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Betting on momentum in contests

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Abstract

With unprecedented access to volumes and prices of state-contingent claims by a major bookmaker, second-by-second in-play football betting markets, we study what happens after major breaking news. We focus on what might look like a shift in momentum to a bettor: equalizing goals. Immediately after this news breaks, the volume of claims sold on the match outcomes increases and is substantially biased toward the equalizing team. But there is no evidence that the prices or values of these claims are functions of whichever team scored last. These findings illustrate the value of integrating high-frequency price and quantity data to evaluate the efficiency and profitability of betting markets.

KEYWORDS

behavioral bias, betting markets, expectations, market efficiency, risk-taking

JEL CLASSIFICATION

G14, G41, L83, Z2

1 | INTRODUCTION

Human performance is rarely perfectly consistent over time. Instead, the same workers and their teams can be outstanding on some days but poor on others. In striving to predict the future, it is natural to fixate on recent or salient patterns in historical performance data, such as streaks or patterns of success and failure, even if the underlying data-generating process is in part driven by white noise and randomness. One such popular fixation is the notion of the "hot hand" (also referred to as "momentum"), according to which there is belief that serial correlation exists in human performance. The truth of this fixation has been tested often in sports, with generally mixed evidence (e.g., Cotton et al., 2019; Gauriot & Page, 2019; Gilovich et al., 1985; Green & Zwiebel, 2017; Miller & Sanjurjo, 2018; Tversky & Gilovich, 1989; Wetzels et al., 2016; Ötting et al., 2020). In this study, we begin by assessing the reality of meaningful momentum during contests watched live by millions—top-level professional football matches. We then ask whether betting activity on the outcomes of these matches suggests a general belief that there is value in ostensible momentum. Such belief will be costly if wrong, to the profit of the price-setting bookmaker.

An earlier version of this work was shared in a working paper as Ötting et al. (2022): "Gambling on Momentum"; https://arxiv.org/abs/2211.06052. We have since doubled the size of our estimation samples, as well as improved the analysis and robustness of our findings.

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To test asset pricing theory and investor behavior, sports betting can provide a real-world laboratory with many advantages over traditional financial markets (Bar-Eli et al., 2020; Paton et al., 2009; Sauer, 1998; Thaler & Ziemba, 1988). In the absence of corruption, the terminal values of betting contracts, or state-contingent claims, are exogenous to investor behavior, and this provides clean identification of mispricing, unlike in other financial markets. In particular, if betting odds (prices) deviate from fundamentals due to cognitive biases or erroneous beliefs among the market participants, they will be corrected on average and exogenously by the sporting outcomes (Moskowitz, 2021). Such biases investigated in betting markets include the overvaluation of longshots (e.g., Angelini & De Angelis, 2019; Ottaviani & Sørensen, 2008; Smith et al., 2006; Vaughan Williams et al., 2018; Vlastakis et al., 2009) and overreactions to salient in-play events, such as the goals scored in football matches (e.g., Angelini et al., 2022; Choi & Hui, 2014; Croxson & Reade, 2014; Docherty & Easton, 2012; Norton et al., 2015).

We have unusual access to high-resolution betting market data from a large European bookmaker. The data cover the second-by-second betting odds and volumes staked on the outcomes of 1224 football matches, covering four recent seasons of the German Bundesliga. We focus on the first equalizing goal in matches that feature a 1-1 intermediate scoreline, since this event is fairly common, is major news that ought to break cleanly, and implies some notion of a well-defined change in apparent momentum during trading. Although an equalizer resets the contest to its relative position at kick-off, the equalizing team might be seen as increasing their chances of scoring the next goal or getting what they regard as a positive result even without another goal (given a match can end in a draw), through snatching the strategic or psychological momentum in the contest.[1] We focus on the betting market activity in the minute immediately after trading resumes following the 1-1 equalizers. We find no evidence that the sequence of goals (who scored the equalizer) on average affects the relative likelihood that one team will win the match compared with the other. Likewise, there is no evidence that the betting odds chosen by the bookmaker immediately after favor a win by the equalizing team, compared with a win for the conceding team. However, the betting activity moves toward the team that has ostensibly gained the momentum, consistent with excess belief that they will "complete a comeback" by going on to win.[2] The traded volumes of bets are considerably higher on the teams that scored the equalizers, compared with the teams that conceded at 1-1. We estimate that equalizers lead to 60% higher stakes on the scoring than the conceding team. We further find that the corresponding betting strategy of always following this false momentum, or at least believing it could be profitable, would yield substantially negative returns.

Closely related to our study, Levitt (2004), in his seminal work discussing the economics of gambling markets, described some data akin to fixed-odds betting stakes. These concerned a pre-game season-long prediction competition for American football game results, with an entry fee and no cost per bet, for a relatively small number of selected participants. Although this did not well represent general betting markets, Levitt used this setting to challenge the contemporary balanced book hypothesis, whereby a bookmaker would only adjust its prices to eliminate all risk from their position in each event, according to the expected flows of bets, instead of acting optimally as a standard profit maximizing risk-neutral firm. Levitt's findings suggested that bookmakers could be good at forecasting not only the demand and common biases of their customers but also the eventual event outcomes. Having systematically better forecasts of outcomes than their customers, as well as good enough forecasts of demand for different bets, would allow a bookmaker to significantly improve on just balancing their books. There is also a vast amount of evidence gathered by economists before and since Levitt that tends to reject the weak or strong forms of Fama's (1970) efficient markets hypothesis in betting prices. However, that evidence remains only suggestive of bookmaker and bettor behavior, and of why prices often appear inefficient, particularly following salient news, because high-frequency and real-world fixed-odds betting volumes have never been studied before, to the best of our knowledge.[3]

While there have been several contributions that analyze some sort of cross-event momentum in betting markets, based on the final outcomes of events that have long since closed and the subsequent mispricing of outcomes for closely related events that have not yet begun (i.e., consecutive sports events involving one or more of the same participants: e.g., Abinzano et al., 2017; Brown & Sauer, 1993; Camerer, 1989; Durand et al., 2021; Goto & Yamada, 2023; Krieger et al., 2021; Legge & Schmid, 2016; Metz & Jog, 2023; Paul & Weinbach, 2005; Paul et al., 2014; Woodland & Woodland, 2000), there is no previous research on the responses of investors (gamblers) to perceived or true momentum within singular open betting markets. The reason for this gap in the literature is that high-frequency data on investments (stakes) is needed but normally unavailable.

Although betting market price movements alone could be an indicator of general investor behavior, they also reflect the strategic price setting of the bookmaker.[4] Moreover, the previous studies of betting markets mentioned above could not cleanly identify both the cause (specific news related to momentum) and effect (investments). Such identification is also typically difficult in financial markets, where multiple bits of news can simultaneously impact investment decisions, while the exact moment that relevant news arrives and is understood (perhaps differently) by all is tough to determine. Hence, some other recent inferences about aspects of general investor behavior and bias have also used sports betting market prices, where the exact time of straightforward news breaking (or not) can be identified (e.g., Angelini et al., 2022; Croxson & Reade, 2014; Gauriot & Page, 2021; Page & Clemen, 2013). However, analyzing the responses to perceived momentum in sports betting requires high-frequency data from *in-play* markets on both prices *and volumes* traded. Since various concurrent factors can drive investment in outcomes before the start of a football match or other events, analyzing pre-event betting would have similar problems as for traditional financial markets, in terms of cleanly identifying the responses to apparent momentum or other news shocks.

