participants studied in the finance literature, the majority of gamblers (63%) participate in this market predominantly "to win in general" or "to win big", while non-pecuniary motives like enjoyment, fandom, or social factors, are secondary. Our finding that individuals exhibit home bias remains robust in a multivariate analysis where we control for wagers' risk as well as for individuals' preference for other team characteristics such as visibility and past performance.

Subsequently, we conduct our direct test for the hypothesis that the home bias is driven by sentiment: we test whether individuals' home bias leads to higher performance. We find that it does not. Specifically, we find that the average returns individuals realize from backing their local, domestic, and domestic-player teams are not significantly different from their returns from backing non-local, non-domestic, and non-domestic-player teams respectively. Furthermore, individuals with a stronger bias toward these teams do not generate significantly higher returns from backing them. Crucially, we conduct an a priori power analysis that shows that our sample size is sufficiently large (almost an order of magnitude larger than necessary) to conduct a test that detects a very small effect with high power. That is, our non-result should not be attributed to low statistical power to detect a true alternative but rather to an economically very small effect. Two additional pieces of evidence corroborate our finding that the overweighting of home teams in our market is driven by an innate behavioral bias. First, we find that individuals overwhelmingly back their home teams even when they play against non-home teams. This indicates that the home bias we observe is more likely due to sentiment, because if it was information-driven we would expect that individuals would be equally likely to bet in favor of their home teams (when they have positive superior information about them) as to bet against them (when they have negative superior information about them). Second, individuals overweight their home teams even in events for which they are unlikely to have superior information, such as the total number of corners or the time of the first goal in a match.

Finally, we examine whether individuals have a *strong* behavioral home bias, by testing whether it is costly for them to exhibit it. Our performance results show that overweighting home assets neither increases nor decreases individuals' returns. But, unless individuals are risk neutral, this does not imply that the home bias is harmless. Indeed, it is well known that, in the stock market, an investor's bias toward home stocks distorts his portfolio away from the optimal according to his risk preferences, hence results in welfare costs (see the review in Beshears et al., 2018). Similarly, in our market, a bias toward home teams may cause individuals to choose suboptimal portfolios. Our analysis verifies this, as we find that time variation in the odds of individuals' home teams affects the odds of the wagers they select. Since it is unlikely that peoples' risk preferences vary systematically with their home teams' odds, this implies that the home bias distorts individuals' choices. In a back-of-the-envelope calculation using Prospect Theory preferences with the commonly used Tversky and Kahneman (1992) estimated parameters, we calculate that the welfare cost of this distortion could be 2% for the local bias and 3.5% for the domestic bias, annually, which is of the same order of magnitude as the cost of domestic bias in the stock market. This is important, as it implies that the home bias we document is strong enough to survive the substantial welfare cost associated with it.

This paper contributes to a large literature that documents home bias in different contexts and tries to identify the underlying mechanisms that give rise to this behavior. Using trading data for retail investors around the world, Ivkovic and Weisbenner (2005), Massa and Simonov (2006) and Ben-David, Birru and Rossi (2019) find that investors exhibit a strong preference for home investments and that they earn superior returns on these investments, supporting the information hypothesis. Huberman (2001), Grinblatt and Keloharju (2001), and Seasholes and Zhu (2010) confirm the existence of a home bias but find that retail investors do not outperform in their home investments, supporting the sentiment hypothesis.[3] Using 401(k) portfolio allocations, Benartzi (2001) finds that employees invest a disproportionate portion of their discretionary contributions in their own company stock.

[3] A similar debate exists for professional investors. See, e.g, Coval and Moskowitz (2001), Hau (2001), Teo (2009), and Sialm, Sun and Zheng (2020) for evidence in favor of the information hypothesis and French and Poterba (1991), Froot, O'Connell and Seasholes (2001), Pool, Stoffman and Yonker (2012) for evidence in favor of the sentiment hypothesis.

Numerous studies have found that trade is more likely to occur between parties located in the same country or geographic area in offline as well as online markets (e.g., Disdier and Head, 2008; Lin and Viswanathan, 2016; Hortaçsu, Martínez-Jerez and Douglas, 2009), and suggest several explanations for this phenomenon such as transaction costs, informational asymmetries, local consumption of goods, and behavioral biases. Our paper contributes to this literature by analyzing a different market setting that allows us to draw a clean conclusion that innate psychological motives are strong enough to give rise to the home bias in the face of welfare costs but in the absence of institutional and informational frictions.

While some studies hint to the existence of a home bias in sports betting, the limited availability of individual-level, real-world data has hitherto prevented a thorough test and measurement of this bias. Some papers use betting odds to study whether bookmakers offer systematically lower odds on their own-country teams in order to balance the increased demand for home-team bets, and find mixed evidence. For example, Page (2009) finds that British bookmakers do not tilt their odds against British teams in international matches, and Braun and Kvasnicka (2013) find that most European bookmakers offer systematically different odds on their own-country teams from foreign bookmakers but the sign of the bias varies across countries. A problem with using only aggregate price data to study the home bias is that it is difficult to disentangle to what extent observed price patterns stem from bettors' biased behavior or the bookmaker's price-setting behavior. In the experimental psychology literature, Massey, Simmons and Armor (2011) and Simmons and Massey (2012) use surveys to show that NFL fans make overly optimistic forecasts about their favorite team winning, and Morewedge, Tang and Larrick (2018) find that experimental subjects are reluctant to hedge negative future outcomes that are associated with their identity, e.g., via betting against their favorite sports teams. A common critique of these studies is that it is hard to extrapolate evidence of behavioral biases to a market setting because biased behavior in the lab is often costless and might not persist if it were costly. To our knowledge, our paper is the first to provide direct evidence of the home bias in the sports betting market by tracking individuals' naturally occurring betting behavior.

This paper also relates to a growing literature that uses the sports betting market as a useful empirical laboratory that can yield valuable insights about other markets with similar characteristics in which biases are observed but are difficult to test cleanly at the individual level. For example, Durham, Hertzel and Martin (2005) and Andrikogiannopoulou and Papakonstantinou (2018) exploit the attractive features of the sports betting market to disentangle two behavioral theories of momentum and reversals in stock returns, Moskowitz (2018) uses sports betting prices to test behavioral asset pricing theories for momentum, value, and size effects, and Andrikogiannopoulou and Papakonstantinou (2020) use sports betting markets to estimate individual risk preferences and explain the prevalence of the disposition effect in the stock market.[4]

In Section 2, we present the data. In Section 3 we conduct tests of home-team overweighting to show a home bias exists, and in Section 4 we conduct tests of superior performance to show that this home bias is behavioral. In Section 5, we show that this behavioral home bias is costly and therefore strong. In Section 6 we present additional results and in Section 7 we conclude.

2 Data

We study individual behavior in a fixed-odds sports betting market. A sports betting market offers participants the opportunity to buy assets that pay a unit of account conditional on the realized outcome of a sports event. For example, given a football match between Arsenal and Chelsea (the event), individuals can place a bet backing Chelsea to win (one of the possible outcomes), which represents an asset that pays 1 unit if Chelsea wins and 0 otherwise. In a fixed-odds betting market, a bookmaker sets the prices or odds (the inverse of the price) of the assets, and individuals who stake money at these odds receive their stake times the odds if they win and lose their stake otherwise. For example, an individual who stakes €1 on an outcome with quoted odds of 2 will receive €2 (i.e., €1 plus his stake) if he wins, otherwise he will lose his stake. In some betting markets, bookmakers dynamically set prices so that demand is "balanced", i.e., the total money staked on each outcome is such that the total payout to winners is (approximately) the same regardless of the realized out-

[4]Earlier studies have also used sports betting prices to perform clean tests of market efficiency. See, for example, Snyder (1978), Zuber, Gandar and Bowers (1985), Gandar et al. (1988), Golec and Tamarkin (1991), Gray and Gray (1997), Woodland and Woodland (1994) and Avery and Chevalier (1999) among others.

come, hence the bookmaker's risk is minimized. However, the empirical evidence from fixed-odds betting markets in general, and from the one we study specifically, is more consistent with an efficient pricing model, where bookmakers optimally set prices that are efficient, as this strategy exposes them to little risk given the large number of sports events and reduces the costs associated with changing prices frequently to keep a balanced book (e.g., Paul and Weinbach, 2008, 2009, 2012).[5] Even though the bookmaker's price-setting behavior is not directly relevant for our study of what drives the home bias, an efficient pricing model implies that exhibiting a behavioral bias does not have a direct monetary cost. This is relevant in our analysis of individuals' performance and of the cost of exhibiting this bias, which we discuss below.

