Home Bias and Investor Sentiment: Evidence from a Quasi-Experimental Financial Market*

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Abstract

We use the sports betting market as a real-world market laboratory to study the home bias in individuals' behavior. In contrast to traditional financial markets, where institutional frictions and the joint hypothesis problem confound explanations of the home bias, the sports betting market's quasi-experimental features enable us to cleanly test whether preferential betting on home teams reflects informational advantages or behavioral forces. We find that individuals systematically favor local teams, domestic teams, and teams featuring players from their home country. This home bias does not yield superior performance but distorts individuals' portfolios, generating welfare costs of similar magnitude to those in the stock market. Our findings help strengthen the foundation of behavioral explanations of the home bias in similar market environments.

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

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1 Introduction

A large finance literature has established that individuals tilt their portfolios toward securities of their home country or local area. But, while this "home bias" is a well-established phenomenon, its causes are the subject of an ongoing debate in the literature. Some authors argue that it is driven by an inherent behavioral bias that leads to suboptimal decisions and substantial welfare costs (*sentiment hypothesis*). Others argue that it arises because individuals have an informational advantage about home assets which leads to superior investment performance (*information hypothesis*). Identifying the correct mechanism is challenging in traditional financial markets because institutional frictions make home assets genuinely easier to trade, and because tests of superior performance are joint tests of an underlying asset pricing model, making it difficult to separate true informational advantages from model misspecification. In this paper, we contribute to this debate by examining a rich dataset of individual activity in an online sports betting market. This setting serves as a clean test bed that enables us to study whether there is an inherent psychological home bias that is strong enough to persist in real-world markets despite substantial welfare costs, and therefore whether it could possibly give rise to the observed home bias in traditional financial markets.

Sports betting markets share many structural features with traditional financial markets. Both settings involve participants with varying sophistication who risk meaningful sums on uncertain future outcomes, enabling informed traders to profit from mispricing while biased individuals make suboptimal decisions. Bookmakers resemble financial market makers who continuously post and update prices, and handicappers serve a role analogous to financial analysts who incorporate public information into forecasts. Prior research also shows that bettors' risk preferences and motives are broadly similar to those of retail investors, suggesting that insights from this setting can meaningfully inform debates about behavioral biases in financial markets. At the same time, sports betting markets possess some unique quasi-experimental features that sharply distinguish them from traditional financial markets. First, informational advantages stem from short-lived match-specific signals with immediate implications about match outcomes, so information readily maps into realized returns. Second, sports wagers bear no systematic risk, allowing performance to be measured accurately without the need to assume an asset-pricing model to calculate risk-adjusted returns. Third, individuals can easily take symmetric positions—betting for or against a team—which has specific testable implications about the behavior of individuals with superior information. Finally, the market structure minimizes institutional frictions that could confound explanations of the home bias; specifically, bettors face uniform transaction costs and no market-integration barriers, ruling out cost-based explanations of the home bias. These features render sports betting a clean environment for testing whether home bias is driven by superior information or by sentiment.

Our data set contains approximately 100,000 wagers on various soccer events placed by about 500 individuals at an online sportsbook over a 5-year period. 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%. It is notable that this is comparable to the 150% overweighting for stocks of locally-headquartered firms found in the literature (see Ivkovic and Weisbenner, 2005).

Subsequently, we examine whether home-team overweighting reflects superior information or a behavioral bias. In the sports-betting setting, the information-based explanation of the home bias yields sharp empirical predictions. First, unlike retail investors in financial markets—who rarely take short positions—bettors can readily wager either for or against a team. Furthermore, any informational advantage about a team should apply symmetrically to favorable and unfavorable information, and so bettors with superior information about a home team should be equally likely to bet for or against it. Second, the absence of systematic risk and the fact that match outcomes reveal a wager's true terminal value imply that realized returns accurately reflect performance, and so, information. Therefore, individuals who possess superior information about home teams should earn higher realized returns on home-team wagers. We find no empirical support for either prediction. Specifically, we find that bettors overwhelmingly back their domestic teams, even when restricting attention to international matches. Also, we find that home-team wagers do not yield higher returns and, furthermore, that individuals with a stronger home bias do not outperform those with a weaker bias.[1] A broad set of robustness tests further reinforces these findings and shows that they do not mask variation across heterogeneous sub-populations and information environments. Home-team overweighting persists even in environments in which information asymmetries should be weakest, including late-season matches for which public information has accumulated throughout the season, matches involving teams in high-visibility leagues, matches with low odds dispersion across bookmakers, and proposition bets on outcomes like total corners or time of first goal. Evidence on individual heterogeneity also points to a behavioral channel: home bias is stronger among men—consistent with stronger fan attachment and overconfidence—and among less experienced bettors, echoing similar results from analyses of the home bias in traditional investing.[2] Importantly, bettors who place larger wagers do not exhibit stronger home bias, contradicting the idea that information acquisition drives the effect. Taken together, these findings strongly indicate that home-team overweighting is driven by a behavioral rather than an informational mechanism.