Unfortunately, despite our unprecedented access to high-frequency aggregate betting market activity, we are unable to say much about the underlying mechanisms behind our main findings. We favor a story that links the surge in betting activity on equalizing teams to incorrect beliefs in momentum. Beneath this, we can consider an individual bettor who, after a goal is scored and the market reopens with large shifts in prices, is quickly attempting to form and revise expectations about each of the three possible match result outcomes (home win, draw, away win). One reason they could see value in an equalizing team is due to simple overreaction to news shocks, or diagnostic expectations, aligning with broad evidence of such behavior among professional forecasters, corporate managers, consumers and investors in other settings (e.g., Bordalo et al., 2018, 2022). Another possibility is that some sort of widespread attribute substitution could be driving aggregate activity within in-play betting markets (e.g., Kahneman & Frederick, 2004.) For example, bettors could be updating their expectations and valuing the claims on offer, after an equalizing goal, by asking themselves the wrong question: "Is the team that just scored doing better now?." Or perhaps even more simply, in the moment, bettors may just prefer to support and invest in teams that are demonstrating attacking intent and scoring goals, representing positivity, as opposed to the negativity associated with conceding goals.

The rest of this paper is structured as follows: Section 2 introduces a dataset of high-frequency betting markets; Section 3 investigates the impact of ostensible momentum on match outcomes and betting markets; and Section 4 concludes. Some robustness checks of our main findings are in Appendix A.

2 | DATA AND SETTING

Our dataset was given to us by a major European bookmaker that has a large customer base in Germany. It covers second-by-second betting odds and volumes for all 1224 German Bundesliga football matches in the 2017/2018 to 2020/2021 seasons, including in-play information about the timing of major events (such as goals and red cards). The betting stakes (amounts, volumes or investments) in the dataset have been multiplied by the same constant for all matches, since we do not have the bookmaker's permission to represent the true amounts of monetary units. Regardless, we can compare the betting volumes across and within matches without providing the actual values or statistics for true stakes.

To investigate how bettors and the bookmaker respond to teams seemingly having momentum, we investigate their staking and odds-setting after an equalizing goal for the scoreline 1-1.[5] An equalizer resets the relative position of teams to what it was at the start of the contest. Nevertheless, it is possible that whichever team scored the most recent goal affects the subsequent behavior of the participants in both the match itself and the associated in-play betting markets. In other words, the sequencing of goals up to and including an equalizer may help to predict what will happen in the remainder of a match, perhaps because of psychological or performance momentum on the pitch. However, in an earlier sample of Bundesliga matches between 1968/1969 and 2010/2011, Heuer and Rubner (2012) found no evidence that the order of goal scoring up to a 1-1 scoreline had significant effects on final match outcomes. We will check whether this still applies in our later sample period. Outside of German football, Parsons and Rohde (2015) also found no significant evidence of within-game goal scoring momentum or hot hand (feet) during three seasons of the English Premier League.

Belief in a momentum effect at 1-1 in football would be consistent with some evidence from professional basketball, that being marginally behind at halftime in a match causes a significant boost in a team's chances of winning (Berger & Pope, 2011). Although, that specific result has been shown as largely particular not only to basketball but also the sample period studied (Klein Teeselink et al., 2023). Also from professional basketball, Morgulev et al. (2019, 2020) found no evidence that a comeback or early lead tend to generate momentum effects. A fitting and well-studied parallel of our hypothesized 1-1 momentum effect is the popular notion that scoring a goal in football just before the half-time break is especially beneficial. Studies have found mixed results on whether this notion should be believed (e.g., Baert & Amez, 2018; Gauriot & Page, 2018; Greve et al., 2020; Meier et al., 2020). Regardless, we focus on what happens around

1-1 scorelines because goals going in just before halftime are relatively rare in the sample of matches and markets available to us; the 1-1 equalizer was scored in the 2 min before halftime in only 4.6% of our sample matches.

We model relative stakes over outcomes, at a particular moment or over some period of time, as the proportion of the total betting volumes that were placed on a team to win a match. We focus on the stakes placed, winning chances, and betting prices soon after a 1-1 equalizer was scored. If a goal is scored, then the bookmaker closes the market and suspends betting for about 30–60 s. Since no bets are observed while the market is closed, we consider the first minute after it reopens, though later we extend this time period in a robustness check. For the 1224 matches in our sample, 463 have an intermediate scoreline of 1-1. If a 1-1 equalizer is scored fairly late in a match, such as in the 85th minute or later, much lower absolute stakes tend to be placed due to there being little time left in the market (i.e., low uncertainty of outcome), and thus the observed relative stakes across the three match outcomes in our sample become noisy. If a 1-1 scoreline arises during injury time, after the regular 90 min of play are complete, then the market does not necessarily reopen at all, depending on the amount of injury time signaled by the referee. Therefore, we consider only observations where an equalizer is scored before the 85th minute, resulting in 431 match-market observations in our analysis.[6]

Figure 1 shows an example minute-by-minute time series of relative stakes from our dataset, for a match between Schalke 04 and VfL Wolfsburg, which kicked off at 18:00 CEST on January 20, 2019, and ended 2-1. Before the match began, the bookmaker's prices suggested that it would be closely fought, with decimal odds of 2.25 for the home team and 3.0 for both the away team and the draw outcomes. This example offers a first glance at how betting activity responds to goals and whatever pricing strategy the bookmaker follows in their aftermath. Slightly higher relative stakes were placed on Wolfsburg, the less-favored away team, than on Schalke early in the match, but increased on Schalke after they scored the first goal. When Wolfsburg scored the equalizer, the relative stakes placed on Wolfsburg to win increased, and were even larger compared to the early stages of the match before the first goal.[7] For all our sample matches that featured a 1-1 scoreline, we observe in the minute after, on average, 51% of the stakes being placed on the equalizing team, 33% placed on the conceding team, and only 16% on the draw. However, for these matches, the draw was the most likely final outcome (40.1%). A defeat for the equalizing team was the second most likely outcome (31.8%), followed by a win for the equalizing team (28.1%). These descriptive statistics give a first impression that bettors believe there is value in the apparent momentum, although in reality a win for the equalizing team tends to be the least likely outcome.

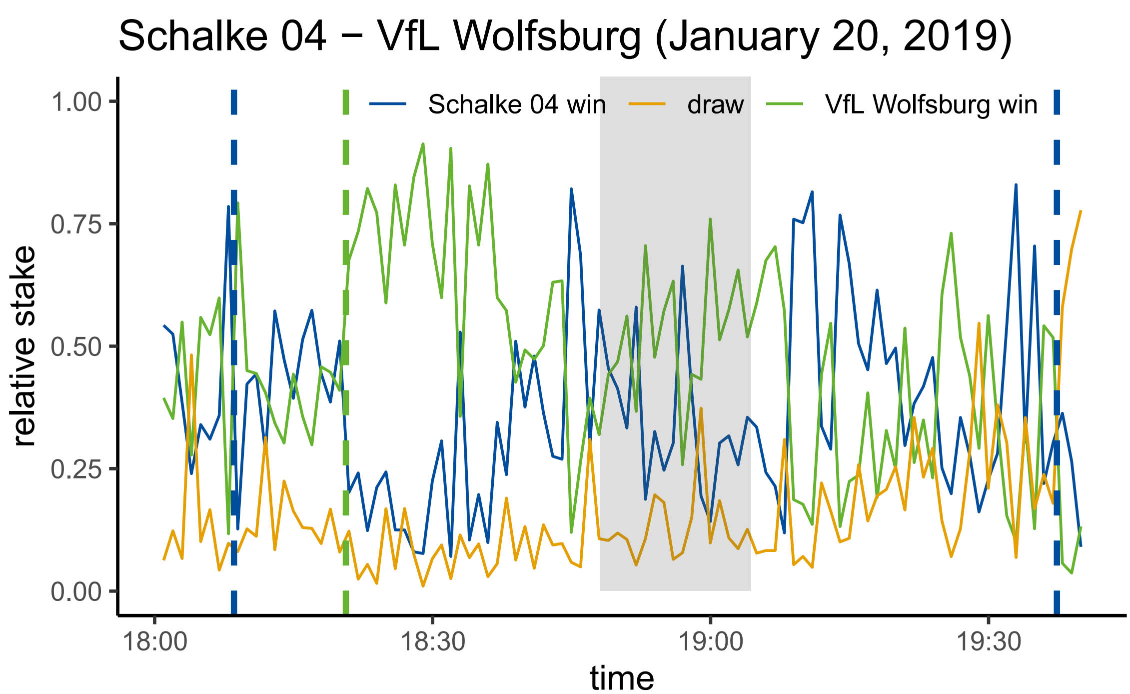

FIGURE 1 Schalke 04 versus VfL Wolfsburg, January 20, 2019: Example time series of in-play relative stakes placed on a win for the home team (Schalke), a draw, and the away team (Wolfsburg). The vertical dashed lines denote when goals were scored by Schalke 04 (blue lines) and VfL Wolfsburg (green lines). The gray shaded area indicates half time.