We use a panel data set of individual betting activity obtained from a large European online sports betting company. Our data contain detailed information about the betting histories of about 550 randomly selected individuals over a period of 5 years, from October 2005 to November 2010. We focus on bets placed by these individuals on soccer matches.[6] For each bet placed by each individual in our sample, we observe the following information: (i) bet date; (ii) bet fixture (e.g., Premier League match between Arsenal and Chelsea); (iii) bet event (e.g., final outcome, total number of bookings); (iv) outcome chosen (e.g., home or away win); (v) bet amount; and (vi) prices associated with all outcomes of the bet event at the time the bet was placed. In addition, we have information about the gender, age, country of residence, and zip code of the individuals.

Furthermore, we use several online sources to obtain a comprehensive list of all soccer matches that were available in the sportsbook under study during the years covered by our sample.[7] Since the number of matches available in the sportsbook

[5]Other studies (e.g., Levitt, 2004) suggest that bookmakers exploit individuals' biases by setting prices between the efficient ones and those that balance the book, but the bookmaker who provided our data has stated they do not use this strategy.

[6]Our data contain bets placed on a variety of sports, but we focus on bets on soccer matches, because the large majority of bets are placed in this market segment. Furthermore, our analysis requires historical data for outcomes, which are significantly more readily available for soccer matches than for other sports events.

[7]We obtain information on available matches and match results from various sources: (i) football-data.co.uk covers all major and many minor national leagues in Europe, for the whole sample period; (ii) matchstatistics.com covers major and minor national leagues and international competitions worldwide, for the period up to the middle of 2009; and (iii) betfair.com covers major and minor national leagues and international competitions worldwide, for the whole sample period.

at any point in time is very large and individuals are unlikely to consider all of them when selecting their wagers, we construct a restricted match universe consisting of 59,192 matches (i.e., 118,384 match/team combinations) that excludes matches from obscure leagues; this universe covers more than 90% of all wagers placed by individuals in our sample. Specifically, it includes matches from all major first-tier leagues (Argentina, Brazil, England, France, Germany, Italy, and Spain), many minor European first-tier (e.g., Austria, Belgium, and Netherlands) and several second-tier leagues (e.g., English Championship, Italian Serie B, and Spanish Segunda Division), as well as international competitions at club level (UEFA cup and Champions' League) and national level (Euro Cup, World Cup, and friendlies). We note that when we use the universe of all available matches rather than this reduced set, our results below on home-team overweighting are stronger, since the vast majority of matches excluded from the reduced set involve teams that are not local/domestic for any individual in our sample.

Our initial sample includes 109,141 wagers on various events associated with the soccer matches included in our restricted match universe. These include both wagers on final match outcomes, which are by far the most common, as well as wagers on various other events such as the total number of corners and the time of the first goal. Since our objective is to examine whether people are biased toward home teams, we drop the 15% of bets placed on draw outcomes, and furthermore we drop the 0.2% of bets placed by individuals who placed fewer than 5 bets in total. Thus, our final sample contains 92,177 wagers placed by 495 individuals.

Variable description We begin by constructing three measures of an individual's proximity to a sports team, progressively expanding our definition of proximity:

1. *Local teams*. We obtain (from stadiumguide.com) zip code information about the location of each team's stadium, and we convert individual and team zip codes into latitudes and longitudes using the geocoder at geocode.localfocus.nl. Then, we compute the pairwise geodesic distances between individuals' and team stadiums' locations using Sodano's (1965) method. Subsequently, we define a team as

local to an individual if the distance between their locations is less than 100 km.[8]

2. *Domestic teams*. A team is domestic to an individual if its stadium is located in the individual's country of residence.
3. *Domestic-player teams*. We obtain (from us.soccerway.com) players' historical team affiliations and we identify, for each individual, teams and time periods for which at least one participating player's country of origin is the same as the individual's country of residence.

Throughout the paper, we collectively refer to teams in these three groups—the local, domestic, and domestic-player team groups—as home teams.

We also construct a set of variables to control for other team characteristics that may affect individual betting behavior. First, we control for the price (*Price*), expressed as decimal odds, associated with each team at the time of the match to account for differences in risk across bets, and for whether the team is playing at home or away (*Home Field*) to account for the possibility that individuals may exhibit a preference for teams playing on their home field. We also control for streaks in team past performance, which accounts for the possibility that individuals may exhibit a preference toward teams on winning streaks.[9] Specifically, we calculate the duration (the number of matches) of the active winning or losing streak of each team at the time of the match *(Streak)*, where positive (negative) values indicate winning (losing) streaks. Furthermore, we control for team visibility, as individuals may prefer to wager on highly visible teams. Our measure of visibility is based on teams' historical success, on the basis that more successful teams tend to be more visible as they attract the media's attention. We construct a team/season-specific dummy variable *(Visible Team)*, that indicates if a team was ranked among the top 20 soccer clubs (top 5 national teams) according to the UEFA club coefficients

[8]The 100 km cutoff is a plausible upper bound for the definition of locality in Europe; results based on a 50 km cutoff are qualitatively similar. Furthermore, we note that, contrary to stock market studies where locality is usually defined simplistically based on each firm's headquarters location (rather than the location of the firm's branch/subsidiary closest to each investor), in our setting there is a single plausible definition of locality based on each team's stadium.

[9]See, e.g., Tversky and Kahneman (1971) for experimental and Clotfelter and Cook (1993) for field studies showing that individuals often expect random sequences to exhibit systematic reversals or excessive persistence. Also see Durham, Hertzel and Martin (2005) and Andrikogiannopoulou and Papakonstantinou (2018) who use sports betting data to show that past performance streaks affect individual behavior.

(FIFA World Rankings) of the preceding season.[10]

[Table 1 about here]

In Table 1, we present summary statistics for our data. In Panel A, we present the characteristics of the individuals in our sample. The vast majority (93%) of individuals are men, the mean (median) age is 33 (32) years, and 49% of the individuals reside in large metropolitan areas.[11] Each individual, on average, has placed €2,865 on 186 wagers, and has participated in the sportsbook for a period of 17.5 weeks. In Panel B, we present the characteristics of the bets placed by our individuals. The majority of bets are placed on standard events (i.e., final match outcome) of soccer matches; 67% of these bets back the home-field team to win. The odds of the selected outcome range from 1.01 to 57.85, with a mean (median) of 2.04 (1.80). 19% of the bets back a highly visible team to win, while 10% (3%) back a domestic (local) team and 12% back a team in which a domestic player is participating. For our universe of 59,192 matches, in Panel C we present the characteristics for the corresponding wagers backing the home-field team or the away team to win. The odds range from 1.01 to 66.33, with a mean (median) of 3.28 (2.56). 4% of the teams available to back during our sample period are classified as highly visible.

3 Analysis of portfolio composition

We begin our empirical analysis by testing whether individuals in the sports betting market exhibit a home bias. In betting, such a bias could manifest itself, e.g., as an overweighting of teams located in the individual's area of residence (local teams) or

[10]In unreported results, we consider alternative team visibility measures and our results are qualitatively the same. One alternative measure is a team-specific dummy that equals one for the 20 largest clubs in the world, as measured by fan-base size, according to the 2010 SPORT+MARKT survey. The other alternative measure is a team/season-specific dummy that equals one for the 20 largest clubs in the world, as measured by net worth in the preceding season, according to Forbes.

