The Missing Link Between Home Bias and Investor Sentiment: Evidence from a Quasi-experimental Financial Market*

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Abstract

It is well known that investors disproportionately invest in "home" assets. Yet, there is much debate on whether superior information or sentiment drives this behavior. Using the sports-betting market as a financial-market laboratory, we find that individuals exhibit a bias toward home-team wagers. This bias does not yield superior performance, but distorts individuals' portfolios, resulting in welfare costs of similar magnitude as in the stock market. Our findings confirm a key yet hitherto-untested assumption underlying the behavioral explanation of home bias in finance: that a cognitive home bias is strong enough to persist in market settings and survive costly implications.

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

JEL Classification: D12, D81, G02, G11, G14

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1 Introduction

A large finance literature has established that individual and professional investors disproportionately invest in "home" assets. For instance, they tend to tilt their portfolios toward stocks of local firms, domestic firms, and firms headquartered in their birth state. But, while this "home bias" is a well-established phenomenon, its causes are the subject of a long and ongoing debate in the literature. Some authors argue that it is driven by an inherent behavioral bias—possibly due to loyalty, patriotism, and/or familiarity—that leads to suboptimal decisions (*sentiment hypothesis*). Others argue that it arises because individuals have an informational advantage about home assets and hence leads to superior investment performance (*information hypothesis*). The main tool for differentiating between these two explanations has been a test of the null that investments in home assets do not outperform other investments: failing to reject this null is interpreted as evidence supporting the sentiment hypothesis, and rejecting it is interpreted as evidence supporting the information hypothesis. However, traditional financial markets constitute a particularly difficult setting for differentiating between these hypotheses, since tests of superior performance are necessarily joint tests of an underlying asset pricing model.

In this paper, we contribute to this debate using a different approach. We turn our attention to an alternative financial market that has several similarities with traditional financial markets but allows us to circumvent the joint hypothesis problem: the sports betting market. Using this market as a real-world laboratory, we conduct a clean test of the hypothesis that there exists a *behavioral* home bias that is strong enough to persist in a *market* setting and in the face of *costly* implications. We find that this hypothesis is indeed true. Furthermore, we find that the behavioral bias that exists in our betting market survives a cost of similar magnitude as the corresponding cost (due to under-diversification) in the stock market. Certainly, we need to be careful not to misinterpret our finding; it does not imply that a behavioral bias explains the home bias phenomenon in the stock market. But it fills an important gap in the extant argument in favor of such a behavioral explanation in the finance literature: while it is known that loyalty, patriotism, and familiarity biases exist and could in principle induce the overweighting of home assets, it has so far only been *assumed* that these are strong enough to persist in a market setting despite the associated welfare costs. Our finding is this missing piece of evidence, which strengthens and therefore increases the likelihood of a behavioral explanation for stock-market home bias.

We use the sports betting market as a real-world test bed for our analysis, because it possesses distinct features that make it possible to conclusively test whether a disproportionate tilt toward specific assets (wagers) is driven by sentiment or by superior information about potential mispricings. First, sports wagers bear no systematic risk. This implies that an asset pricing model is unnecessary, therefore tests of superior individual performance do not suffer from the joint hypothesis problem. 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 performance can be measured accurately and cleanly. Finally, individuals in the sports betting market do not face frictions that might force them to concentrate their portfolios on specific assets, and hence could confound the analysis of the home bias.[1]

Furthermore, as the finance literature has long recognized, sports betting markets have several similarities with traditional financial markets. They are populated with a large number of participants with different levels of sophistication who risk capital on the uncertain outcome of future events; information about events is widely available in the media; sports bookmakers are analogous to financial market makers; and sports handicappers play the role of financial analysts. It has also been shown that many individual investors in the stock market view trading as an entertaining gambling activity and prefer stocks with lottery characteristics (e.g., Grinblatt and Keloharju, 2009; Dorn and Sengmueller, 2009; Kumar, 2009). Moreover, in both markets, individuals who possess more information than their fellow market participants can exploit market mispricings and make profits, while individuals who suffer from behavioral biases will make suboptimal portfolio choices. In view of these similarities, findings from sports betting markets could provide valuable insights about analogous patterns that we observe in financial markets. For example, sports betting markets have been used to learn about market efficiency (Gray and Gray, 1997; Gandar et al., 1988), asset pricing

[1] For example, constraints due to limited stock market integration and moral hazard could tilt individuals' portfolios toward home stocks. While the literature generally agrees that these likely play a small role in explaining the home bias in the stock market, it is in any case advantageous that they do not confound the analysis in our setting.