TABLE 1 Sample descriptive statistics for 431 matches in German Bundesliga seasons 2017/2018 to 2020/2021 featuring a 1-1 scoreline.

	Mean	St. dev.	Min.	Max.
relstake (equalizing team)	0.514	0.252	0.049	0.960
relstake (conceding team)	0.330	0.237	0.012	0.911
probstart (equalizing team)	37.46	18.50	3.167	88.25
probstart (conceding team)	38.99	18.12	3.812	90.50
minute	46.56	20.13	4	84
redcarddiff	0	0.193	−1	1

Note: *relstake*: the relative betting stakes placed in the minute after the equalizer for the 1-1 scoreline; *probstart*: the inverse of decimal odds at kick-off, then normalized to sum to one across the three possible match outcomes; *minute*: the minute of the match when the 1-1 equalizer arrived; and *redcarddiff*: the difference in red cards received between the equalizing and conceding teams before the 1-1 equalizer.

In the example described by Figure 1, we observe absolute betting activity increasing after the equalizer. From the kick-off until the first goal was scored, there was an average amount staked of 47 per minute (transformed values). During the 3 min before the 1-1 equalizer, the betting activity was slightly reduced, with an average amount staked of 30. The amounts staked climaxed in the minute after the equalizer at an average of 60 per minute. However, the betting activity quickly reduced thereafter, with an average stake per minute of 49 in the 10 min following the equalizer.

The main variables used in our analysis are summarized in Table 1. As bettors are generally more likely to wager their money on favorites, we consider a team's odds-implied probability (*probstart*) of winning—at the kick-off—which is derived by taking the inverse of the posted decimal odds for them to win, and normalized to sum to one with the inverse odds for the other two possible match outcomes. Teams conceding the equalizer generally had at the kick-off a higher implied probability of winning, unsurprisingly indicating that favorites are more likely to first have a lead and then concede an equalizing goal in matches that get to 1-1.[8] This is also in line with the findings described above, that an eventual defeat is more likely than a win for an equalizing team. If an equalizer is scored a few minutes before the final whistle, then bettors may be unlikely to place their money on either team to win but rather on a draw. We thus consider the *minute* of an equalizer, which is on average just after halftime, but also occurs in our sample as early as the 5th and as late as the 84th minutes. As undermanned teams have a reduced chance of winning a match, we consider any red cards received before the 1-1 equalizer.[9] In particular, the variable *redcarddiff* gives the difference in the number of red cards received between the equalizing and conceding teams before a match arrives at 1-1, which in our sample lies strictly between minus and positive one.

3 | THE IMPACT OF MOMENTUM ON MATCH OUTCOMES AND BETTING MARKETS

While the summary statistics in the previous section suggest that betting market activity tends to adjust with the dynamics of football matches, we next test whether goal-scoring momentum predicts the following: (i) the final match outcome, (ii) how the bookmaker sets prices, and (iii) how bettors respond.

3.1 | Do equalizing goals generate momentum?

In the absence of any momentum and everything else equal (i.e., the same balance of winning probabilities and thus team strengths as at kick-off, the minute in the match, and the number of red cards received), the probability of a team winning a football match would be the same regardless of whether they conceded or scored the equalizing goal at 1-1. A greater probability to go on and win a match after scoring an equalizer instead of conceding would indicate a genuine sense of momentum being grasped.

For our regression analysis, each match appears twice in the estimation samples, both from the perspective of the equalizing and conceding teams. The response variable is $win_{i,m} = 1$ if the considered team i actually won match m and is zero otherwise. The main explanatory variable of interest is $equalizer_{i,m} = 1$ if the considered team i scored the equalizing goal in match m, and is zero if they conceded. For the control variables, $probstart_{i,m}$ covers the winning chances of team i prior to match m. This odds-implied probability will also capture the influence of any expected advantage for the team playing in their home stadium. The higher is $probstart_{i,m}$, the higher we would expect the winning chances of team i to be right after an equalizing goal.[10] $minute_m$ captures the minute of the match that the equalizing goal was scored. The later in the match that the equalizer is scored, the more likely it ends in a draw and the less likely either team is going to win. $redcarddiff_{i,m}$ is the difference in the number of red cards between the teams. If $redcarddiff_{i,m} > 0$, then team i received more red cards than their opponent and hence has fewer players on the field. We expect the winning chances of a team to decrease as $redcarddiff_{i,m}$ increases. We model whether a team's chances of winning increase after scoring an equalizer, relative to their opponent's chances, using logistic regression:

$$\begin{aligned}\text{logit}\left(\Pr\left(win_{i,m}=1\right)\right) = {} & \beta_0 + \beta_1 \cdot probstart_{i,m} + \beta_2 \cdot equalizer_{i,m} \\ & + \beta_3 \cdot minute_m + \beta_4 \cdot redcarddiff_{i,m}\end{aligned} \tag{1}$$

Since each match appears twice in the estimations, we cluster standard errors at the match level.[11] Football matches and their final scorelines are often modeled according to some bivariate process of goal scoring (e.g., Boshnakov et al., 2017; Dixon & Coles, 1997; Heuer & Rubner, 2012; Reade et al., 2021). However, we prefer the reduced form of such models given by Equation (1), which focuses on testing our specific hypothesis. Ordered probit and logit models have also been used to model and forecast football results using pre-match information (e.g., Goddard, 2005; Hvattum & Arntzen, 2010). We instead favor the logistic regression model given by Equation (1), estimated over both teams in a match, since this is more straightforward to interpret when equalizing goals can go in at any time. Further, the likelihood of a drawn match in this model is implicitly then just determined by how late in the match a 1-1 equalizer is scored and the pre-match odds.

Table 2 displays the estimation results for the full sample of 431 matches (Column I) and for observations in the first (Column II) and second half (Column III), respectively. We do not find significant evidence that equalizing goals generate momentum in the full sample, nor separately in the first or second halves of matches. Although these statistical tests are somewhat under-powered, due to the small sample sizes and inherent unpredictability of football match outcomes, the model coefficient estimates are in fact quite large and negative despite being not significantly different

TABLE 2 Does scoring momentum impact match outcomes?

	Timing of equalizer for 1-1		
	Any time (I)	**First half (II)**	**Second half (III)**
probstart (β_1)	0.034***	0.033***	0.036***
	(0.005)	(0.007)	(0.008)
equalizer (β_2)	−0.124	−0.186	−0.100
	(0.187)	(0.267)	(0.269)
minute (β_3)	− 0.011***	− 0.014**	− 0.037***
	(0.003)	(0.007)	(0.009)
redcarddiff (β_4)	− 2.005***	0.009	− 2.430***
	(0.467)	(0.166)	(0.546)
Constant (β_0)	− 1.668***	− 1.597***	−0.088
	(0.276)	(0.379)	(0.616)
N of matches	431	211	220
N of observations	862	422	440
McFadden R^2	0.086	0.071	0.12

Note: Logistic regression estimates of Equation (1).