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

[1] Crucially, an a priori power analysis shows that our sample size is sufficiently large (almost an order of magnitude larger than required) to detect even very small effects with high power, indicating that our non-results reflect economically negligible informational advantages rather than a lack of statistical power.

[2] For example, Karlsson and Nordén (2007) find that home bias is more pronounced among individuals with less experience investing in risky assets, and Graham, Harvey and Huang (2009) find that that it is more pronounced among those who report lower financial competence, a trait that is correlated with gender.

neither increases nor decreases individuals' returns. But, unless individuals are risk neutral, this does not imply that the home bias is harmless. A bias toward home teams may cause individuals to choose suboptimal portfolios, resulting in welfare costs. 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 people's 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. This is of the same order of magnitude as the estimated cost of domestic bias in the stock market, which ranges from about 1% annually for large developed markets up to about 7% for smaller or less integrated markets (Levy, 2017; Mishra and Anwar, 2026; see also Coeurdacier and Rey, 2013). This is important, as it implies that the home bias we document is strong enough to survive the substantial welfare cost associated with it.

While one should be cautious in extrapolating findings from one set of individuals to another, there are reasons to believe that our sample selection should be mild hence our finding applies more widely. Sports betting is a widespread 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).[3] Furthermore, studies of sports wagering markets have found that participants' risk preferences are similar to those estimated in experiments (Andrikogiannopoulou and Papakonstantinou 2020), and surveys have shown that the primary driver of participants' behavior is financial gain while non-pecuniary motives like entertainment are secondary (2018 UK Gambling Commission report), indicating that sample selection is likely not severe. It is also notable that these motives are surprisingly similar to those of financial market participants: Hoffman

[3] *Online* sports betting in particular is becoming ever more popular. 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.

(2007) finds that the second strongest motive for investing is that it is “a nice free-time activity,” behind “financial gain,” Gao Bakshi and Lin (2015) find that, when there is a large lottery jackpot, some investors substitute trading stocks for buying lottery tickets, and many studies show that individuals prefer stocks with lottery-like characteristics (e.g., Barberis and Huang, 2008; Kumar, 2009; Boyer and Vorkink, 2014). While our findings do not imply that sentiment fully explains the home bias in all financial markets, they may be particularly relevant for segments that are most similar to betting markets, e.g., for individual (rather than professional) investors who are generally considered to be less sophisticated, and for stocks with lottery-like features. More generally, our finding that there exist non-information motives that underlie the home bias and persist in a real market setting despite substantial welfare costs speaks to fundamental aspects of human psychology, thereby strengthening the behavioral foundations of home-bias explanations across contexts.

This paper contributes to a large finance literature that documents home bias in individual trading and tries to identify the underlying mechanisms that give rise to this behavior. Coval and Moskowitz (1999) first proposed that geographic proximity lowers information frictions, and so home bias reflects information asymmetries. For example, home investors may have access to different information or they may more cheaply interpret and synthesize relevant information. Consistent with this view, Ivkovic and Weisbenner (2005), Massa and Simonov (2006) and Ben-David, Birru and Rossi (2019) find that retail investors earn superior returns on home investments, suggesting that home bias can reflect genuine informational advantages. At the same time, another body of work finds no superior performance on home investments, especially among less sophisticated investors (Grinblatt and Keloharju, 2001; Seasholes and Zhu, 2010), and proposes non-information explanations for local bias, including familiarity, loyalty, patriotism, and trust (Huberman, 2001; Cohen, 2009; Morse and Shive, 2011; Shao and Wang, 2021).[4] Our paper contributes to this literature by analyzing a different market setting in which performance can be measured accurately and institutional frictions are minimal, allowing for a cleaner test of these competing explanations. We show that the home

[4] 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 informational advantages explanation and French and Poterba (1991), Froot, O’Connell and Seasholes (2001), Pool, Stoffman and Yonker (2012) for evidence in favor of behavioral explanations.

bias in our setting reflects behavioral rather than informational motives, even though such choices entail welfare costs, thereby reinforcing behavioral interpretations of home bias in equity markets.