(Moskowitz, 2018), investor sentiment (Avery and Chevalier, 1999, Durham, Hertzel and Martin, 2005), and investor risk preferences (Andrikogiannopoulou and Papakonstantinou, 2019).

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 on average overweight in their 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. 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%, which is comparable to the 150% overweighting for stocks of locally-headquartered firms found by Ivkovic and Weisbenner (2005). 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. Furthermore, we find that individuals overwhelmingly back their home teams even when they play against non-home teams. This result is a first indication 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).

Next, we study how home-team overweighting is related to a number of individual and team characteristics. The idea behind this analysis—often performed in stock market studies to gain insights into what drives the overweighting of certain assets—is that if the home bias is more pronounced among sophisticated individuals and among assets with higher information asymmetries, then the bias is more likely driven by superior information, otherwise it is more likely due to a behavioral bias. In the analysis involving the demographic characteristics usually associated with trading sophistication—youth, education, urban residence, and trading experience—we find mixed evidence. Specifically, we find that home bias is not related to individuals' age and that it is, in fact, concentrated among individuals with less trading experience, which lends support to the sentiment hypothesis, but also that it is strongest among educated individuals and those who reside in large metropolitan areas, which is consistent with the information hypothesis. These findings are not only inconclusive, but also raise concerns regarding the reliability of using demographics-based proxies of sophistication to disentangle the drivers of the home bias in the stock market. On the other hand, the analysis involving team characteristics yields clearer conclusions. We find that home bias is weaker when publicly available information is scarcer and/or information asymmetries are higher (e.g., early in the season or when price dispersion is high), which contradicts the prediction of the information hypothesis but could be consistent with the sentiment hypothesis.

Subsequently, we formally test whether individuals' home bias leads to higher performance. We find that the returns individuals realize on average 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. Hence, we conclude that the overweighting of home teams is not driven by an informational advantage but rather by an innate behavioral bias. We further confirm this finding by showing that 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.

Our performance results mentioned above show that overweighting home assets does not harm individuals' returns. But, unless individuals are risk neutral, this does not imply that the home bias is harmless. Indeed, 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 (see the review in Beshears et al., 2018). Similarly, a bias toward home teams may cause individuals to choose suboptimal portfolios. We examine this in our next set of tests. We find that home-team odds affect selected wagers' odds. As it is unlikely that peoples' risk preferences vary systematically with the odds of their home teams, 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 that calculated for domestic bias in the stock market (see French and Poterba, 1991). This result is important, because it implies that the home bias we document is strong enough to survive the substantial welfare cost associated with it. Indeed, one argument often made against extrapolating evidence of behavioral biases from the lab to a market setting is that biased behavior in the lab is often costless and might not persist if it were costly.

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. Using trading data from individual and institutional investors around the world, many studies have documented that people invest disproportionately in home assets, e.g., companies located in the country or area where they live or grew up. The evidence on whether this home bias is induced by sentiment or by superior information is mixed. On the one hand, Coval and Moskowitz (2001), Hau (2001), Teo (2009), Jagannathan, Jiao and Karolyi (2017) and Sialm, Sun and Zheng (2019) among others find that professional investors earn abnormal returns on their home holdings, and Ivkovic and Weisbenner (2005), Massa and Simonov (2006) and Ben-David, Birru and Rossi (2019) corroborate this finding for retail investors, supporting the information hypothesis. On the other hand, French and Poterba (1991), Froot, O'Connell and Seasholes (2001), Pool, Stoffman and Yonker (2012), and Giannetti and Laeven (2016) find that professional investors do not outperform in their home investments, and Huberman (2001), Grinblatt and Keloharju (2001), and Seasholes and Zhu (2010) corroborate this finding for retail investors, supporting the sentiment hypothesis. Korniotis and Kumar (2013) attempt to reconcile this evidence by suggesting that the two explanations apply to different sets of investors characterized by a demographics-based sophistication proxy. Instead of studying individuals' investments directly, Giannini, Irvine and Shu (2018) extract investors' sentiment about home versus non-home firms from Twitter posts and find that sentiment about non-home firms is negatively related to future returns.