[11]These average characteristics are not very different from the average characteristics for samples of individuals who invest in the stock market through online brokers. In a sample of 1,607 U.S. individuals who switched from a phone-based service and made online trades between 1991 and 1996, Barber and Odean (2002) find that 86% of investors are men and that the mean (median) age is 49.6 (48) years. In a sample of 3,079 German individuals holding online brokerage accounts between 1997 and 2001, Glaser (2003) finds that 95% of investors are men and that the mean (median) age is 40.8 (39) years.

country (domestic teams), or as an overweighting of teams in which a player from the same country of origin participates (domestic-player teams). To study this home-team overweighting, we compare individual versus market portfolio weights, and then we conduct multivariate analyses to control for possible confounding factors.

3.1 Individual versus market portfolio weights

First, we examine whether individuals overweight in their weekly betting portfolios their home teams relative to an equal-weighted "market" portfolio that backs all teams available to wager on in the sportsbook at the time the portfolio is formed. Specifically, for each home team group $g \in \{Local, Domestic, Domestic\ Player\}$,[12] we compute the portfolio weight that individual i allocates to this group in week t as

$$Individual_{igt} := \frac{B_{igt}}{\sum_g B_{igt}}, \tag{1}$$

where B_{igt} is the amount of money staked by individual i on team group g in week t.[13] In addition, we compute the weight that corresponds to team group g in the market portfolio in week t as

$$Market_{gt} := \frac{N_{gt}}{\sum_g N_{gt}}, \tag{2}$$

where N_{gt} is the number of wagers that back team group g in week t. Essentially, $Market_{gt}$ is the weight of team group g in week t in the equal-weighted market portfolio that buys all available wagers, or its expected weight in a portfolio constructed by picking wagers at random.

[Table 2 about here]

In Table 2, we present the mean portfolio weight $Individual_{igt}$ that individuals allocate to their local, domestic, and domestic-player teams (in columns labeled

[12]Team groups are individual-specific as home teams differ across individuals; while it is more accurate to denote groups by g_i to indicate this, we use g for ease of notation.

[13]The results we present in this section are very similar if instead of value-weighted we use equal-weighted portfolios for individuals, i.e., we define $Individual_{igt} := \frac{N_{igt}}{\sum_g N_{igt}}$, where N_{igt} is the number of teams that belong to group g and are backed by individual i in week t. Using monthly instead of weekly portfolios also yields very similar results.

‘Individual’), the mean weight $Market_{gt}$ of the respective team group in the contemporaneous market portfolio (in columns labeled ‘Market’), and the ratio (difference) of the individual-to-market portfolio weights for each team group in columns labeled ‘Ratio’ (‘Difference’). We find that, on average, individuals allocate significantly higher portfolio weights to all home-team groups: 5.4% of the average individual portfolio is allocated to local teams, while these teams make up only 1.3% of the market portfolio; 14.5% of the average individual portfolio is allocated to domestic teams, while these teams constitute on average 5.6% of the market portfolio; and 16.6% of the average individual portfolio is allocated to teams in which at least one compatriot is playing, while these teams constitute on average 6.9% of the market portfolio. Furthermore, we note that individuals’ overweighting of domestic (domestic-player) teams in their portfolios is not entirely driven by an overweighting of local (domestic) teams. To see this, we observe that the ratios of individual-to-market portfolio weights remain quite large even if we constrain attention to domestic but non-local teams (domestic-player but non-domestic teams). Overall, looking at the ‘Ratio’ column in the table, we see that the portfolio weight that individuals allocate to home teams is 2 to 4 times the market portfolio weight. This effect is comparable to that found in the stock market. For example, Ivkovic and Weisbenner (2005) find that the portfolio weight a typical U.S. household allocates to local stocks is 2.5 times the market portfolio weight on these stocks.

In Figure 1a (1b), we plot histograms of the ratio (difference) of the individual-to-market portfolio weights for each team group across individuals. We see that there is heterogeneity across individuals in exhibiting a home bias, but the ratio (difference) for all team groups is greater than 1 (0) for the majority of individuals, which shows that the results of our aggregate analysis are representative of the majority. Although this preliminary analysis lacks the controls included in the regressions below, it provides a strong indication that individuals exhibit a home bias, defined in various different ways.

3.2 Multivariate analysis

In this section, we use multivariate regressions to document home bias in individuals' betting portfolios after controlling for potentially confounding factors that may affect individual betting behavior. To examine the portfolio weight individuals place on their home teams, we estimate various forms of the following specification:

$$Individual_{ijmt} = \alpha_i + \beta_1 HomeTeam_{ijmt} + \beta_2 Market_{jmt} + \beta_3 Controls_{ijmt} + \varepsilon_{ijmt}, \tag{3}$$

where $Individual_{ijmt}$ is the portfolio weight that individual i allocates to team j in match m that is available in the sportsbook in week t. α_i are individual fixed effects. $HomeTeam_{ijmt}$ is a dummy variable that indicates whether team j is a home team for individual i, where a home team is defined as (i) a team that is local to individual i; (ii) a team that is domestic to individual i, and (iii) a team in which a player from individual i's country of residence plays in week t. $Market_{jmt}$ is the weight that corresponds to team j in match m in an equal-weighted market portfolio in week t. $Controls_{ijmt}$ is a vector of control variables that include (i) the price (expressed in decimal odds) associated with team j in match m, (ii) the duration of the active winning or losing streak of team j at the time of match m, (iii) a dummy variable indicating whether team j is highly visible at the time of match m, and (iv) a dummy variable indicating whether team j is playing at home or away in match m. For each week during our sample period and for each individual active during that week, our analysis contains one observation for each team/match combination available to bet on during that week, with zero portfolio weights allocated to the combinations that the individual has not selected. Since we include in the analysis multiple observations for the same match, we cluster standard errors at the match level to account for possible correlations in the residuals. If individuals tilt their portfolios toward their home teams, then β_1 should be positive.

[Table 3 about here]

In Table 3, we report the results from the estimation of various forms of the model in Equation 3. We find that the estimated coefficients on all home-team measures are positive and statistically significant, suggesting that individuals tilt their portfolio toward home teams. Specifically, the portfolio weight is 0.7% (0.4%) higher for local (domestic) teams than for non-local (foreign) teams, and 0.3% higher for teams that involve a domestic player. In specification 4, which includes all home-team measures simultaneously, we find that the portfolio weight increases by 0.1% for foreign teams involving domestic players, by a further 0.2% for domestic teams that are not local, and by a further 0.4% for local teams.[14] This indicates that there is a separate effect for local teams, for domestic teams, and for domestic-player teams. To get a better sense of the economic magnitude of the estimated coefficients in Table 3, we note that the mean market portfolio weight of a team is 0.2%. So, for example, an estimated portfolio weight increase of 0.2% for domestic teams represents a doubling of a team's portfolio weight, while a further increase of 0.4% for local teams represents a quadrupling of a team's portfolio weight. These results are very much consistent with those in Table 2.

In specifications 5–7, we repeat the analysis separately for different match types. Specifically, in specification 5, we constrain attention to matches between domestic teams to isolate the effect of local teams. In specification 6, we constrain attention to matches between foreign teams to isolate the effect of domestic-player teams. We see that the effect survives in both specifications, which further strengthens our finding from specification 4 that individuals' overweighting of local and domestic-player teams is not driven by an overweighting of domestic teams. In specification 7, we constrain attention to matches of domestic against foreign teams to get a first indication of whether the domestic bias is due to sentiment or superior information. As domestic teams are equally likely to be overvalued or undervalued in international matches, if individual behavior was driven by superior information we would expect to see that individuals are equally likely to bet for or against these teams, hence β_1 would equal zero. However, we see that individuals overwhelmingly bet for the domestic team in international matches. This evidence suggests that the observed overweighting of domestic teams is likely driven by a behavioral bias. We find similar results if we constrain attention to matches of local vs. non-local teams and domestic-player vs. non-domestic-player teams.

[14]Our results are similar (i) when we use a logit model and (ii) when we condition our analysis on the matches selected by each individual and examine how home bias affects which of the two teams participating in each match is backed to win.