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 traditional financial markets 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 (2021) 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.

Finally, our findings relate to the experimental literature on behavioral biases. For example, 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 a home bias that persists in the face of substantial welfare costs by tracking individuals' naturally occurring betting behavior.

The rest of the paper is organized as follows. 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 irrespective of the realized outcome, 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.

Our data is from an online sports betting company that operates in the European market. The company is a large, established operator, with a broad customer base and standardized odds-setting practices. We note that the company does not use region-specific incentives and marketing that would artificially increase the attractiveness of home wagers. Our data contains information on the

[5]Other studies (e.g., Levitt, 2004) suggest that bookmakers take advantage of behavioral biases by setting prices between those that balance the book and the efficient ones, but our bookmaker has stated they do not use this strategy.

complete betting histories of about 550 randomly selected customers over the period 2005 to 2010. We focus on all bets placed by these individuals on soccer matches.[6] For each bet, we observe: (i) the date; (ii) the fixture (e.g., Premier League match between Arsenal and Chelsea); (iii) the event (e.g., final outcome, total number of bookings); (iv) the outcome chosen (e.g., home or away win); (v) the amount staked; and (vi) the price of each outcome of the event when the bet was placed. We also observe the gender, age, country of residence, and zip code of the individuals.

We also compile a list of all soccer matches for which bets were offered by the sportsbook over our sample period.[7] Since, at any point in time, there is a very large number of matches to choose from and individuals likely only consider some of them when placing their bets, 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 the wagers we observe. 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 even 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.

To construct our final sample, we first keep individuals who have placed at least five wagers in total, of which at least one is on a soccer match, yielding a sample of 495 individuals. These individuals have placed 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,

[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 more widely accessible 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 has data on national leagues in Europe, for the entire sample period; (ii) matchstatistics.com has data on national leagues and international competitions worldwide, before the middle of 2009; and (iii) betfair.com has data on all the above for the entire sample period.

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 study if people have a bias toward home teams, we drop the 15% of bets placed on draw outcomes. Thus, we analyze 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) the zip code 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. That is, a player is defined as domestic or not in relation to the bettor, not the team.

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*) associated with each outcome at match time to account for differences in risk across bets, as well as for whether the team plays at home or away (*Home Field*) to control for a possible preference for teams playing on their home field. We also control for streaks in team past performance, to control for a possible preference toward

[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.

teams on winning streaks.[9] Specifically, we calculate the length (number of matches) of each team's active streak at match time *(Streak)*, where negative (positive) values indicate losing (winning) streaks. Furthermore, we control for team visibility, as individuals may prefer to wager on highly visible teams. Our visibility measure is based on teams' historical success, on the basis that more successful teams attract more attention by the media. Specifically, we construct an indicator variable *(Visible Team)* that is specific for each team each season and indicates whether a team was one of the top 20 club (top 5 national) teams according to UEFA's (FIFA's) rankings for the previous year.[10]

[Table 1 about here]

Table 1 shows summary statistics for our sample. Panel A shows statistics for individual characteristics. Most individuals (93%) are men, the median (mean) age is 32 (33) years and 49% of the individuals reside in large metropolitan areas.[11] The average individual has staked €2,865 on 186 wagers over a period of 17.5 weeks. Panel B shows statistics for the bet characteristics. 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. The odds of the placed bets range from 1.01 to 57.85, with a median (mean) of 1.80 (2.04). 19% of the bets back a highly visible team, 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, Panel C shows statistics for the characteristics of the following two bets for each match: one on the home-field team and one on the away team. The odds of these

[9] See, e.g., Tversky and Kahneman (1971) for experimental and Clotfelter and Cook (1993) for field studies showing that individuals often believe in systematic reversals or persistence in random sequences. 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.