Our paper takes a different approach to this question by analyzing a different market setting whose experimental-like features allow us to draw a clean conclusion that people have an innate costly home bias, which verifies a key assumption behind any behavioral explanation of the home bias in finance.

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 behavior in financial markets. 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 (2019) use sports betting markets to estimate individual risk preferences and explain the prevalence of the disposition effect in the stock market.[2] This paper contributes to this literature by using individual-level sports betting data to test whether the sentiment hypothesis has any merit in explaining individuals' portfolio distortions.

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

[2] Earlier studies have also used sports betting prices to perform clean tests for 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.

winners is (approximately) the same regardless 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). 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.[3] 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. We match the gender, age, and zip code information with the relevant census data of each individual's country of residence to create an individual-level proxy for education level, which is often used as a proxy for financial sophistication and cognitive abilities (e.g., Calvet, Campbell and Sodini, 2009; Korniotis and Kumar, 2013).

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.[4] Since

[3] 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.

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

the number of matches available in the sportsbook 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.[5] Specifically, it includes matches from all major first-tier leagues (Argentina, Brazil, England, France, Germany, Italy, and Spain), many European first-tier (e.g., Austria, Belgium, and Netherlands) and second-tier leagues (e.g., English Championship, Italian Serie B, and Spanish Segunda Division), as well international competitions at club level (UEFA cup and Champions' League) and national level (Euro Cup, World Cup, and friendlies).

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. Teams that are local to an individual (*local teams*). We obtain (from www.stadiumguide.com) zip code information about the location of each team's stadium, and combine it with individuals' zip codes to identify the teams that are local to each individual. Specifically, we translate individual and team zip codes into latitudes and longitudes using the geocoder at https://geocode.localfocus.nl. Then, we compute the pairwise geodesic distances between individuals' and team stadiums' locations using the Sodano (1965) method for calculating geodesic distances on an ellipsoid. Subsequently, we define a team as local to a given individual if the

[5] When we use the universe of all available matches rather than this reduced set, our results 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.

distance between their locations is less than 100 km.[6]

2. Teams that are domestic to an individual (*domestic teams*). A team is defined as domestic to an individual if the team's stadium is located in the same country as the individual's country of residence.
3. Teams with players whose country of origin is the same as the individual's country of residence (*domestic-player teams*). We obtain (from https://us.soccerway.com/players/players_abroad/) historical team affiliation information about players, and we use this information to 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.[7] 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

[6] The 100km cutoff is a plausible upper bound for the definition of locality in Europe; results based on a 50km 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.

[7] See, e.g., Tversky and Kahneman (1971) for experimental and Clotfelter and Cook (1993) for field studies demonstrating that individuals often expect outcomes of random sequences to exhibit systematic reversals or excessive persistence. Also see Durham, Hertzel and Martin (2005) who use aggregate price data from a sports betting market and Andrikogiannopoulou and Papakonstantinou (2018) who use the same data as the current study, both showing that past performance streaks affect individual behavior.

(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 (FIFA World Rankings) of the preceding season.[8,9]

[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.[10] 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 we use in our analysis. 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). The performance streak of the team that is backed to win ranges from -20 to 25, with a mean (median) of 1.2 (1). 19% of the bets back a highly visible team to win, while 10% (3%) of the bets back a domestic (local) team and 12% of the bets 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) . The length of team performance streaks ranges from -24 to 25, with almost half of the teams being on winning streaks and the other half on losing streaks. Finally, 4% of the teams available to back during our sample period are classified as highly visible.

[8]FIFA (Fédération Internationale de Football Association) is the international governing body for soccer, and UEFA (Union of European Football Associations) is the administrative body for soccer in Europe.

[9]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.

[10]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 more recent 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.