***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses that account for match-level clustering.

from zero—scoring the equalizer in the first (second) half reduces the likelihood of a win by 17% (9.5%) compared with conceding. All the control variables generate coefficients with expected signs for the likelihood of a team going on to win after a 1-1 equalizer: positive for the pre-match expectations of a win according to odds—for each one point increase in the pre-match odds-implied probability that a team will win there is approximately a 3% increase in the likelihood they will do so after the equalizer; negative for a late equalizer—each minute elapsed reduces the likelihood of a win by 1.4% in the first half and 3.6% in the second half; and negative for having received more red cards than the opponent—on average over the whole match, being a man down at the time of an equalizer reduces the likelihood of winning by 86.5% compared with if they had 11 men on the pitch, consistent with what Titman et al. (2015) found in English football.

In Table A1, we show that the main findings in column (I) of Table 2 are robust to extensions of the model given by Equation (1), including: a squared term for the minute of the equalizing goal; interacting the minute of the equalizer and $redcarddiff_{i,m}$, which is insignificant; interacting $probstart_{i,m}$ and $equalizer_{i,m}$, in case there is evidence of momentum only for either equalizing favorites or longshots, which there is not; and interacting $equalizer_{i,m}$ and $minute_m$, in case there is evidence of momentum only for either late or early goals, which there is not. We have also checked and confirmed that our findings in this section are robust to dropping matches involving the two top Bundesliga teams from the sample, Bayern Munich and Borussia Dortmund, as well as including equalizers at scorelines of 2-2, 3-3, etc., which increases the estimation sample from 429 to 542 matches (results available on request).

3.2 | Does the bookmaker value momentum?

While we find no evidence that goal-scoring momentum actually occurs in our sample, the bookmaker could still systematically alter odds according to the sequence of goals in a 1-1 scoreline for two reasons. First though unlikely, the price setting could be biased because the bookmaker believes in the impact of momentum on the final match outcomes. Second, the bookmaker could anticipate that bettors believe in momentum and adjust betting odds accordingly to secure greater profits.

To check whether bookmaker pricing of the win outcomes is affected by the sequence of goals scored up to an equalizer, we consider the probability implied by the bookmaker's posted *odds* for each team i to win in the minute after the 1-1 scoreline in match m, $prob_{i,m}$. Just like $probstart_{i,m}$, $prob_{i,m}$ is derived by taking the inverse of the posted decimal odds for them to win, and normalized to sum to one with the inverse odds for the other two possible match outcomes.

We use the same control variables as for the match outcome in Equation (1) and estimate the following linear regression model:

$$\begin{aligned} prob_{i,m} = \lambda_0 + \lambda_1 \cdot probstart_{i,m} + \lambda_2 \cdot equalizer_{i,m} + \lambda_3 \cdot minute_m \\ + \lambda_4 \cdot redcarddiff_{i,m} + u_{i,m} \quad . \end{aligned} \tag{2}$$

Table 3 reports the estimated parameters, again for both the full sample and the sub-samples of first and second half equalizers. Notably, the simple model given by Equation (2) has substantial predictive power, with an R^2 of 0.89 for the whole match, 0.92 for the first half, and 0.90 for the second half. For all three sets of model estimates, the identity of who scored the *equalizer* has an insignificant effect on the bookmaker win odds. The estimated directions of the control variable effects on the post-equalizer betting odds are all in line with our expectations. The pre-match likelihood of a win for a team, proxied by $probstart_{i,m}$, can significantly and positively explain their odds-implied probability to win after the equalizer. The later in the match that the equalizer is scored, the lower are both teams' subsequent implied probability to secure a win, and implicitly the odds-implied probability of a draw is increased. The difference in the number of red cards received prior to the equalizer decreases the implied winning probability of a team. Notably but unsurprisingly, the magnitudes of the estimated coefficient effects from the logistic regression match outcomes models in Table 2 are similar to their equivalents in Table 3 for the match outcome probabilities implied by bookmaker pricing.

Our estimates of λ_2 in Equation (2), which we use to test whether pricing is affected by who scored an equalizing goal, would be biased toward zero if changes to odds beforehand predict which team ends up scoring next. This is our principal concern for a causal interpretation of λ_2. It is possible that there are common in-play events which strongly predict that one team is going to score. The (expected) award of a penalty kick would be one such event. However, we

TABLE 3 Do bookmaker odds-implied probabilities for the win reflect momentum?

	Timing of equalizer for 1-1		
	Any time (I)	**First half (II)**	**Second half (III)**
probstart (λ_1)	0.791***	0.890***	0.675***
	(0.015)	(0.016)	(0.020)
equalizer (λ_2)	−0.440	−0.035	−0.605
	(0.484)	(0.692)	(0.540)
minute (λ_3)	− 0.231***	− 0.085***	− 0.404***
	(0.007)	(0.007)	(0.011)
redcarddiff (λ_4)	− 16.776***	− 30.977***	− 14.297***
	(1.741)	(2.503)	(1.278)
Constant (λ_0)	13.501***	5.085***	29.125***
	(0.775)	(0.825)	(0.959)
N of matches	431	211	220
N of observations	862	422	440
R^2	0.889	0.922	0.898

Note: Estimates of Equation (2).

***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses that account for match-level clustering.

are unconcerned about this specific example because the bookmaker simply closes the market as soon as a goal looks so likely (over 80% of penalty kicks awarded in regular time are scored). Regardless, sequences of consistent attacking play by one team, such as corner kicks, could both affect bookmaker pricing and predict who scores the equalizer, conditional on the other variables in Equation (2). To check this is not biasing our results, we estimate an event-study version of the model, using observations in the 5 min before and after the equalizer for all 431 matches. We include dummy variables for each minute before and after, interacted with $equalizer_{i,m}$. The coefficient estimates for these variables are shown below in Figure 2. There are clearly no significant jumps in the odds-implied probabilities prior to the equalizing goal, which reassures us that our estimates of λ_2 can be interpreted causally; we find no evidence that bookmaker pricing at 1-1 is affected by the apparent goal scoring momentum in the match.

In columns (I)–(IV) of Table A2, we show that the main findings in column (I) of Table 3 are robust to extensions of the model given by Equation (2), including: a squared term for the minute of the equalizing goal; interacting the minute of the equalizer and $redcarddiff_{i,m}$, which is insignificant; interacting $probstart_{i,m}$ and $equalizer_{i,m}$, in case there is evidence that the bookmaker only alters odds according to whether it was either the pre-match favorite or longshot that scored the equalizer, which there is not; and interacting $equalizer_{i,m}$ and $minute_m$, in case there is evidence that the bookmaker only alters odds according to whether it was a late or early equalizing goal, which there is not. All these extensions barely improve the overall predictive power of the model.

3.3 | Do bettors "believe" that momentum has value?

The findings from the previous two parts of our analysis provide evidence neither for teams generally gaining momentum after scoring a 1-1 equalizer nor for the bookmaker pricing the win according to which team scored last. In the third part of our analysis, we study the relative market stakes placed by bettors after 1-1 equalizers, to investigate whether bettors generally believe there is value in momentum and place more money than they should on the equalizing teams.