4 Tests of investment performance

Our results thus far have shown that individuals overweight their home teams in their portfolios. In this section, we analyze performance to test the sentiment hypothesis. If the home bias we observe is due to sentiment, then individuals' home-team bets should not yield higher returns. The fact that in the sports betting market the exogenous terminal value of all assets is revealed at the conclusion of the relevant events allows us to carry out direct tests of superior performance. This stands in stark contrast to other asset markets, where true fundamentals are unknown so tests of superior performance are joint tests of an assumed asset pricing model.

We estimate the following model that controls for several team and match characteristics:

$$Return_{ijmt} = \alpha_s + x'_{ijmt}\beta + \varepsilon_{ijmt}, \tag{4}$$

where $Return_{ijmt}$ is the rate of return realized by individual i on the wager backing team j in match m in week t;[15] α_s are time fixed effects, where s is the season during which match m took place; x_{ijmt} contains (i) the wager's characteristics including its price, the home-team dummies, and other controls, (ii) individual-specific measures of the home bias measured as the mean difference between the individual and the market portfolio weights allocated to these teams, and (iii) interaction terms between the home-team dummies and the individual-specific home-bias measures. Our panel analysis includes one observation for each bet placed by each individual; since it is possible that multiple individuals have placed bets on the same match, we cluster standard errors at the match level to account for possible correlations in the residuals.

[Table 4 about here]

In Panel A of Table 4, we report the results from the estimation of various forms of Equation 4; in Columns 1–4 we consider all matches; in Columns 5–7, we constrain attention to matches between (i) domestic teams only, (ii) foreign teams only, and (iii) domestic versus foreign teams. In all specifications, the estimated

[15] Note that no commission is paid after this return is realized; the commission is implicitly paid by all individuals placing wagers since the return from placing a wager with unit payout on each of the possible outcomes of an event is smaller than one.

coefficients on home teams are statistically insignificant, suggesting that the overweighting of these teams does not lead to superior betting performance. That is, the returns individuals generate from backing their local, domestic, and domestic-player teams are not significantly different from the returns they generate from backing non-local teams, non-domestic teams, and teams with no domestic players respectively. These results hold both when we consider wagers on all matches (Columns 1–4) as well as when we constrain attention to wagers on specific match types (Columns 5–7). Furthermore, in all specifications, the coefficients on the individual-specific home-bias measures are insignificant, suggesting that individuals with a stronger bias do not generate returns that are significantly different from the returns of individuals with a weaker bias. Finally, in all specifications, the coefficients on the interaction terms are insignificant, suggesting that individuals who exhibit a stronger home bias do not earn higher returns from backing their home teams. Overall, our findings imply that the overweighting of local, domestic, and domestic-player teams is due to a behavioral bias. In Panel B of Table 4 we repeat the same analysis, but include individual fixed effects instead of season fixed effects, and the results are qualitatively identical. In the Internet Appendix, we present results from further alternative specifications. First, we exclude the wagers with extreme realized returns (the top 1% of the distribution) to check for the possibility that outliers affect our results. Second, we estimate a model in which the dependent variable is not a wager's return but a dummy indicating whether the wager's selected outcome was realized. Third, we repeat the estimation using a logistic rather than a linear probability model. In all cases, the adjusted (or pseudo) R^2 increases substantially, from less than 0.1% to between 2% and 15%, mainly reflecting the fact that the price of a wager predicts its win probability, but the estimation coefficients of interest (on the home-team dummies, the measures of home bias, and their interactions) are qualitatively unchanged and remain statistically insignificant.

It is important to note that we conduct an a priori power analysis of our hypothesis tests. For our specifications, with the number of independent variables and fixed effects we include, we calculate that to detect a very small effect size of 0.1% with power of 0.9 and at significance level of 0.05 we need about 10,000 observations. This is almost an order of magnitude smaller than our sample size of about

80,000 observations for our baseline specifications (columns 1–4 in both panels of Table 4). Thus, we are confident that our finding of no superior performance for home-team betting is due to a tiny (if any) effect size rather than due to a lack of statistical power. The same holds for our specification that focuses on foreign vs. foreign matches (column 6). Our additional specification that focuses on domestic vs. domestic matches (column 5) has about 7,000 observations, so it has slightly lower but still quite high power at 0.8 (0.9) for significance level of 0.05 (0.10).[16]

We have already discussed that the finding of no superior performance from home-team betting is consistent with the sentiment hypothesis. But what about the finding of no *inferior* performance? Why would individuals with an innate bias for home teams not pay higher prices hence experience significantly worse returns from bets on their home teams? That is, why are the prices for these bets efficient? While the answer to this question has no bearing on our study on what drives the home bias, some plausible explanations are the following. First, market participants live in various locations, so home-team is an individual-team-specific (hence individual-bet-specific) characteristic, meaning that the market for each asset (wager) may clear at the efficient prices despite the prevalence of the home bias. Second, prices may in any case not deviate from efficient ones due to the presence of arbitrageurs or because the bookmaker optimally sets efficient prices to save on the costs of dynamically balancing the book, consistent with the findings of some empirical studies (see Section 2).

5 The cost of the home bias

Next, we turn our attention to the important issue of determining the cost of the home bias. Essentially, we want to determine whether the home bias we have documented is a weak behavioral trait that is exhibited when it is costless to do so, or whether it reflects a strong affinity to home assets that is exhibited even when it is costly.

Our performance results above show that overweighting home assets does not

[16]The specification that focuses on domestic vs. foreign matches (column 7) is less important as it contains just 1,700 observations, i.e., about 2% of our sample. While this specification has lower power, it estimates a negative effect for domestic bias, so the evidence is consistent with that from our other specifications.

harm individuals' average returns. But, unless individuals are risk neutral, this does not imply that the home bias is harmless. For example, it is well known that an investor's bias toward home stocks distorts his portfolio away from the optimal according to his risk preferences, hence results in welfare costs. Similarly, a bias toward home teams may cause individuals to choose suboptimal portfolios. For example, this could be the case if bets backing an individual's home teams carry different risk from bets backing non-home teams. In this section, we examine whether home bias affects individuals' choices and subsequently we conduct a back-of-the-envelope calculation to get a sense of how costly this might be.

To examine whether home bias affects choices, we estimate the relationship between the average odds of the wagers an individual places during a week and the average odds of wagers backing his home teams during the week. While it is possible to conduct this analysis at the wager level, we conduct it at the weekly level to account for potential substitution effects. For example, if an individual likes wagers with odds of 2, on average, but his home team's odds are longer, e.g., 2.5, he could still back his home team and keep the average odds of selected wagers around 2 by choosing shorter odds for his other bets; a wager-level analysis would show that a selected wager's odds depend on whether the wager backs a home team or not, while a weekly-level analysis would—more conservatively—show no effect. We consider two specifications for this analysis: one which estimates a common effect across all individuals, and one which estimates a separate effect for the two groups of individuals—those who exhibit the home bias, who are of interest here, and those who do not. Table 5 shows results from both specifications, but in our discussion here we focus on the latter. Specifically, we estimate

$$Price_{it} = \alpha + \beta_1\, HomeBias_i + \beta_2\, Price_{it,Home} + \beta_3\, HomeBias_i \cdot Price_{it,Home} + \varepsilon_{it}, \tag{5}$$

where $Price_{it}$ is the average odds of wagers placed by individual i in week t, $Price_{it,Home}$ is the average odds across all wagers backing individual i's home teams in week t, and $HomeBias_i$ is a dummy indicating that individual i has a bias toward home teams. The sum $\beta_2 + \beta_3$ is the effect of home-team odds on the weekly average of selected wagers' odds for individuals who exhibit the home bias. In principle, individuals should select their wagers' odds optimally, therefore $\beta_2 + \beta_3$

captures the distortion caused by home bias as home-team odds vary over time, with a zero value corresponding to the null hypothesis of home bias having no effect hence being harmless.