3 Tests of the home bias

In this section, we analyze the composition and the performance of individuals' portfolios, to determine whether the home bias exists and which of the two competing hypotheses—information vs. sentiment—better explains it.

3.1 Analysis of portfolio composition

We begin our empirical analysis by testing whether individuals in the sports betting market exhibit a home bias similar to the one exhibited by stock market investors. 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 and to uncover which individual and team characteristics may be related to the home bias.

3.1.1 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 $g \in \{Local, Domestic, Domestic\ Player\}$,[11] we compute the portfolio weight that individual i allocates to this group in week t as

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

[11] Notice that 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.

where B_{igt} is the amount of money staked by individual i on team group g in week t.[12] 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 'Indiv.'), 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

[12] 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.

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.

3.1.2 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:

$$Individual_{ijmt} = \alpha_i + \beta_0 HomeTeam_{ijmt} + \beta_1 Market_{jmt} + \beta_3 Controls_{ijmt} + \varepsilon_{ijmt}, \qquad (3)$$

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_0 should be positive.

[Table 3 about here]

In Table 3, we report the results from the estimation of various forms of the regression 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 remote (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.[13] 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 an 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

[13] 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.

superior information we would expect to see that individuals are equally likely to bet for or against these teams, hence β_0 would equal zero. However, we see that individuals overwhelmingly bet for the domestic team in international matches. This evidence provides an important first indication that the observed overweighting of domestic teams is driven by a behavioral bias rather than an informational advantage. We find similar results if we constrain attention to matches of local vs. non-local teams and domestic-player vs. non-domestic-player teams.

3.1.3 Individual and team characteristics

In this section, we investigate which individual and team characteristics are related to home-team overweighting. Several studies on the stock market use this type of analysis to gain insights into what drives individuals to overweight home assets. Specifically, these studies posit that if the overweighting of home assets is more pronounced among individuals whose demographics are typically associated with higher sophistication (e.g., higher education), among assets with higher information asymmetries (e.g., smaller stocks), and at times of higher uncertainty about valuations, then this overweighting is more likely driven by superior information. Otherwise, it is more likely that the overweighting is due to an innate behavioral bias. Here, we conduct an analogous analysis in our sports betting setting.

First, we test if home-team overweighting is related to individual characteristics that have been shown to be associated with sophistication. For example, Korniotis and Kumar (2013) find that people who are younger and more educated are more sophisticated—as measured by verbal and quantitative ability and memory—and that more sophisticated people tend to live in urban areas; furthermore, it is often thought that experience improves trading behavior. Thus, we augment the model in Equation 3 with interactions of $HomeTeam_{ijmt}$ with dummy variables indicating (i) individuals whose age is below the sample median (*Young*), (ii) individuals whose education is above the sample median (*Educated*), (iii) individuals who reside in large metropolitan areas (*Urban*), and (iv) individuals whose trading experience—measured by the cumulative number of bets they have placed at each point in time—is above the sample median (*Experienced*). If home-team overweighting is, on average, due to superior information rather than sentiment, then we would expect the coefficients on these interaction terms to be positive.

[Table 4 about here]

In Table 4, we report the results from a regression analysis of this augmented model: we focus on the effect of local teams in Columns 1–4, domestic teams in columns 5–8, and domestic-player teams in Columns 9–12. The results are mixed. On the one hand, we find that home-team overweighting is not related to individuals' age (Columns 1, 5, and 9), and that it is, in fact, concentrated among individuals with less betting experience (Columns 4, 8, and 12), which lends support to the sentiment hypothesis. On the other hand, we find that home-team overweighting is strongest among more educated individuals and those who reside in large metropolitan areas (Columns 2–3, 6–7, and 10–11), which is more consistent with the information hypothesis, as these individuals are believed to be more likely to trade for information reasons. One possible explanation for this (seemingly contradictory) finding is that more-educated individuals and those living in urban areas may be more over-optimistic—not more informed—about their home teams and therefore more likely to overweight these teams in their portfolios; for relevant evidence, see Strong and Xu (2003) and Puri and Robinson (2007).[14] In any case, the fact that this evidence is mixed—which is also the case in similar studies on the stock market[15]—raises the possibility that demographics-based measures of sophistication may be poor proxies and that this type of analysis may yield misleading insights about the drivers of the home bias.