As a first look, Figure 3 shows histograms of the relative stakes placed on the team that scores or concedes the 1-1 equalizer, in the first minute that the market is open afterward. We split the sample according to money bet on strong favorites (pre-match odds < 1.5), slight favorites (pre-match odds between 1.5 and 2.69), longshots (pre-match odds

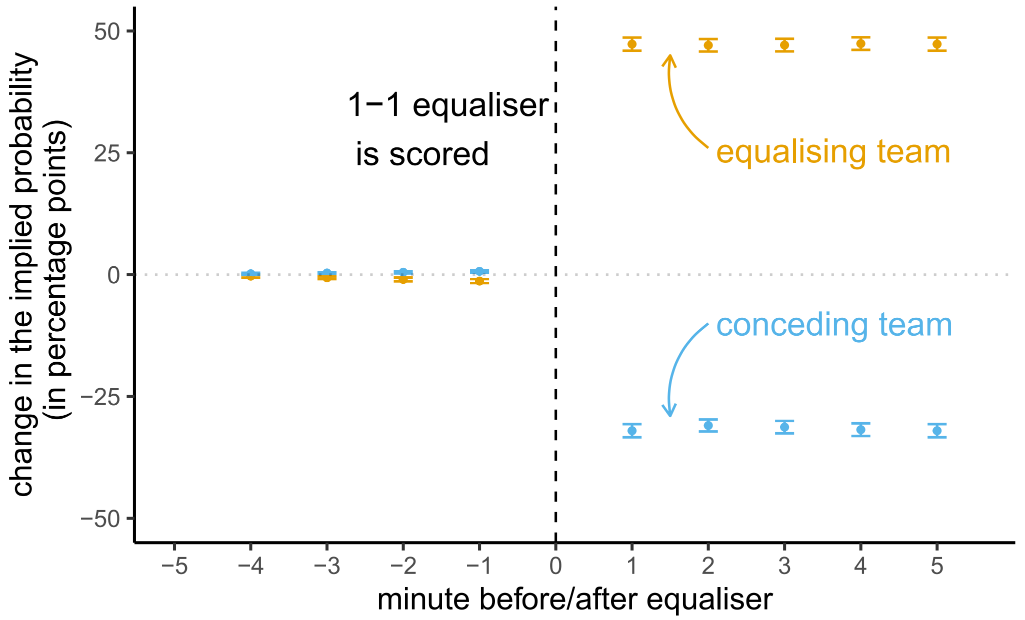

FIGURE 2 Event-study style estimates of bookmaker pricing of match win outcomes, before and after 1-1 equalizing goals. Estimates from an event-study version regression of Equation (2), using observations 5 min before and after the goal. Dots show the point estimates for dummy variables interacting the minute of the match, relative to the equalizing goal, with $equalizer_{i,m}$. The 95% confidence intervals shown for each point estimate are robust to match-level clustering.

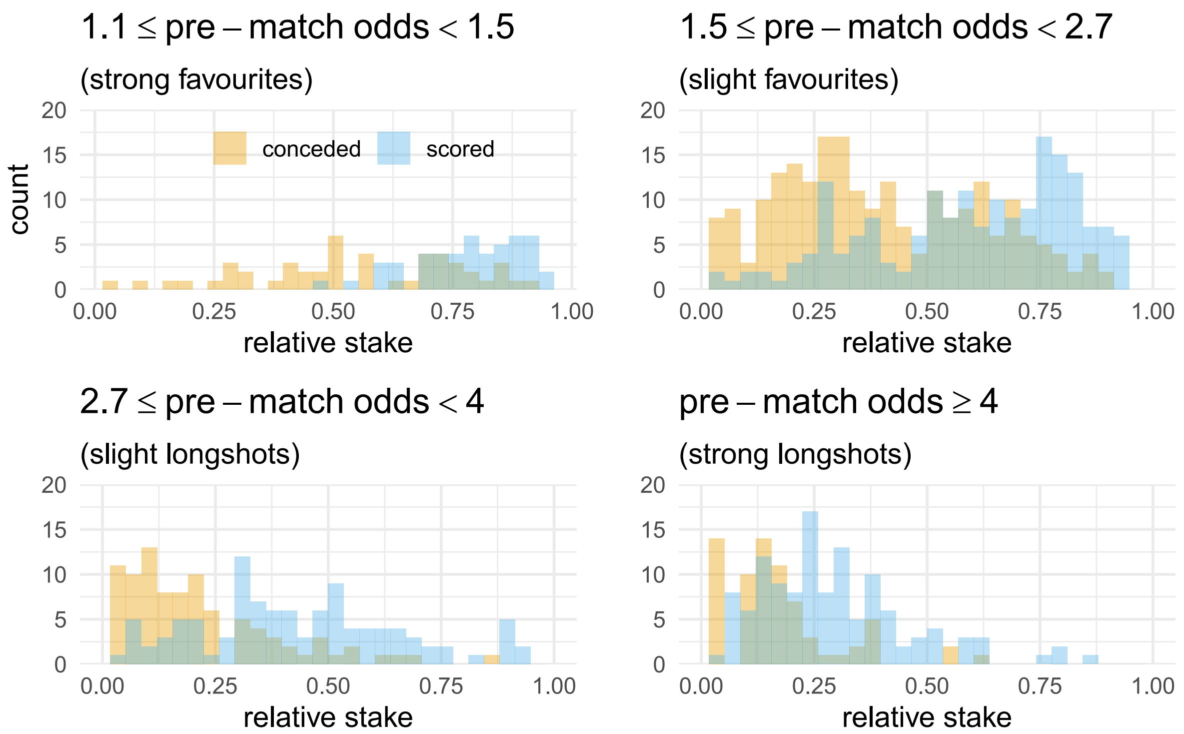

FIGURE 3 Histograms of relative stakes placed on teams to win in the minute following a 1-1 equalizer. Panels show counts of relative stakes on conceding or equalizing teams to win over the 431 matches in seasons 2017/2018 to 2020/2021 that featured a 1-1 scoreline. The green areas are where the yellow "conceded" and blue "scored" bars overlap, such that only the differences between the two distributions are actually highlighted by the displayed yellow and blue areas.

between 2.7 and 4) and strong longshots (pre-match odds > 4).[12] As our previous findings showed no evidence of significant momentum effects for the match outcome nor corresponding pricing response by the bookmaker, the histograms for both equalizing and conceding teams should theoretically overlap if bettors and the market generally behave rationally. However, Figure 3 shows clear differences in betting activity between stakes placed on the equalizing and conceding teams.

The top-left panel in Figure 3, corresponding to bets placed on strong pre-match favorites, suggests that relative stakes are generally larger if that team scores the 1-1 equalizer compared to when they concede it. Following a hypothetical simple betting strategy of always betting the same fixed amount on clear pre-match favorites who just scored a 1-1 equalizer, however, would have yielded a return on investment (ROI) of −20.8% (49 bets, 26 won). The reverse strategy, always betting the same amount on clear pre-match favorites that just conceded the equalizer, would have yielded an ROI of −13.9% (46 bets, 27 won). For context, the average overround (sometimes called the "vig" or "profit margin") implied by the bookmaker odds in our data after the equalizing goals is 7.9%.[13] Similar patterns can be observed in the respective panels of Figure 3 for the stakes placed on pre-match moderate favorites, moderate longshots and strong longshots. Reinforcing the patterns earlier shown in Figure 1 for the example match earlier, there is clear observational evidence that the relative stakes placed on the team that scores at 1-1 are on average substantially larger afterward than on the team that concedes, thus suggesting that bettors believe betting on momentum will be profitable for them, given the prices offered. They were clearly wrong, at least if they were following the simple strategy of always betting the same amount on equalizing teams. The ROIs from always backing equalizing pre-match slight favorites, slight longshots, and strong longshots in such a way, in our sample, would have been −21.7% (170 bets, 56 won), −16.5% (100 bets, 23 won), and −18.1% (112 bets, 16 won), respectively.

To support what appears to be conclusive visual findings in Figure 3, that betting activity tends to follow the team with apparent momentum, we use an econometric approach. To explain $relstake_{i,m}$—the share of the total volume bet in market/match m, in the minute after a 1-1 equalizing goal, that was placed on team i to win—we estimate the following model:

$$\begin{aligned} relstake_{i,m} = \gamma_0 + \gamma_1 \cdot probstart_{i,m} + \gamma_2 \cdot equalizer_{i,m} + \gamma_3 \cdot minute_m \\ + \gamma_4 \cdot prerelstake_{i,m} + \gamma_5 \cdot redcarddiff_{i,m} + e_{i,m}\ , \end{aligned} \tag{3}$$

where control variables once again include $probstart_{i,m}$, $minute_m$ and $redcarddiff_{i,m}$.[14] Further, we include the relative stakes prior to the first goal of the match, $prerelstake_{i,m}$, to model the general tendency of the market to favor betting on one team over the other possible match outcomes. For this variable, we divide the stakes placed on the equalizing/conceding team to win, before the first goal was scored, by the total stakes placed in that same time period on all three possible match result outcomes.