[10] In unreported results, we consider alternative team visibility measures and our results are qualitatively the same. One alternative measure is an indicator variable that is team-specific and 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] The characteristics of the individuals in our data are not too dissimilar from those of individuals in studies of online stock market investing. For example, in a U.S. sample of individuals with an online trading account used by a series of seminal studies (e.g., Barber and Odean, 2002), investors are mostly men (86%) with median (mean) age of 48 (49.6) years. Similarly, in a German sample of individuals with an online trading account, investors are mostly men (95%) and the median (mean) age is 39 (40.8) years (Glaser, 2003).

bets range from 1.01 to 66.33, with a median (mean) of 2.56 (3.28). 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 exhibit a home bias in the sports betting market. 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 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] for each week t, we calculate that individual i allocates portfolio weight

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

where B_{igt} is the money that individual i stakes on team group g in week t.[13] In addition, we calculate the market portfolio weight on team group g 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, this market portfolio weight is the expected weight in a portfolio constructed by randomly picking wagers.

[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]Our results are unaffected if we use equal- rather than value-weighted portfolios. They are also unaffected if we use monthly rather than weekly portfolios.

[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 (see the 'Individual' column), the mean weight $Market_{gt}$ of the respective team group in the contemporaneous market portfolio (see the 'Market' column), and the ratio of (difference between) the individual and the market portfolio weights for each team group in columns labeled 'Ratio' ('Difference'). On average, the individual portfolio weight is higher than the corresponding market portfolio weight, for all home-team groups: individuals allocate 5.4% of their portfolio to local teams, while the corresponding market portfolio weight is only 1.3%; they allocate 14.5% of their portfolio to domestic teams, while the corresponding market portfolio weight is only 5.6%; and they allocate 16.6% of their portfolio to teams in which at least one player is domestic, while the corresponding market portfolio weight is only 6.9%. 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.

[Figure 1 about here]

In Figure 1a (1b), we plot histograms of the ratio of (difference between) the individual and the 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 indicates 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 equals 1 if 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 on 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 associated with team j in match m, (ii) the duration of the active streak of team j at the time of match m, (iii) a dummy variable that equals 1 if j is highly visible at the time of match m, and (iv) a dummy variable that equals 1 if team j plays 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. In our analysis, multiple observations are included for each match, so standard errors are clustered at the match level to allow for residual correlation across observations. 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 5–6, 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.

4 Testing information versus sentiment

Our results thus far have shown that individuals overweight their home teams in their portfolios. In this section, we study whether this behavior is driven by superior information or a behavioral bias. A key advantage of the sports-betting setting is that it provides much cleaner empirical tests of the information-versus-sentiment hypothesis than is feasible in traditional financial markets. First, unlike retail investors in financial markets—who rarely take short positions—bettors can readily wager either for or against a team. Since any informational advantage about a team should apply symmetrically to favorable and unfavorable information, this implies that bettors with superior

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

information about a home team should be equally likely to bet for or against it. Second, while private information in financial markets typically relates to long-run fundamentals and is difficult to map into realized returns over any specific horizon, informational advantages in betting must stem from short-lived, match-specific signals (e.g., injuries, lineups, tactical changes) with immediate implications for outcomes, which reveal a wager's (hence the information's) true value. Furthermore, in contrast to financial markets, in betting markets there is no systematic risk hence no need to assume an asset pricing model and calculate risk adjusted performance measures. As a result, realized returns accurately reflect information so, if bettors possess superior information about their home teams, it should translate into higher realized returns. These predictions form the basis of our tests below.

First, in specification 7 of Table 3, we examine whether individuals overweight their domestic teams in international matches in which a domestic team plays against a foreign opponent. In these matches, if individuals possess superior knowledge about their domestic teams, they should be equally likely to bet for or against them, depending on whether their private information is favorable or unfavorable. Thus, under the null hypothesis of no behavioral home bias, the coefficient β_1 in Equation 3 should be close to zero. Instead, we find that individuals overwhelmingly bet for the domestic team in these international fixtures. We obtain similar results when restricting the sample to matches involving local versus non-local teams and domestic-player versus non-domestic-player teams. These asymmetric patterns are difficult to reconcile with the superior information explanation and are more consistent with a behavioral preference for home teams.

Second, in Table 4, we directly examine whether individuals earn higher returns on their home-team wagers. To evaluate whether home-team preferences reflect informational advantages, we estimate the following model controlling for a rich set of team and match characteristics:

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

where $Return_{ijmt}$ is the return earned 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;

[15]Note that the bookmaker's commission is included in this realized return, since a wager with fixed payout regardless of the event's outcome has return below one.

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 portfolio weights that the individual and the market place on these teams, and (iii) interaction terms between the home-team dummies and the individual-specific home-bias measures. Our analysis includes an observation for each bet. Since multiple bets may involve the same match, standard errors are clustered at match level to allow for residual correlation across observations.