[Table 5 about here]

Looking at the results in Table 5, we see that the effect of home-team odds on selected odds is positive. Specifically, looking at the estimated coefficients in columns (2), (4), and (6) we see that the effect of the odds of local teams is $-0.031+0.068 = 0.037$ (significant at the 10% level), for domestic teams it is $0.014+0.121 = 0.135$ and for teams with domestic players it is $0.056+0.109 = 0.165$ (both significant at the 1% level). That is, for an individual who exhibits the local (domestic) bias, a unit change (e.g., from 2 to 3) in the average odds of the local (domestic) teams causes a 0.037 (0.135) change in the average odds of the wagers he selects. Since the weight of local (domestic) teams in these individuals' portfolios is, on average, about 12% (28%), these distortions are not one-to-one but they are still very substantial.

To get a sense of the economic significance of these distortions, we make the following back-of-the-envelope calculation. Rather than take a stance on what individuals' optimal choices are, we calculate a sensible cost for a unit distortion in odds. Specifically, we use Prospect Theory preferences—whose features have been shown to explain well individuals' behavior in wagering markets (Barberis, 2012; Andrikogiannopoulou and Papakonstantinou, 2020; Snowberg and Wolfers, 2010), as well as in the stock market (Polkovnichenko, 2005; Barberis and Huang, 2008)—with the standard Tversky and Kahneman (1992) estimated parameters. For the average binary lottery we observe (median odds about 2.5), these preferences imply that a unit change in odds results in about a 1.25% change in the certainty equivalent, which we use as the unit cost of distortion. For each individual, we calculate the mean of the weekly odds for his home teams, and then the weekly deviations from this mean. Pooling observations across weeks and individuals, we obtain the empirical distribution of deviations in home-team odds over time; the mean of this distribution for local (domestic) teams is 0.87 (0.40). Multiplying this by the estimated effect, 0.037 for local (0.135 for domestic), we calculate an average distortion of $0.87 \times 0.037 = 0.032$ ($0.40 \times 0.135 = 0.054$) in the average weekly odds of selected wagers. In certainty equivalent terms, this corresponds to a cost of $0.032 \times 1.25\% = 0.04\%$ per week (2.1% annualized) from wagering on local teams, and to a cost of $0.054 \times 1.25\% = 0.068\%$ per week (3.5% annualized) from wagering on domestic teams.

Thus, we find that there exists a behavioral home bias that is strong since people exhibit it even though doing so carries a cost. Crucially, this cost of about 2% to 3.5% annualized is economically significant and of a similar order of magnitude as the purported cost of the home bias in the stock market.[17]

6 Additional results

In this section, we present additional results. In Section 6.1, we investigate which team characteristics are related to home-team overweighting, and in Section 6.2 we study individual behavior when betting on exotic events related to soccer matches. These analyses provide an alternative, indirect way to test whether superior information may be driving home-team overweighting. While our preceding tests from Section 4 are more direct and provide cleaner evidence, the following tests offer an opportunity to further validate our results.

6.1 Analysis of team characteristics

In this section, we examine whether home teams with certain characteristics are more likely to be overweighted in individuals' betting portfolios than others. The idea behind this analysis is that if superior information is driving home-team overweighting then we would expect to find the overweighting to be stronger when publicly available information is scarcer and/or information asymmetries are higher, i.e., for (i) teams participating in matches early in the season, (ii) teams participating in less popular/visible leagues, and (iii) teams for whom the prices quoted by different bookmakers are highly dispersed.[18]

[17] See French and Poterba (1991) for a calculation of this cost using a different model from ours.

[18] Similar indirect tests have been conducted in financial markets. For example, it has been studied whether the home advantage is likely to be stronger among firms (i) with no public news coverage (see Giannini, Irvine and Shu, 2018), (ii) with higher levels of information asymmetries such as non-S&P 500 stocks (Ivkovic and Weisbenner, 2005; Seasholes and Zhu, 2010), and (iii) when there is more uncertainty or ambiguity about valuations (Daniel, Hirshleifer and Subrahmanyam, 1998).

Specifically, we test if there are differences in home-team overweighting across teams/matches with specific characteristics by augmenting the model in Equation 3 with interactions of $HomeTeam_{ijmt}$ with (i) a dummy variable indicating whether team j participates in a match m that is in the first one-third of the matches of the league/season (*Early In Season*), (ii) a dummy indicating whether team j does not compete in a top league at the time of match m (*Non-Top League*), and (iii) the standard deviation of the prices associated with team j in match m by different bookmakers, scaled by the mean price (*Odds Std. Dev.*). If home-team overweighting is due to superior information, then we would expect the coefficients on these interaction terms to be positive.

[Table 6 about here]

In Table 6, we report the results from a regression analysis of this augmented model: we focus on the effect of local teams in Columns 1–3, domestic teams in Columns 4–6, and domestic-player teams in Columns 7–9. We find the estimated coefficients on all interaction terms to be *negative*, and mostly statistically significant. That is, we find that the overweighting of local, domestic, and domestic-player teams is *less* pronounced for teams for which there is more room for superior information. This is inconsistent with the information hypothesis, but could be consistent with the sentiment hypothesis. For example, it could be that when there is a higher degree of uncertainty it becomes more costly (e.g., due to ambiguity aversion) to exhibit this behavioral bias, so the bias is reduced. In unreported results, we confirm that individuals' returns from their home bets are not related to these team characteristics.

6.2 Analysis of non-standard events

In our analysis so far, we have considered wagers on the final outcome of soccer matches, i.e., on the match winner. Here, we briefly focus on more "exotic" events—e.g., the total number of corners, the time of the first goal, and the total number of bookings accumulated by both teams—for which it is unlikely that one could have superior information. The idea is that, if we observe that individuals overweight their home teams in these non-information-related events, then this would provide additional evidence that sentiment rather than superior information must be driving their behavior.

[Table 7 about here]

In Table 7, we report the mean portfolio weight that individuals allocate to non-information-related events associated with their local, domestic, and domestic-player teams (in columns labeled 'Individual'), the mean weight of the respective team group in the contemporaneous market portfolio (in columns labeled 'Market'), and the ratio (difference) of the individual-to-market portfolio weights for each team group in columns labeled 'Ratio' ('Difference'). Consistent with our intuition and our results above, individuals also overweight their local, domestic, and domestic-player teams in events for which there can't reasonably be much (if any) superior information. In unreported results, we also confirm that individuals do not generate superior returns from their home-team overweighting in these bets. These results further strengthen our earlier conclusion that individuals' home bias is rooted in a behavioral bias.

7 Concluding remarks

This study is the first to find evidence of a home bias in the sports betting market using a rich panel dataset of individuals' naturally occurring behavior in an online sportsbook. We show that individuals in this market exhibit a bias toward local teams, domestic teams, and teams in which a compatriot is participating, tilting their selections away from their optimal portfolio. However, individuals do not generate higher returns from betting on these teams, indicating that their bias is driven by sentiment. Furthermore, individuals' bias toward home-team wagers distorts their portfolios, resulting in welfare losses of similar magnitude as in the stock market. The results in this study have practical implications for individuals who participate in sports betting markets, as well as bookmakers, who could increase their profits by systematically exploiting their clients' home bias in their price-setting behavior.

While our findings help explain the drivers of the home bias in the sports betting market, they may also be relevant for other market settings where the home bias has been observed. The scope of markets for which our results are relevant is debatable. On the one hand, one may argue that individuals participating in the sports betting market are fundamentally different from those participating in any other market or that the same individuals behave differently in different contexts. On the other hand, one could argue that cognitive biases are an innate part of human psychology and should therefore manifest across individuals and settings. Our view is somewhere in between. We are more comfortable extrapolating our results to settings that are closer to the sports betting market. For example, the finance literature has provided ample evidence that gambling motives explain a substantial part of individual investors' speculative trading behavior in the stock market: individuals view stock trading as an entertaining gambling activity (Grinblatt and Keloharju, 2009; Dorn and Sengmueller, 2009; Gao Bakshi and Lin, 2015; Doran, Jiang and Peterson, 2012),[19] and prefer stocks with lottery-like characteristics (e.g., Barberis and Huang, 2008; Kumar, 2009; Boyer and Vorkink, 2014). Similar evidence has recently been found in online peer-to-peer lending markets, where individuals seem to view gambling as a (partial) substitute for crowdfunding (e.g., Demir, Mohammadi and Shafi, 2021; Ryu and Kim, 2016). Our results help strengthen the behavioral explanation of the home bias in these markets or market segments (e.g., the market for lottery-type assets) wherein an analysis of the home bias is complicated by confounding factors.