Second, we study whether home-team overweighting is related to certain team characteristics. If superior information is driving this behavior, 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

[14] Strong and Xu (2003) show that fund managers are more optimistic toward their home equity market which leads them to overweight domestic equities in their portfolios. Based on survey evidence, Puri and Robinson (2007) find that more educated individuals are also more optimistic and that higher optimism leads individuals to tilt their portfolios toward individual stocks.

[15] Consistent with the information hypothesis, Lindblom, Mavruk and Sjögren (2018) find that the local bias is concentrated among individuals residing in urban areas, Korniotis and Kumar (2013) find that younger and more educated investors exhibit stronger preference for local stocks, and Grinblatt and Keloharju (2001) also find a positive link between education and the propensity to invest in local stocks. On the other hand, Pool, Stoffman and Yonker (2012) find that fund managers' age does not affect home-state bias and that managerial experience has a negative effect.

dispersed. Analogous arguments have been made in studies on the stock market, and the empirical evidence is mixed. For example, it has been hypothesized that, if investors have value-relevant information about their home stocks, then 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).

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 5 about here]

In Table 5, 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.

3.2 Tests of investment performance

Our results thus far have shown that individuals overweight their home teams in their portfolios. Moreover, we have found some preliminary evidence suggesting that this overweighting is more likely due to sentiment rather than superior information. In this section, we formally test the information and sentiment hypotheses using performance-based analyses. The two hypotheses yield different empirical predictions concerning performance: The information hypothesis implies that individuals' home-team bets should yield higher returns while the sentiment hypothesis implies that they should yield the same or even possibly lower 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.

To study individuals' performance, we first sort individuals into quintiles based on the magnitude of their preference toward local, domestic, and domestic-players teams, as measured by the mean difference between the individual and the market portfolio weight allocated to these teams. In Table 6, we report the average realized return by quintile of home bias. As expected, individuals in all quintiles experience negative mean returns from their wagers due to the bookmaker's commission. However, as we can see in the row labeled 'Q5-Q1', individuals who exhibit a stronger preference toward local, domestic, or domestic-player teams do not earn significantly different returns from their wagers than those who exhibit a weaker preference toward these teams.

To examine this further, 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;[16] 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

[16]Note that no commission is paid after this return is realized; it 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.

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 7 about here]

In Table 7, 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 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 rooted in behavioral biases rather than driven by superior information.

We have already discussed that the finding of no superior performance from home-team betting is consistent with the sentiment hypothesis rather than the superior information 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).

3.3 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 8 about here]

In Table 8, 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 'Indiv.'), 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 rather than driven by information.

4 The cost of the home bias

Finally, 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 though 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. Indeed, 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.

Furthermore, 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 that exhibit the home bias, who are of interest here, and those that do not. Table 9 shows results from both specifications, but in our discussion here we focus on the latter. Specifically, we estimate

$$Price_{it} = \alpha + \beta_1 \; HomeBias_i + \beta_2 \; Price_{it,Home} + \beta_3 \; HomeBias_i \cdot Price_{it,Home} + \varepsilon_{it}, \qquad (5)$$

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 that 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 9 about here]

Looking at the results in Table 9, 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. Given that 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, 2019; 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 binary lotteries, 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 and that people exhibit it even though doing so carries a cost. Crucially, this cost of about 2% to 3.5% annualized in our setting is of the same order of magnitude as the cost calculated for domestic bias in the stock market (see French and Poterba, 1991).

5 Conclusion

In this paper, we have used a panel data set of individual activity in a soccer wagering market to shed light on the sentiment hypothesis that has been put forward to explain the home bias we observe in the stock market. We find that, similar to stock market investors, 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 rather than by superior information. Furthermore, individuals' bias toward home-team wagers distorts their portfolios, resulting in welfare losses of similar magnitude as in the stock market. These findings verify the key assumption behind any behavioral explanation of the home bias in finance: that there exists a cognitive home bias that is strong enough to persist in market settings and survive the costly implications therein. As a result, our confidence in such explanations in the literature—both in the past and in the future—is greatly enhanced.