Since relative stakes on match outcomes sum to one at all times, Equation (3) also implies the following for the expected relative stakes on a draw after a 1-1 equalizer, for two teams $i = 1, 2$ in match m:

$$\begin{aligned} E[drawrelstake_m] = 1 - 2\gamma_0 - \gamma_1 \cdot \left(probstart_{1,m} + probstart_{2,m}\right) - \gamma_2 - 2\gamma_3 \cdot minute_m \\ - \gamma_4 + \gamma_4 \cdot predrawrelstake_m \end{aligned}$$

We would expect the relative stakes on the draw outcome to generally increase following an equalizer, though not always. For example, if a strong favorite equalizes early in a match, the likelihood of a draw as the final outcome may decrease. It is straightforward to interpret whether market activity tends to follow the apparent momentum of an equalizer by the amounts backing one team to win over another, as per Equation (3). But the residual betting activity on the draw outcome does not have a clear mapping to momentum-following behavior. Instead, there is some suggestive evidence of "splitting" bias (black-and-white thinking) in football match outcome prediction, both from betting prices (Angelini et al., 2022) and an experimental setting (Na et al., 2019). But exploring this issue using our dataset would require a completely different analysis, modeling the pricing and betting activity throughout a match rather than only after equalizing goals have reset the scoreline to parity.

The estimation results in Table 4 show that relative stakes placed on teams after a 1-1 equalizer significantly increase with the pre-match odds-implied probabilities, though this effect is weaker when we control for betting activity before the goal. This result suggests that bettors generally tend to bet more on pre-match favorites than longshots, and increasingly so after an equalizer, regardless of who scored. Since the later an equalizer is scored the lower are the

TABLE 4 Do bettors follow the apparent momentum?

	Timing of equalizer for 1-1			
	Any time (I)	**Any time (II)**	**First half (III)**	**Second half (IV)**
probstart (γ_1)	0.008***	0.002**	0.002*	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
equalizer (γ_2)	0.198***	0.191***	0.163***	0.217***
	(0.017)	(0.014)	(0.020)	(0.017)
minute (γ_3)	−0.001***	−0.001***	0.0001	−0.003***
	(0.000)	(0.000)	(0.0003)	(0.0004)
prerelstake (γ_4)		0.618***	0.693***	0.529***
		(0.042)	(0.058)	(0.061)
redcarddiff (γ_5)	−0.209***	−0.224***	−0.092	−0.239***
	(0.045)	(0.051)	(0.169)	(0.050)
Constant (γ_0)	0.057***	0.023	−0.013	0.158***
	(0.017)	(0.015)	(0.023)	(0.026)
N of matches	429	429	209	220
N of observations	858	858	418	440
R^2	0.229	0.621	0.644	0.623

Note: Estimates of Equation (3).

***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses that account for match-level clustering. The sample contains 429 instead of 431 matches since in two matches no stakes were placed in the next minute after the 1-1 equalizer.

chances that one team goes on to win, we unsurprisingly see that the relative stakes placed on a win significantly decrease with the minute of the match. As a team receiving a red card reduces their chances of winning, bettors tend to back wins less for undermanned teams after an equalizer. The relative stakes placed on a team prior to an equalizing goal significantly predict the relative stakes thereafter, though the estimated coefficient for this effect in the model is also significantly less than one.

Most importantly, column (II) of Table 4 supports the exploratory findings from above, showing that significantly and substantially higher betting volumes tend to back teams that score the equalizer compared to teams that concede. The model estimates show that the relative stakes placed on a team to win are on average 19.1 percentage points higher in the minute after they scored the equalizer compared with if they had instead conceded, conditional on the other history of the match and market, and remembering also that absolute betting volumes tend to double in our sample after the equalizer compared with the 3 min before. For the model shown in column (II), fixing all control variables at their respective means, the stakes placed on the equalizing team are 61.8% higher than those placed on the conceding team. Our findings hold for sub-samples according to when the equalizer went in, shown in columns (III–IV) of Table 4. The relative stakes placed on equalizing teams are especially pronounced in the second half of matches, being 21.7 percentage points greater compared with conceding teams, holding everything else in the model equal. This suggests that the market tends to believe there is value in the match momentum and a comeback being completed if the equalizer comes later.[15]

As discussed in the previous section, causal interpretation of γ_2 in Equation (3) could be doubted if there were in-play patterns in football matches, just before equalizing goals, that correlate with both relative betting activity and who subsequently scores. If anything though, we might expect something of that nature to attenuate our estimates of γ_2; given that there is no evidence that bookmaker pricing predicts who is going to equalize (see Figure 2), any foresight among bettors should lead them toward backing the team they expect to equalize. In any case, to convince that our estimates of γ_2 are not confounded by any such general foresight among market participants, we estimate an event-study version of Equation (3), using observations in the 5 min before and after the equalizer for all 429 matches. As before, we include dummy variables for each minute before and after, interacted with $equalizer_{i,m}$. The coefficient estimates for these variables are shown below in Figure 4. There is no significant difference in relative betting activity before the goal according to who is about to equalize. In the words of causal inference, there are no pre-trends in relative staked amounts before the event. As such, we are confident that our estimates of γ_2 can identify the effects on betting activity of the momentum encapsulated by an equalizing goal.

In Table A3, we show that the main findings in column (II) of Table 4 are robust to extensions of the model given by Equation (3), including: squared terms for the minute of the equalizing goal and the relative stakes prior to the first goal of the match; interacting the minute of the equalizer and $redcarddiff_{i,m}$, which is insignificant; interacting $prerelstake_{i,m}$ and $equalizer_{i,m}$, in case there is evidence that bettors tend to back pre-match equalizing favorites more greatly than longshots, which there is not; and interacting $equalizer_{i,m}$ and $minute_m$. Table A3 further includes a robustness check with relative stakes 3 min after the equalizer as the response variable (shown in the first column). In that model formulation, stakes on the win are also substantially larger for teams that score the equalizer than for teams that concede.

3.4 | Further analyses

3.4.1 | Bookmaker behavior and the overround

Given the significant response of betting activity to equalizing goals, a natural follow-up question is why the bookmaker does not capitalize on this by significantly lowering their odds for the team that scored the equalizer to win. To explore this, we first repeat our main estimations of model (2) without normalizing the odds-implied probabilities for the match outcomes (see Table A4). The results confirm that normalizing probabilities across the potential match outcomes does not obscure evidence of a significant response of betting odds to the equalizing team. Additionally, we check whether the overround ("vig") significantly responds to an equalizing goal. Event-study estimates presented in Figure A2 show no evidence of such a response.