Our analysis also points to an interesting avenue for future research, which is to use real-world market settings with experimental-like features (like the sports-betting market) to cleanly test whether other behavioral biases that the economics literature commonly appeals to (e.g., attention effects, belief biases) are sufficiently strong to exist in other similar market settings and in the face of costs. This line of research would help address the common criticism that it is difficult to extrapolate evidence of behavioral biases from the lab to a market setting where suboptimal behavior may incur substantial welfare costs.

[19] Grinblatt and Keloharju (2009) show that sensation seekers (measured by the number of speeding tickets received) and those who exhibit overconfidence (measured by psychological tests) trade more frequently. Dorn and Sengmueller (2009) find that investors who reported in a survey that they enjoy investing or gambling turn over their stock portfolios at twice the rate of their peers. Gao Bakshi and Lin (2015) find that when there is a large jackpot lottery, some individuals substitute toward buying lottery tickets and away from trading stocks. Doran, Jiang and Peterson (2012) find that lottery-type financial assets have higher retail demand at the turn of the New Year when gambling preferences are strongest.

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Table 1: Summary Statistics

This table presents summary statistics for the data we use in our analysis. Panel A presents statistics for the characteristics of the 495 individuals in the sample. *Female* is a dummy indicating gender. *Age* is in years. *Number of Bets* (*Value of Bets*) is the number (value) of bets placed per individual. *Number of Bet Weeks* is the number of weeks during which an individual places at least one bet. Panel B presents statistics for the characteristics of the bets placed by the individuals in our sample. *Standard Event* is a dummy indicating the selected bet is on the final outcome of the match. *Price* is the price—expressed as decimal odds—associated with the selected outcome. *Streak* is the duration—the number of matches—of the active winning or losing streak of the backed team at the time of the match; positive (negative) values indicate winning (losing) streaks, and the draw outcome is assumed to maintain a team's current streak. *Home Field* is a dummy indicating the selected team has home-field advantage. *Visible Team* is a dummy indicating bets that back teams that are highly ranked according to the previous season's annual rankings. *Local* (*Domestic*) *Team* is a dummy indicating bets in which an individual backs a local (domestic) team, and *Domestic-player Team* is a dummy indicating bets in which an individual backs a team with at least one player whose country of origin is the same as the individual's country of residence. Panel C presents statistics for the characteristics of the bets (two for each match, one backing the home-field team and one backing the away team) available in the sportsbook during our sample period. *Price*, *Streak*, and *Visible Team* are defined as above.

Panel A: Characteristics of individuals

	N	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Female	495	0.07	0	0.25	0	1
Age	495	32.98	32	9.48	18	67
Number of Bets	495	186.19	104	247.38	1	2,136
Value of Bets	495	2,865.27	550	9,071.86	8.00	127,978
Number of Bet Weeks	495	17.52	11	18.32	1	152

Panel B: Characteristics of bets placed

	N	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Standard Event	92,177	0.94	1	0.24	0	1
Price	86,382	2.04	1.80	1.17	1.01	57.85
Streak	80,555	1.20	1	3.03	-20	25
Home Field	86,382	0.67	1	0.47	0	1
Visible Team	86,382	0.19	0	0.39	0	1
Local Team	86,382	0.03	0	0.17	0	1
Domestic Team	86,382	0.10	0	0.30	0	1
Domestic-player Team	86,382	0.12	0	0.33	0	1

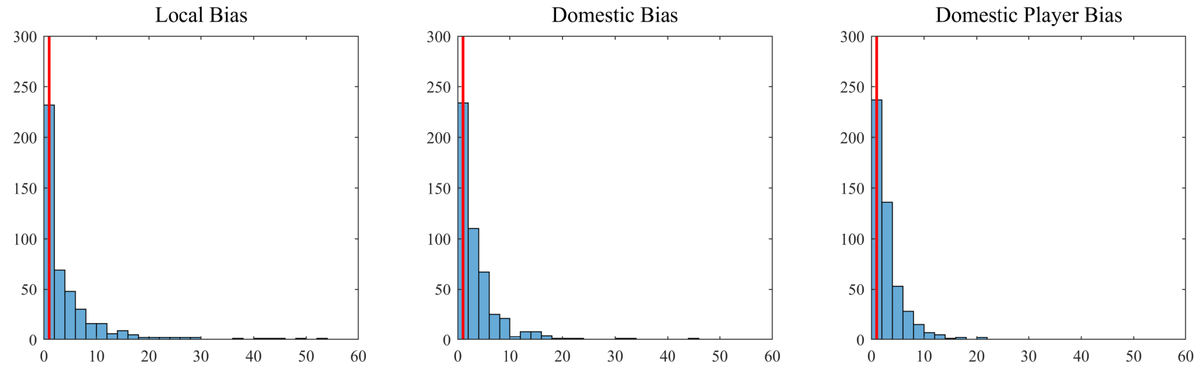
Panel C: Characteristics of bets available in the sportsbook

	N	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Price	118,384	3.28	2.56	2.53	1.01	66.33
Streak	111,027	0.13	1	2.88	-24	25
Visible Team	118,384	0.04	0	0.20	0	1

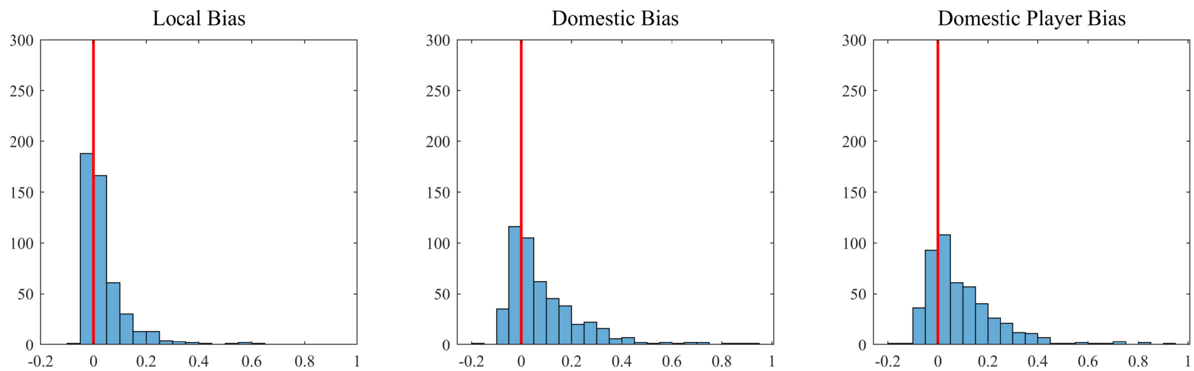
Table 2: Weight of Home Teams in Individuals' vs. Market Portfolio

This table shows the weights that individuals allocate to various home team groups in their betting portfolios and the weight of the respective groups in the market portfolio. The column labeled 'Individual' reports the mean across individuals of the time-series mean of the shares of weekly portfolio value wagered by each individual on each team group. The column labeled 'Market' reports the cross-sectional mean of the time-series mean of the proportion of all bets available in the sportsbook each week that involve this team group. The column labeled 'Ratio' ('Difference') reports the ratio (difference) of the individual to the market portfolio weight on each team group. */**/*** indicate that the ratio (difference) is significantly different from 1 (0) at the 10% /5% /1% levels.

	Individual	Market	Ratio	Difference
Local	5.41%	1.27%	4.25 ***	4.13% ***
Domestic	14.49%	5.58%	2.60 ***	8.91% ***
Domestic Player	16.59%	6.86%	2.42 ***	9.72% ***
Domestic, not Local	9.08%	4.31%	2.11 ***	4.77% ***
Domestic Player, Not Domestic Team	2.10%	1.28%	1.64 ***	0.82% ***



(a) Distribution of individual over market portfolio weight.