[Table 4 about here]

In Panel A of Table 4, we show 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 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 the performance of individuals with a stronger bias is similar to that of individuals that have a weaker bias. Finally, in all specifications, the coefficients on the interaction terms are insignificant, meaning that individuals with a stronger home bias do not have superior performance when they back 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.

We 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 conclude 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

[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.

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 document 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 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 individuals 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 examine how home-team overweighting varies across different market environments and across individuals. Specifically, in Section 6.1 we examine whether our results are sensitive to conditioning on specific team and match characteristics that proxy for the availability of public information, such as early- versus late-season matches, high- versus low-visibility leagues, and matches with high versus low dispersion in bookmaker odds. In Section 6.2, we analyze proposition bets on events that are largely unrelated to team-specific information, such as total corners or

[17] See Coeurdacier and Rey (2013) for a review of the relevant literature.

the time of the first goal. Finally, in Section 6.3, we explore heterogeneity across individuals, including differences by gender, age, betting experience, and stake size. Together, these tests validate our baseline findings and show that they do not mask variation across subsamples of contextual features.

6.1 *Analysis of team characteristics*

In this section, we study 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. Similar indirect tests have been conducted in financial markets to gain insights into what drives individuals to overweight home assets. 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 that equals 1 if 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 that equals 1 if 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 pattern is inconsistent with information-based explanations, but could be consistent with a sentiment-driven interpretation. 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 match winner of soccer matches. 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 (see the 'Individual' column), the mean weight of the respective team group in the market portfolio contemporaneously (see the 'Market' column), and the ratio of (difference between) the individual and the 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.

6.3 *Analysis of individual characteristics*

To further explore the nature of home-team overweighting, in this section we examine whether this behavior varies systematically across individuals. If overweighting were driven by superior information rather than sentiment, it should be most pronounced among individuals who are more likely to acquire, process, and act on relevant information. For example, prior work shows that men exhibit stronger and more frequent fan behavior (Dietz-Uhler et al., 2000); that younger individuals generally display greater cognitive flexibility (Korniotis and Kumar, 2013); and that trading experience reduces behavioral mistakes (Nicolosi, Peng and Zhu, 2009). In addition, bettors who routinely place larger wagers face stronger financial incentives to gather and use information. Under an information-based explanation, we would therefore expect home-team overweighting to be more pronounced among men, younger individuals, more experienced bettors, and high-stake participants.

To test these implications, we augment the model in Equation 3 with interactions between $HomeTeam_{ijmt}$ and dummy variables indicating (i) female bettors (*Female*), (ii) individuals whose age is below the sample median (*Young*), (iii) individuals with above-median trading experience—measured as the cumulative number of bets placed (*Experienced*), and (iv) individuals whose average wager size is above the sample median (*Large Wagers*).[18]

[Table 8 about here]

In Table 8, we report estimates of this augmented model: Columns 1–4 examine the overweighting of local teams, Columns 5–8 the overweighting of domestic teams, and Columns 9–12 the overweighting of domestic-player teams. We find that home-team overweighting is significantly

[18]Alternative measures of experience based on cumulative stakes, and an alternative proxy for an incentive to gather information based on the frequency of wagers, yield similar results.

stronger among men (Columns 1, 5, and 9) and among individuals with less betting experience (Columns 3, 7, and 11). We find no significant differences between younger and older bettors. Moreover, individuals who place larger stakes—those for whom financial incentives to acquire information are strongest—do not overweight home teams more than lower-stake bettors. These patterns mirror findings from financial markets: experience mitigates behavioral biases, while men display stronger entertainment-driven and sentiment-driven trading behavior. The results are difficult to reconcile with superior information as the driver of home-team overweighting and instead provide additional evidence that the behavior we observe reflects a sentiment-based mechanism.

7 Concluding remarks

In this study, we have analyzed a panel data set of individuals' naturally occurring behavior in an online sportsbook to shed light on the behavioral forces that have been proposed as an explanation for the home bias observed in the stock market. We show that, similar to stock market investors, individuals in this market exhibit a bias toward local teams, domestic teams, and teams with domestic players. 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 to those in the stock market.