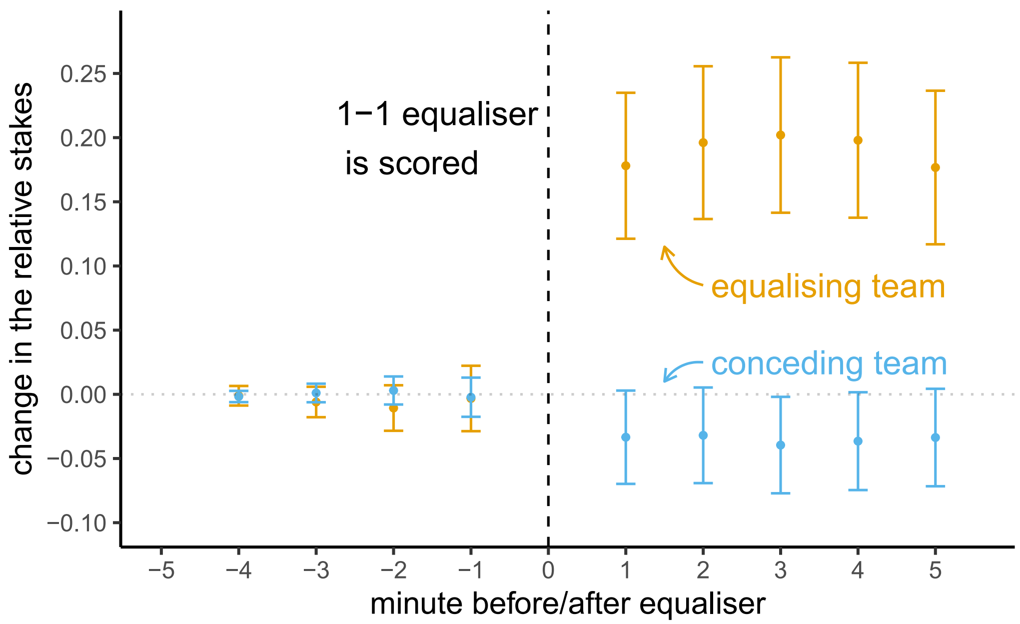

FIGURE 4 Event-study style estimates of relative betting activity for match win outcomes, before and after 1-1 equalizing goals. Estimates from an event-study version regression of Equation (3), using observations 5 min before and after the goal. Dots show the point estimates for dummy variables interacting the minute of the match, relative to the equalizing goal, with $equalizer_{i,m}$. The 95% confidence intervals shown for each point estimate are robust to match-level clustering.

Together, these additional results provide further confidence that the bookmaker's odds on average do not reflect the identity of the equalizing team, conditional on the pre-match odds and the minute of the match. For a profit maximizing bookmaker, this can be rationalized in two ways: either the bookmaker is making an error, or the betting demand is price elastic. The latter seems plausible, because a multitude of alternative sporting events and betting lines are available to bettors at the bookmaker, as well as there being extensive competition provided by other bookmakers and betting exchanges. Moreover, it is worth noting that live betting markets provide the bookmaker here with an overround of nearly 7.5%, as shown in Figure A2, which is larger than the typical overround implied by pre-match odds (usually around 5%). This may reduce the incentive to deviate live betting odds from their optimal levels.

3.4.2 | Momentum versus home advantage bias

In Table A5, we examine whether the significant tendency of betting activity to favor equalizing rather than conceding teams depends on whether it was the home or away team that scored, by repeating the estimation of model (3) separately only for either home or away team observations; that is, one observation for each match in our original samples. Specifically, we investigate and test whether the relative betting stakes on equalizing home teams are significantly greater than on conceding home teams, and the same for away teams, conditional on the model control variables, including the relative stakes prior to the equalizing goal. This allows us to check whether our main results are potentially confounded by a tendency of bettors to favor home teams more so than away teams after an equalizer, regardless of whether they scored the equalizer or not.

The results in Table A5 show coefficient estimates for the equalizer effect, γ_2, in the samples of home and away teams, overall and in each half, that are of a similar magnitude to the pooled results in Table 4. The coefficients for the home team effect are larger than for the away team, consistent with the idea that bettors believe there is even more value, given the odds, in backing an equalizing home team than an equalizing away team. However, these differences between the home and away team sample effects appear to not be statistically significant.

3.4.3 | Momentum and other scorelines

To this point, we have proposed that the significant response of betting activity toward the equalizing team may be explained by biased bettor beliefs in momentum. Our focus has been on the equalizing goal because it offers a relatively clear and straightforward framework for analyzing these markets. By using pre-match odds as a benchmark for expected match outcomes when the scoreline is level, we have been able to test whether bookmaker pricing also reflects the identity of the equalizing team. But for the momentum explanation to have greater credibility, we would expect betting activity also to respond significantly to other events in the football matches that could signal a palpable shift in momentum.

For example, when one team scores the first two goals in a match, a third goal by their opponent might signal a potential “comeback,” threatening a draw for the final result or even a complete reversal of the outcome. In our sample of matches, there are 142 instances before the 85th minute where the scoreline shifts to 2-1 (1-2) from 2-0 (0-2), with 26 of these occurring in the first half and 116 in the second half. Using this sample, we estimate Equation (3), replacing $equalizer_{i,m}$ with a dummy variable for the scoring team. The results, presented in Table A6, show that relative betting activity significantly favors the scoring team after these comeback goal events. Notably, these estimated effects are even greater than for the equalizing goals, especially in the first half. This latter evidence may be explained by the abundance of time remaining in the match, which fosters (over-)confidence among bettors in the scoring team's ability to complete its comeback. This is further supported by the (negative) magnitude of the coefficient for the *minute* variable in column (III) of Table A6, which is approximately one-third of that observed for the second half in column (IV). However, the sample size is relatively small for these scoreline shifts occurring in the first half, and thus the inference may be less reliable.

Therefore, interestingly, we find evidence of stronger beliefs in the value of betting on momentum during the earlier stages of the game, in contrast to the results observed for the equalizing case in Table 4. This could indicate a certain aversion among bettors to wagering on a draw. Specifically, our findings suggest that when a game reaches 1-1 late in the match, bettors appear more inclined to bet on a win for the equalizing team, compared to scenarios when a game shifts to 2-1 from 2-0 late in the match, where the potential comeback in the latter case is more likely to result in a 2-2 draw. Conversely, when a game moves from 2-0 to 2-1 early in the match, bettors seem to exhibit greater confidence in the likelihood of a complete comeback by the trailing team. This could be attributed to the ample time remaining in the game and a potential reluctance to place bets on a draw.

4 | CONCLUSION

Our study asks whether gamblers tend to see value in following the ostensible momentum within a market. We use a novel and rich dataset from a large and well-known international bookmaker, focusing on betting markets just after 1-1 equalizers are scored during matches in the German Bundesliga. We assess whether the sequence of scoring impacts the final match outcome, the price setting by the bookmaker, and ultimately the amount and direction of betting activity. We hypothesize that the equalizing team has gained momentum, being more likely then to win and complete the comeback than pre-match odds and the other history of the match would imply. However, we find no evidence that the sequencing of the goals leading up to a 1-1 scoreline thereafter influences the relative winning chances of the teams involved or the odds set by the bookmaker. This is consistent with most of the existing evidence about other momentum myths within strategic professional team sports. Still, we find convincing evidence that bettors believe there is value in momentum, as considerably higher stakes are placed on teams that have just equalized to eventually win, compared with teams that conceded. This does not translate into profits, as always backing the team that seems to have momentum would on average lead to significant losses.

Our study is the first that can cleanly isolate a singular event within open betting markets that creates ostensible momentum and influences investor behavior. While there is no evidence that the sequencing of goals is relevant to the match outcome, the betting market behaves as though it is important. This indicates that investors indeed have difficulty valuing even the most important situations in a football match and reacting to major news. Still, there are some potential limitations or caveats to our approach and findings. First, since our high-frequency market data only provide totals of betting activity, it is impossible to connect bets made by individuals over time. Bettors can stake money on one particular outcome before or during a match before later staking on a different outcome, to hedge the first bet. Betting after the equalizer may partly reflect activity from the same bettors prior to the goal. The impacts of such strategic and dynamic betting behavior on our findings should be quite low, as this would likely only make sense when somebody had staked money after but not prior to the first goal in a match. Second, the detail level of in-play statistics that we could reliably link to the betting market dataset is low. While goals and red cards are by far the most meaningful events to impact football match outcomes, others, such as yellow cards, substitutions, shots on target and corner kicks, could impact how bettors perceive the direction of momentum in a match. For instance, an interesting extension could involve distinguishing equalizers that went “against the run of play.” There is a popular notion in football that such goals are particularly demoralizing for teams that concede. Last, our match-by-match analysis neglects any cross-market momentum or how teams handle certain in-play situations they experienced in the past. If one team scored an equalizer in a previous match to later go on and win, then bettors could predict the re-occurrence of such a dynamic in the next match. A further interesting extension could be to compare the in-play betting activity at a bookmaker with what is happening on person-to-person exchange markets. For instance, Franck et al. (2013) demonstrated that consistent arbitrage opportunities exist when comparing the two sources for pre-match bets on football match outcomes. These authors found that bookmakers were the source of the arbitrage opportunities, suggesting they probably offered favorable pre-game odds to keep customers for some later long-term gain. Our findings suggest that keeping customers on board till they graduate from pre-match to in-play betting might be part of a bookmaker's long-term profit strategy.