(b) Distribution of individual minus market portfolio weight.

Figure 1: Plots of the distribution, across individuals, of the ratio (in Panel *a*) and difference (in Panel *b*) between individual and market portfolio weights allocated to home teams. Individual portfolio weights correspond to the shares of weekly portfolio value wagered by each individual on each team group, and market portfolio weights correspond to the weight of each team group in a contemporaneous equal-weighted market portfolio that buys all available wagers. In each panel, we plot this distribution for the weights allocated to local teams (in the left plot), domestic teams (in the middle plot), and teams with at least one player whose country of origin coincides with the individual's country of residence (in the right plot).

Table 3: Overweighting of Home Teams in Individuals' Portfolio

This table presents results from OLS regressions in which the dependent variable is the portfolio weight (as a percent) that individual i allocates to team j in match m in week t. *Local* (*Domestic*) is a dummy indicating bets in which an individual backs a local (domestic) team, and *Domestic Player* is a dummy indicating bets in which an individual backs a team with at least one player whose country of origin is the same as the individual's country of residence. *Market Weight* is the weight (as a percent) that corresponds to team j in match m in an equal-weighted market portfolio in week t. *Price* is the price (expressed as decimal odds) associated with team j at the time of match m. *Home Field* is a dummy indicating the selected team has home-field advantage. *Visible Team* is a dummy indicating bets that back teams that are highly ranked according to the previous season's annual rankings. *Streak* is the duration—the number of matches—of the active winning or losing streak of the backed team at the time of the match; positive (negative) values indicate winning (losing) streaks, and the draw outcome is assumed to maintain a team's current streak. The regression includes all teams in the universe of matches in week t. In column 5 (6), the sample is limited to matches between domestic teams (foreign teams), and in column 7, the sample is limited to matches between domestic and foreign teams. t-statistics using standard errors clustered at the match level are reported below the coefficients. * /** /*** indicate significance at the 10% /5% /1% levels.

	(1) Local	(2) Domestic	(3) Domestic Player	(4) All	(5) Domestic vs. Domestic	(6) Foreign vs. Foreign	(7) Domestic vs. Foreign
Local	0.694 ***			0.398 ***	1.910 ***		
	18.177			10.946	12.121		
Domestic		0.400 ***		0.225 ***			9.017 ***
		23.160		9.776			4.386
Domestic Player			0.335 ***	0.086 ***		0.110 ***	
			23.547	5.049		5.276	
Market Weight	1.116 ***	1.118 ***	1.124 ***	1.121 ***	0.994 ***	1.110 ***	0.987 ***
	18.466	18.583	18.664	18.612	16.569	18.497	23.477
Price	-0.026 ***	-0.027 ***	-0.027 ***	-0.027 ***	-0.471 ***	-0.027 ***	-1.883 ***
	-26.660	-26.576	-26.566	-26.601	-14.733	-24.924	-4.068
Home Field	0.095 ***	0.092 ***	0.093 ***	0.093 ***	0.450 **	0.111 ***	6.206 **
	21.871	21.186	21.304	21.300	2.347	23.596	2.583
Visible Team	0.782 ***	0.795 ***	0.788 ***	0.794 ***	4.370	0.997 ***	8.832 ***
	37.539	38.197	37.760	38.149	1.372	39.213	2.801
Streak	0.019 ***	0.019 ***	0.019 ***	0.019 ***	0.276 ***	0.020 ***	0.086
	23.356	23.317	22.981	23.251	8.732	22.285	0.195
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-square	0.009	0.010	0.010	0.010	0.023	0.011	0.114
Observations	3,789,931	3,789,931	3,789,931	3,789,931	97,245	3,356,043	6,406

Table 4: Individuals' Returns

This table presents results from OLS regressions in which the dependent variable is the return realized by individual i on the wager backing team j in match m. In Panel A, the explanatory variables include home-team dummies, individual-specific measures of home-team preference, interaction terms, controls, and season fixed effects. Panel B is identical to A, except that the season fixed effects and the individual-specific measures of home-team preference are replaced with individual fixed effects. *Local* (*Domestic*) is a dummy indicating bets in which an individual backs a local (domestic) team, and *Domestic Player* is a dummy indicating bets in which an individual backs a team with at least one player whose country of origin is the same as the individual's country of residence. *Local Bias*, *Domestic Bias*, and *Domestic-player Bias* are individual-specific measures of the preference toward local, domestic, and domestic-player teams. *Price* is the decimal odds of a wager backing team j in match m. *Home Field* is a dummy indicating the selected team has home-field advantage. *Visible Team* is a dummy indicating bets that back teams that are highly ranked according to the previous season's annual rankings. *Streak* is the duration of the backed team's active winning/losing streak. The regression includes all wagers in our sample. In column 5 (6), the sample is limited to matches between domestic teams (foreign teams), and in column 7 to international matches. t-statistics using standard errors clustered at the match level are reported below the coefficients. * /** /*** indicate significance at the 10% /5% /1% levels.

Panel A: With Season Fixed Effects

	(1) Local	(2) Domestic	(3) Domestic Player	(4) All	(5) Domestic vs. Domestic	(6) Foreign vs. Foreign	(7) Domestic vs. Foreign
Price	-0.000	-0.000	-0.000	0.000	-0.060 ***	0.000	0.104
	-0.013	-0.023	-0.024	0.003	-3.088	0.027	0.969
Home Field	-0.018	-0.018	-0.018	-0.018	-0.042	-0.014	-0.176
	-0.962	-0.976	-0.974	-0.967	-0.587	-0.737	-0.764
Streak	-0.001	-0.001	-0.001	-0.001	-0.012	-0.001	0.035
	-0.488	-0.485	-0.485	-0.506	-1.312	-0.321	0.899
Visible Team	-0.006	-0.007	-0.007	-0.007	-0.375	-0.003	-0.346
	-0.286	-0.349	-0.327	-0.343	-1.417	-0.153	-1.354
Local	0.007			0.006	-0.018		
	0.160			0.156	-0.477		
Domestic		0.007		-0.007			-0.112
		0.199		-0.125			-0.542
Domestic Player			0.011	0.012		0.014	
			0.376	0.237		0.277	
Local Bias	0.102			0.100	0.028		
	1.386			0.959	0.134		
Domestic Bias		0.064		-0.128			0.017
		1.420		-0.609			0.054
Domestic-player Bias			0.066	0.151		0.057	
			1.461	0.754		1.266	
Local	-0.054			0.068	0.056		
× Local Bias	-0.283			0.309	0.212		
Domestic		-0.106		-0.202			-0.463
× Domestic Bias		-1.191		-0.746			-1.073
Domestic Player			-0.102	0.084		0.081	
× Domestic-player Bias			-1.168	0.319		0.294	
Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-square	0.000	0.000	0.000	0.000	0.008	0.000	0.060
Observations	80,468	80,468	80,468	80,468	6,960	71,795	1,713

Panel B: With Individual Fixed Effects

	(1) Local	(2) Domestic	(3) Domestic Player	(4) All	(5) Domestic vs. Domestic	(6) Foreign vs. Foreign	(7) Domestic vs. Foreign
Price	0.003	0.003	0.003	0.003	-0.056 ***	0.004	0.107
	0.273	0.276	0.272	0.283	-2.757	0.401	0.981
Home Field	-0.020	-0.020	-0.020	-0.020	-0.044	-0.016	-0.169
	-1.068	-1.078	-1.074	-1.069	-0.612	-0.843	-0.759
Streak	-0.002	-0.002	-0.002	-0.002	-0.013	-0.001	0.035
	-0.646	-0.650	-0.645	-0.668	-1.346	-0.443	0.814
Visible Team	-0.008	-0.010	-0.009	-0.009	-0.094	-0.004	-0.450 *
	-0.402	-0.469	-0.437	-0.451	-0.310	-0.208	-1.948
Local	-0.006			-0.002	-0.029		
	-0.152			-0.041	-0.635		
Domestic		-0.003		-0.013			-0.128
		-0.076		-0.222			-0.635
Domestic Player			0.003	0.011		0.011	
			0.088	0.221		0.218	
Local	0.093			0.166	0.083		
× Local Bias	0.407			0.649	0.274		
Domestic		-0.046		-0.159			-0.315
× Domestic Bias		-0.425		-0.559			-0.469
Domestic Player			-0.045	0.078		0.111	
× Domestic-player Bias			-0.433	0.291		0.393	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-square	0.004	0.004	0.004	0.004	0.010	0.004	0.024
Observations	80,468	80,468	80,468	80,468	6,929	71,795	1,616