More generally, our analysis 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 finance literature commonly appeals to (e.g., attention effects, belief biases) are sufficiently strong to exist in a market setting 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.

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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. *Urban* is a dummy indicating the individual resides in a large metropolitan area. *Age* is in years. *Education* is a proxy based on census data, and takes values 1, 2, and 3 corresponding to middle-, high-, and post-high-school education. *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 FIFA (for national teams) or UEFA (for clubs) 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
Education	495	1.99	2	0.27	1.13	2.80
Urban	495	0.49	0	0.50	0	1
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

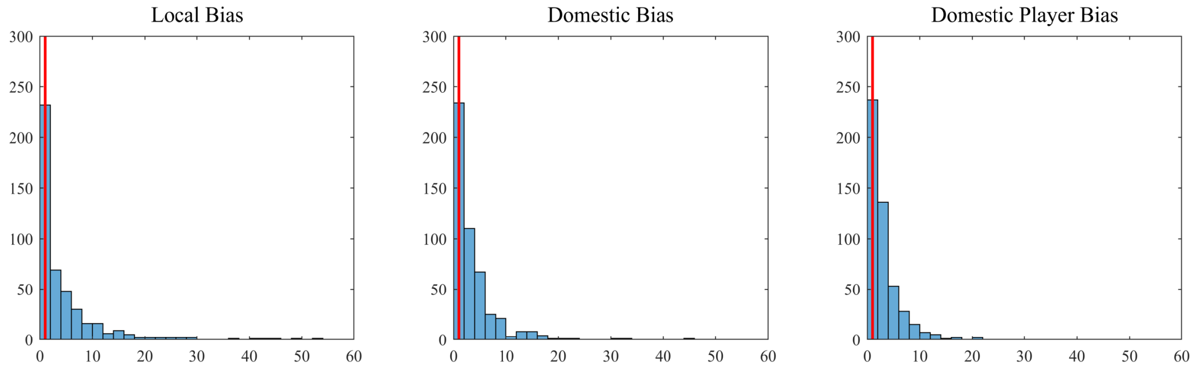
Panel C: Characteristics of bets available in the sportsbook

	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

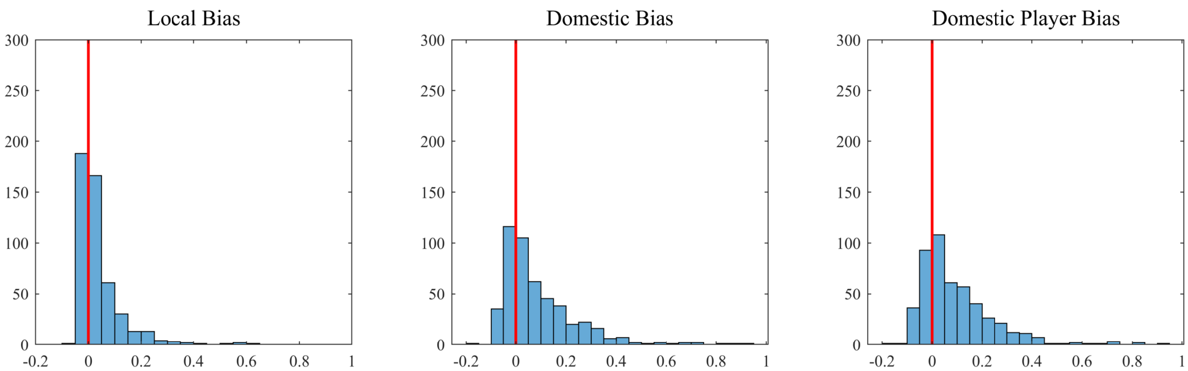
Table 2: Weight of Home Teams in Individuals' vs. Market Portfolio — Standard Events

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 'Indiv.' 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' ('Diff') 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.