These results strengthen the behavioral explanation for the home bias in similar equity markets. In stock-market settings, distinguishing between informational and behavioral channels is complicated by the joint-hypothesis problem and the presence of institutional frictions. In our setting, outcomes are exogenous and performance can be measured without relying on an asset-pricing model, and we find no evidence that home-team wagers outperform. These findings indicate that the home bias observed in financial markets is unlikely to be driven by informational advantages alone and that behavioral forces play a meaningful role.

Our findings carry important policy implications. If sentiment-driven biases distort portfolios, then initiatives that increase investor awareness, promote debiasing strategies, and highlight the potential costs of such behavior could help individuals make more informed choices and reduce welfare losses. Furthermore, improving the presentation of risk–return information or reducing the salience of country-specific cues in financial products may help limit the impact of similar sentiment-driven distortions in investment decisions.

Our analysis also points to several promising avenues for future research. First, our analysis provides a blueprint for using real-world market settings with quasi-experimental features to cleanly test whether other behavioral biases that the finance literature commonly appeals to (e.g., attention effects, or belief distortions such as overconfidence) are sufficiently strong to manifest in market settings. Second, examining whether similar sentiment-driven distortions arise in prediction markets, retail trading apps, or other low-friction trading platforms would help assess the external validity of our findings. Together, this line of research would help address the common criticism that it is difficult to extrapolate evidence of behavioral biases from the lab to real-world market settings where suboptimal behavior may entail substantial welfare costs.

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Table 1: Summary Statistics

This table presents summary statistics for our sample. Panel A shows statistics for individual characteristics. *Female* is a gender dummy. *Age* is measured in years. *Number of Bets* (*Value of Bets*) is the number (value) of bets placed by each individual. *Number of Bet Weeks* is the number of weeks during which each individual places a bet. Panel B shows statistics for bet characteristics. *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 streak of the backed team at the time of the match; negative (positive) values indicate losing (winning) streaks, and draws are counted as maintaining a streak. *Home Field* is a dummy indicating the selected team has home-field advantage. *Visible Team* is a dummy that equals 1 for bets backing teams that ranked highly in the previous season's 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 shows statistics for the characteristics of the bets (two for each match, one on the home-field team and one on the away team) available in the sportsbook during our sample period.

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

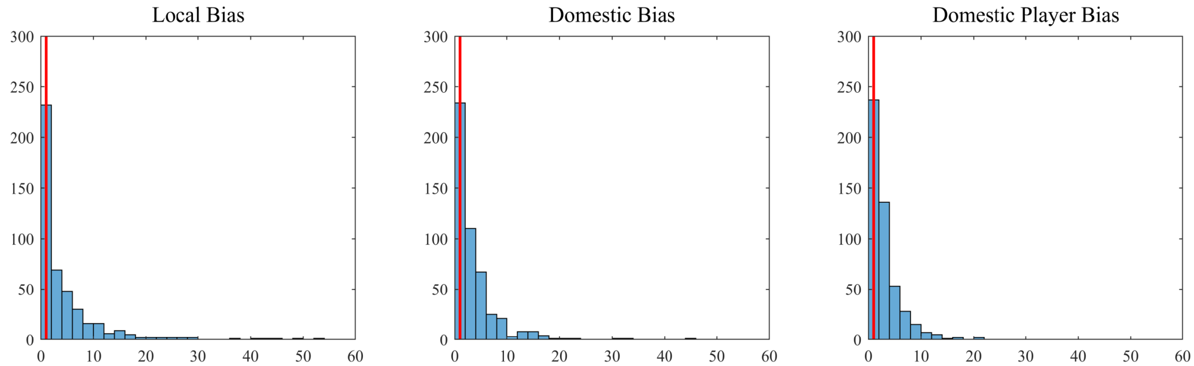
Panel C: Characteristics of bets available in the sportsbook