Table 5: Distortions due to Home Bias

This table shows the effect of the average odds of wagers backing home teams on the average odds of wagers that individuals select. The dependent variable is the weekly average *Price* (expressed in decimal odds) of wagers placed by individuals in our sample. $Price_{Local}$ ($Price_{Domestic}$) is the weekly average price of wagers backing an individual's local (domestic) team, and $Price_{Domestic\ Player}$ is the weekly average price of wagers backing teams with at least one player whose country of origin is the same as the individual's country of residence. *Local Bias*, *Domestic Bias*, and *Domestic-player Bias* are individual-specific dummies indicating a preference toward local, domestic, and domestic-player teams measured as the mean difference between the individual and market portfolio weights allocated to the respective team group. Specifications (1), (3), and (5) include individual-level fixed effects. Specifications (2), (4), and (6) include the individual-specific preference dummies and interactions of the preference dummies and the weekly average price of wagers backing each team group. *t*-statistics are reported below the coefficients. * /** /*** indicate significance at the 10% /5% /1% levels.

	(1) Local	(2) Local	(3) Domestic	(4) Domestic	(5) Domestic Player	(6) Domestic Player
$Price_{Local}$	0.004	-0.031 **				
	0.372	-2.167				
Local Bias		-0.193 **				
		-1.997				
Local Bias		0.068 ***				
× $Price_{Local}$		2.616				
$Price_{Domestic}$			0.059 ***	0.014		
			2.657	0.461		
Domestic Bias				-0.303 *		
				-1.752		
Domestic Bias				0.121 **		
× $Price_{Domestic}$				2.548		
$Price_{Domestic\ Player}$					0.088 ***	0.056 *
					3.642	1.765
Domestic-player Bias						-0.291
						-1.626
Domestic-player Bias						0.109 **
× $Price_{Domestic\ Player}$						2.132
Individual FE	Yes	No	Yes	No	Yes	No
Adj. R-square	0.220	0.001	0.161	0.003	0.164	0.003
Observations	6,085	6,103	7,541	7,555	7,823	7,837

Table 6: Overweighting of Home Teams in Individuals' Portfolio — With Team Characteristics

This table presents results from OLS regressions in which the dependent variable is the portfolio weight (as a percent) that individual i allocates to team j in match m in week t. The explanatory variables include home-team dummies, team characteristics and interaction terms. *Local* (*Domestic*) indicates teams that are local (domestic) to the individual, and *Domestic Player* indicates teams with at least one player whose country of origin is the same as the individual's country of residence. *Market Weight* is the weight (as a percent) that corresponds to team j in match m in an equal-weighted market portfolio in week t. *Price* is the price (expressed as decimal odds) associated with team j at the time of match m. *Home Field* indicates teams with home-field advantage. *Visible Team* indicates teams that are highly ranked according to the previous season's annual rankings. *Streak* is the duration of the team's active winning/losing streak. *Early in Season* indicates the first one-third of the matches of the team's league/season. *Non-Top League* indicates teams that do not compete in a major first-tier league. *Odds Std.Dev.* is the standard deviation, across bookmakers, of the prices associated with team j in match m, scaled by the mean price. The regression includes all teams in the universe of matches in week t. t-statistics using standard errors clustered at the match level are reported below the coefficients. * /** /*** indicate significance at the 10% /5% /1% levels.

	(1) Local	(2) Local	(3) Local	(4) Domestic	(5) Domestic	(6) Domestic	(7) Domestic Player	(8) Domestic Player	(9) Domestic Player
Market Weight	1.127 ***	1.120 ***	0.755 ***	1.126 ***	1.127 ***	0.753 ***	1.133 ***	1.134 ***	0.767 ***
	17.967	18.909	12.722	18.032	19.148	12.925	18.111	19.200	12.956
Price	-0.027 ***	-0.030 ***	-0.029 ***	-0.028 ***	-0.031 ***	-0.031 ***	-0.028 ***	-0.031 ***	-0.030 ***
	-26.352	-28.796	-26.881	-26.274	-28.306	-26.633	-26.270	-28.336	-26.646
Home Field	0.094 ***	0.087 ***	0.064 ***	0.092 ***	0.085 ***	0.060 ***	0.092 ***	0.086 ***	0.061 ***
	21.381	20.150	14.816	20.648	19.536	14.000	20.780	19.646	14.008
Visible Team	0.781 ***	0.711 ***	0.608 ***	0.795 ***	0.732 ***	0.623 ***	0.788 ***	0.719 ***	0.610 ***
	37.240	34.018	33.113	37.895	35.125	34.010	37.454	34.222	32.856
Streak	0.019 ***	0.018 ***	0.015 ***	0.019 ***	0.018 ***	0.015 ***	0.018 ***	0.018 ***	0.014 ***
	23.026	23.059	19.235	22.969	23.381	19.621	22.634	22.639	18.553
Local	0.695 ***	1.249 ***	1.631 ***						
	14.489	19.392	15.245						
Domestic				0.410 ***	0.799 ***	1.072 ***			
				18.146	26.832	20.846			
Domestic Player							0.344 ***	0.624 ***	0.695 ***
							18.450	26.088	18.763
Early in Season	-0.046 ***			-0.047 ***			-0.047 ***		
	-12.110			-12.815			-12.690		
Non-Top League		-0.166 ***			-0.146 ***			-0.145 ***	
		-46.104			-43.027			-42.378	
Odds Std.Dev.			-0.057			0.017			0.018
			-1.284			0.418			0.439
Local × Early in Season	-0.007								
	-0.089								
Local × Non-Top League		-1.100 ***							
		-15.808							
Local × Odds Std.Dev.			-5.537 ***						
			-4.790						
Domestic × Early in Season				-0.040					
				-1.197					
Domestic × Non-Top League					-0.713 ***				
					-22.333				
Domestic × Odds Std.Dev.						-4.217 ***			
						-8.163			
Domestic-player × Early in Season							-0.035		
							-1.240		
Domestic-player × Non-Top League								-0.547 ***	
								-21.154	
Domestic-player × Odds Std.Dev.									-2.691 ***
									-6.689
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-square	0.010	0.011	0.009	0.010	0.012	0.010	0.010	0.012	0.009
Observations	3,723,631	3,789,931	2,701,551	3,723,631	3,789,931	2,701,551	3,723,631	3,789,931	2,701,551

Table 7: Weight of Home Teams in Individuals' vs. Market Portfolio — Non-information Events

This table shows the weights that individuals allocate to various home team groups in their betting portfolios and the weight of the respective groups in the market portfolio. The column labeled 'Individual' reports the mean across individuals of the time-series mean of the shares of weekly portfolio value wagered by each individual on a non-information-related event associated with each team group. The column labeled 'Market' reports the cross-sectional mean of the time-series mean of the proportion of all bets available in the sportsbook each week that involve this team group. The column labeled 'Ratio' ('Difference') reports the ratio (difference) of the individual to the market portfolio weight on each team group. $^{*}/^{**}/^{***}$ indicate that the ratio (difference) is significantly different from 1 (0) at the 10% /5% /1% levels.

	Individual	Market	Ratio	Difference
Local	5.33%	1.28%	4.17 ***	4.05% ***
Domestic	15.83%	5.22%	3.03 ***	10.61% ***
Domestic Player	17.93%	6.58%	2.72 ***	11.35% ***
Domestic, not Local	10.50%	3.94%	2.67 ***	6.56% ***
Domestic Player, Not Domestic Team	2.09%	1.36%	1.54 ***	0.73% ***