	Indiv.	Market	Ratio	Diff
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 FIFA (for national teams) or UEFA (for clubs) 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
Constant	-0.027 **	-0.036 ***	-0.040 ***	-0.039 ***	1.099 ***	-0.039 ***	-0.801
	-2.191	-2.982	-3.262	-3.176	4.347	-3.010	-0.283
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: Overweighting of Home Teams in Individuals' Portfolio — With Individual 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, individual characteristics, and interactions. *Local* (*Domestic*) indicates bets in which an individual backs a local (domestic) team, and *Domestic Player* indicates bets in which an individual backs a team with at least one player with the same country of origin as the individual's country of residence. *Market Weight* is the weight (as a percent) that corresponds to team j in in an equal-weighted market portfolio in week t. *Price* is the price (as decimal odds) associated with team j in match m. *Home Field* indicates the selected team has home-field advantage. *Visible Team* indicates the selected team is highly ranked according to the previous season's rankings. *Streak* is the duration of the active winning/losing streak of the backed team. *Young* indicates that individual i's age is below the sample median. *Urban* indicates their residence is in a metropolitan area. *Educated* indicates their proxied education is above the sample median. *Experienced* indicates their trading experience—measured by the number of bets placed until week t—is above the sample median. 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
Market Weight	1.116***	1.116***	1.116***	1.116***	1.118***	1.118***	1.118***	1.119***	1.125***	1.125***	1.124***	1.125***
	18.864	18.869	18.868	18.869	18.987	18.995	18.988	18.997	19.068	19.077	19.071	19.078
Price	-0.026***	-0.026***	-0.026***	-0.026***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***
	-26.638	-26.638	-26.632	-26.636	-26.554	-26.555	-26.554	-26.552	-26.544	-26.545	-26.545	-26.542
Home Field	0.095***	0.095***	0.095***	0.095***	0.093***	0.093***	0.093***	0.093***	0.093***	0.093***	0.093***	0.093***
	21.890	21.893	21.916	21.894	21.206	21.208	21.208	21.208	21.323	21.324	21.325	21.324
Visible Team	0.781***	0.782***	0.782***	0.782***	0.794***	0.794***	0.794***	0.794***	0.788***	0.788***	0.788***	0.788***
	37.502	37.505	37.513	37.505	38.156	38.156	38.157	38.157	37.719	37.718	37.718	37.715
Streak	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***
	23.368	23.362	23.370	23.365	23.331	23.334	23.335	23.336	22.998	22.998	22.998	22.997
Local	0.663***	0.571***	0.797***	0.767***								
	13.029	13.134	16.714	15.738								
Domestic					0.411***	0.364***	0.438***	0.439***				
					18.680	19.069	20.597	21.047				
Domestic Player									0.342***	0.304***	0.365***	0.369***
									18.871	19.302	20.590	21.235
Young	0.002				-0.002				-0.001			
	0.800				-0.640				-0.490			
Educated		-0.004				-0.004*				-0.005*		
		-1.466				-1.682				-1.884		
Urban			-0.014***				-0.006***				-0.006**	
			-5.259				-2.593				-2.523	
Experienced				0.004				0.006**				0.006**
				1.372				2.214				2.328
Local × Young	-0.045											
	-0.766											
Local × Educated		0.222***										
		3.954										
Local × Urban			0.363***									
			6.290									
Local × Experienced				-0.161***								
				-2.971								
Domestic × Young					0.024							
					1.121							
Domestic × Educated						0.065***						
						3.262						
Domestic × Urban							0.077***					
							3.730					
Domestic × Experienced								-0.081***				
								-3.705				
Domestic-player × Young									0.013			
									0.763			
Domestic-player × Educated										0.058***		
										3.503		
Domestic-player × Urban											0.059***	
											3.441	
Domestic-player × Experienced												-0.069***
												-3.780
Constant	-0.026**	-0.025**	-0.034***	-0.029**	-0.037***	-0.034***	-0.040***	-0.039***	-0.041***	-0.037***	-0.043***	-0.043***
	-2.154	-2.060	-2.841	-2.397	-3.127	-2.844	-3.327	-3.295	-3.394	-3.102	-3.605	-3.591
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