	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

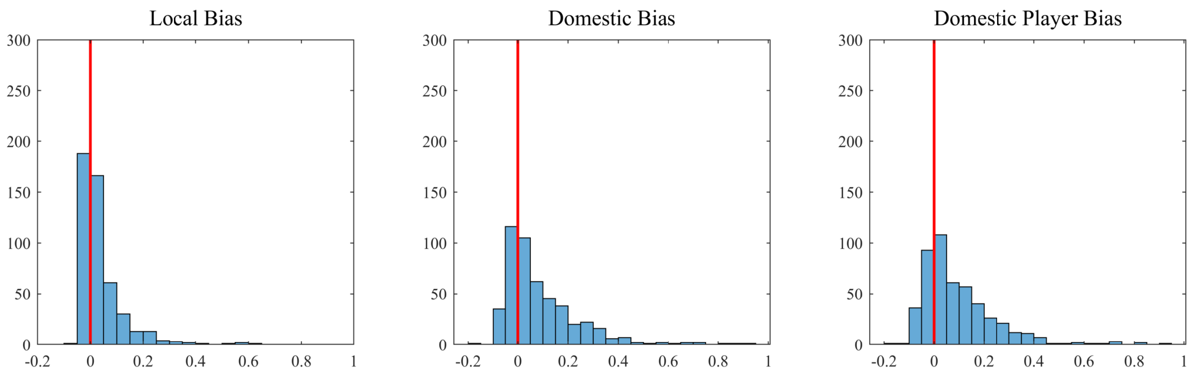
Table 2: Weight of Home Teams in Individuals' vs. Market Portfolio

This table shows the portfolio weights that individuals place on various home-team groups and the market portfolio weight of the respective team groups. 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 shows results from OLS estimation of models 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 that equals 1 for bets backing teams that ranked highly in the previous season's rankings. *Streak* is the duration—the number of matches—of the active streak of the backed team at the time of the match; negative (positive) values indicate losing (winning) streaks, and draws are counted as maintaining a 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 shows results from OLS estimation of models in which the dependent variable is the return earned 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. textitVisible Team is a dummy that equals 1 for bets backing teams that ranked highly in the previous season's 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 ***				
$\times$ $Price_{Local}$		2.616				
$Price_{Domestic}$			0.059 ***	0.014		
			2.657	0.461		
Domestic Bias				-0.303 *		
				-1.752		
Domestic Bias				0.121 **		
$\times$ $Price_{Domestic}$				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 **
$\times$ $Price_{Domestic\ Player}$						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 shows results from OLS estimation of models 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* is a dummy that equals 1 for teams that ranked highly in the previous season's 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 portfolio weights that individuals place on various home-team groups and the market portfolio weight of the respective team groups. 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% ***

Table 8: Overweighting of Home Teams in Individuals' Portfolio — With Individual Characteristics

This table presents results from OLS estimation of models with dependent variable 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, individual characteristics and interactions. *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 individual's country of residence. *Female* indicates the individual's gender. *Young* indicates that the individual's age is below the sample median. *Experienced* indicates that the individual's trading experience—measured by the cumulative number of bets placed—is above the sample median. *Large Wagers* indicates that the individual's average wager size is above the sample median. All specifications include controls for *Market Weight*, *Price*, *Home Field*, *Visible Team*, and *Streak*. 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) Local	(5) Domestic	(6) Domestic	(7) Domestic	(8) Domestic	(9) Domestic Player	(10) Domestic Player	(11) Domestic Player	(12) Domestic Player
Local	0.698 ***	0.708 ***	0.767 ***	0.729 ***								
	17.878	15.449	15.738	14.741								
Domestic					0.405 ***	0.387 ***	0.439 ***	0.397 ***				
					22.888	20.927	21.047	20.435				
Domestic Player									0.339 ***	0.328 ***	0.369 ***	0.336 ***
									23.250	21.352	21.235	20.761
Female	-0.001				0.002				0.001			
	-0.173				0.335				0.247			
Young		0.002				-0.002				-0.001		
		0.800				-0.640				-0.490		
Experienced			0.004			0.006 **					0.006 **	
			1.372			2.214					2.328	
Large Wagers				0.002			0.001					0.001
				0.732			0.404					0.490
Local × Female	-0.138 *											
	-1.734											
Local × Young		-0.045										
		-0.766										
Local × Experienced			-0.161 ***									
			-2.971									
Local × Large Wagers				-0.072								
				-1.282								
Domestic × Female					-0.091 ***							
					-2.576							
Domestic × Young						0.024						
						1.121						
Domestic × Experienced							-0.081 ***					
							-3.705					
Domestic × Large Wagers								0.003				
								0.149				
Domestic-player × Female									-0.063 **			
									-2.103			
Domestic-player × Young										0.013		
										0.763		
Domestic-player × Experienced											-0.069 ***	
											-3.780	
Domestic-player × Large Wagers												-0.002
												-0.120
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-square	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
Observations	3,789,931	3,789,931	3,789,931	3,789,931	3,789,931	3,789,931	3,789,931	3,789,931	3,789,931	3,789,931	3,789,931	3,789,931