Table 5: 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*) 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 FIFA (for national teams) or UEFA (for clubs) rankings. *Streak* is the duration of the active winning/losing streak of the backed team. *Early in Season* indicates the first one-third of the matches of the league/season of team j/week t. *Non-Top League* indicates that team j does 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 ***	0.149 ***	1.631 ***						
	14.489	5.628	15.245						
Domestic				0.410 ***	0.087 ***	1.072 ***			
				18.146	7.427	20.846			
Domestic Player							0.344 ***	0.077 ***	0.695 ***
							18.450	7.690	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
Constant	-0.010	-0.096 ***	0.059 ***	-0.019	-0.097 ***	0.045 ***	-0.022 *	-0.100 ***	0.040 ***
	-0.788	-7.827	5.211	-1.438	-7.940	4.029	-1.720	-8.182	3.533
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 6: Average Realized Return by Home Bias Quintile

This table reports the average realized total return for individuals belonging to each quintile of local bias (Columns 2-3), domestic bias (Columns 4-5) and domestic-player bias (Columns 6-7). Local Bias, Domestic Bias, and Domestic-player Bias are measured as the mean difference between the individual and market portfolio weights allocated to the respective team group. The bottom line reports the difference in the average return between the highest and lowest bias quintile and the p-value (in parenthesis) of the paired t-test of the null hypothesis that the difference is equal to zero.

	Local Bias		Domestic Bias		Domestic-player Bias	
Bias Quintile	Avg. Bias	Avg. Return	Avg. Bias	Avg. Return	Avg. Bias	Avg. Return
Q1 (Low Bias)	-1.34%	-5.22%	-4.73%	-3.10%	-4.49%	-4.69%
Q2	-0.19%	-3.33%	-0.25%	-5.95%	0.73%	-5.12%
Q3	0.69%	-4.37%	4.07%	-4.33%	5.40%	-3.14%
Q4	4.15%	-3.33%	12.36%	-2.68%	13.65%	-3.58%
Q5 (High Bias)	17.68%	-5.06 %	33.16%	-4.91%	33.40%	-4.45%
Q5-Q1		0.16%		-1.81%		0.23%
		(0.95)		(0.48)		(0.93)

Table 7: 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 week t. Panel A presents results from specifications in which the explanatory variables include home-team dummies, individual-specific measures of the preference for home teams, interaction terms, and controls, as well as season fixed effects. Panel B is identical to Panel A, except that the season fixed effects and the individual-specific measures of the preference for home teams 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 measured as the mean difference between the individual and market portfolio weights allocated to the respective team group. *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 FIFA (for national teams) or UEFA (for clubs) rankings. *Streak* is the duration of the active winning/losing streak of the backed team. 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 × Local Bias	-0.054			0.068	0.056		
	-0.283			0.309	0.212		
Domestic × Domestic Bias		-0.106		-0.202			-0.463
		-1.191		-0.746			-1.073
Domestic Player × Domestic-player Bias			-0.102	0.084		0.081	
			-1.168	0.319		0.294	
Constant	-0.018	-0.017	-0.019	-0.020	0.127	-0.024	0.024
	-0.579	-0.560	-0.600	-0.643	1.469	-0.857	0.065
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 × Local Bias	0.093			0.166	0.083		
	0.407			0.649	0.274		
Domestic × Domestic Bias		-0.046		-0.159			-0.315
		-0.425		-0.559			-0.469
Domestic Player × Domestic-player Bias			-0.045	0.078		0.111	
			-0.433	0.291		0.393	
Constant	-0.020	-0.018	-0.019	-0.019	0.123	-0.027	0.017
	-0.632	-0.577	-0.595	-0.599	1.414	-0.927	0.048
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 8: 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 'Indiv.' 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' ('Diff') 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.

	Indiv.	Market	Ratio	Diff
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 9: 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 × $Price_{Local}$		0.068 ***				
		2.616				
$Price_{Domestic}$			0.059 ***	0.014		
			2.657	0.461		
Domestic Bias				-0.303 *		
				-1.752		
Domestic Bias × $Price_{Domestic}$				0.121 **		
				2.548		
$Price_{Domestic\ Player}$					0.088 ***	0.056 *
					3.642	1.765
Domestic-player Bias						-0.291
						-1.626
Domestic-player Bias × $Price_{Domestic\ Player}$						0.109 **
						2.132
Constant	2.139 ***	2.244 ***	1.956 ***	2.062 ***	1.859 ***	1.935 ***
	48.582	38.516	24.297	19.289	21.993	17.405
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