The above-mentioned issues could be tackled in future work, as knowledge of the drivers of real-world betting behavior is still in its infancy—almost all the literature to date has only studied prices. We also believe that betting markets can be valuable settings to test general theories of price setting and behavioral biases that affect risk-taking. The availability of both odds and actual staked amounts allows investigation of how gamblers make potentially biased decisions, which bookmakers or sophisticated traders on betting exchanges can exploit. However, to go further and start to unpick the root causes and specific cognitive biases generally at play, researchers will need to convince bookmakers to part with even more valuable data, at the level of individual bettors, or simulate high-frequency betting markets in controlled experiments among regular gamblers. To generalize beyond getting markets, however, such experiments would need to also test whether non-gamblers behave differently.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in OPENICPSR under the title as Ötting (2025) at https://doi.org/10.3886/E216602V5.

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ENDNOTES

[1] There is evidence that reference dependent behavior of football players and coaches, acting when they are behind in a match relative to their expectations, tends to lead to poor outcomes (Bartling et al., 2015). This mechanism could also plausibly lead to momentum effects within a match. Further, 1-1, despite being parity in the scoreline, could represent a relatively more positive or negative final outcome for either team depending on their pre-match expectations and ambition; that is, the underdog team might be happy for the game to end in a draw and secure a point, thus reducing their scoring effort but increasing their defending, while the favorite team may see a draw as a failure.

[2] Coming back from one goal down to win in football is normally a modest "comeback" within the whole sporting landscape. The high-scoring nature of North American sports readily lends itself to comebacks that end up in folklore, recently in Super Bowl LI (see "The Six Biggest Comebacks in Super Bowl History," February 2021; https://www.si.com/nfl/2021/02/08/six-biggest-comebacks-super-bowl-history). Perhaps the most infamous association football comeback completed around a 1-1 scoreline, at least to the mostly German and English authors of this study, would be the 1999 UEFA Champions League Final (see "Watch: Incredible fan footage of Man Utd's 1999 Champions League final comeback shared for first time," May 2022; https://www.goal.com/en-gb/news/watch-incredible-fan-footage-of-man-utd-s-1999-champions-league-final-comeback-shared-for-first-time/blt96f9dbb77ad3cc5a).

[3] Several studies have analyzed real-world pre-event activity in parimutuel or pool betting markets, typically on horse-racing of some form (e.g., Suhonen & Saastamoinen, 2018; Suhonen, Saastamoinen, Kainulainen, & Forrest, 2018; Suhonen, Saastamoinen, & Linden, 2018). However, these markets have no prices on individual outcomes, and the operator's problem is only to set an optimal commission rate (percentage of the pool) long before the events begin.

[4] Likewise, in high-liquidity betting exchange prediction markets, such as operated by the market-leader Betfair, where back and lay positions can be traded by individuals, there are likely strategic market makers as well as regular bettors.

[5] Football is a low-scoring game, and in the entire history of professional football, 1-1 has been the most likely final outcome of a match Reade et al. (2021).

[6] While the 85th minute might seem like an arbitrary cut-off, we believe we have good reason for choosing it. Figure A1 shows that later equalizers disproportionately attract more betting activity. Here, the blue line indicates the mean values applying locally estimated scatterplot smoothing.

[7] There are notable spikes in relative betting activity toward Schalke or Wolfsburg throughout the match, not coinciding with goals, but possibly related to other notable events in the match. For instance, just before halftime there was a 2-min delay for an injury to Wolfsburg's striker Admir Mehmedi, who was not substituted and completed the match (see https://www.espn.co.uk/football/

commentary/gameId/517738; accessed 31/5/2024). It is possible that during this delay bettors believed that Schalke's chances of winning were significantly improved because it appeared they may have to substitute Mehmedi.

[8] If the pre-match odds are at all meaningful, then the favorites will tend to score goals at a higher rate than their opponent and thus earlier in the match; in our sample, the favorite scored the first goal in 63% of the matches.

[9] A red card, or sending off, is a relatively rare but severe punishment in a football match, with the receiving team having to play with one fewer player for the remainder of the match. For the top two divisions of English football in the 2009/2010 & 2010/2011 seasons, Titman et al. (2015) found that a red card to the away (home) team increased the home (away) team's scoring rate persistently by 83.5% (62%).

[10] Several studies have favored using Elo ratings of football teams to form match result predictions or model the role of relative dynamic team strengths in other outcomes (e.g., Bryson et al., 2021). This is a method adapted from chess and widely used across sports to form rankings based on the entire histories of whichever teams or players have played and defeated each other. However, for the specific issue of accurately predicting football match results, Hvattum and Arntzen (2010) show that methods using match odds tend to do significantly better than Elo-based predictions.

[11] Alternatively, rather than clustering at the match level, we could at random use one observation, home and away, from each match, but this would also imply discarding information.

[12] In the sample, it is always the case that if one team has pre-match decimal odds to win of at most 2.69, then the other team has odds of at least 2.7 to win. This margin corresponds to a non-normalized probability of a win of around 0.37, or 0.34 after normalizing. We refer to "longshots" for consistency with the literature, though another commonly used term would be "underdogs."

[13] Calculated as the sum of the odds-implied probabilities for the three potential match outcomes minus one.

[14] We also considered a specification using the odds-implied match outcome probabilities last observed before an equalizer as controls. However, we found these models had significantly weaker explanatory power for the relative betting activity. As indicated by our descriptive results above, it is important to control for pre-match expectations about relative team strengths.

[15] Note that our findings are also not impacted notably if we include the following as controls in the regression model: (1) the average minute-level relative stakes between the first goal and the equalizer; (2) a dummy for the home team. These variables are highly collinear with other controls. Therefore, we prefer to present and focus on the results of our parsimonious specifications that have relatively straightforward margins to interpret.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A

ADDITIONAL TABLES AND FIGURES—MODEL ROBUSTNESS CHECKS

TABLE A1 Robustness checks on "Does scoring momentum impact match outcomes?".

	Timing of equalizer for 1-1			
	Any time (I)	**Any time (II)**	**Any time (III)**	**Any time (IV)**
probstart	0.034***	0.034***	0.033***	
	(0.005)	(0.005)	(0.006)	
equalizer	−0.126	−0.145	−0.224	−0.268
	(0.187)	(0.188)	(0.358)	(0.971)
minute	0.014	0.013	0.013	0.012
	(0.014)	(0.013)	(0.013)	(0.025)
$minute^2$	− 0.0003***	− 0.0003***	− 0.0003***	− 0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
redcarddiff	− 2.020***	3.709**	3.716**	3.729**
	(0.468)	(1.610)	(1.616)	(1.635)
minute · *redcarddiff*		− 0.206**	− 0.206**	− 0.207**
		(0.090)	(0.091)	(0.091)
$minute^2$ · *redcarddiff*		0.002*	0.002*	0.002*
		(0.001)	(0.001)	(0.001)
probstart · *equalizer*			0.002	0.002
			(0.007)	(0.007)
minute · *equalizer*				0.002
				(0.043)
$minute^2$ · *equalizer*				− 0.00002***
				(0.000)
Constant	− 2.127***	− 2.102***	− 2.060***	− 2.039***
	(0.362)	(0.359)	(0.397)	(0.581)
N of matches	431	431	431	431
N of observations	862	862	862	862
McFadden R^2	0.088	0.092	0.092	0.092

Note: Logistic regression estimates of Equation (1) with added control variables and interactions. See Table 2.

***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses that account for match-level clustering.

TABLE A2 Robustness checks on “Do bookmaker odds for the win reflect momentum?”.

	Timing of equalizer for 1-1			
	Any time (I)	**Any time (II)**	**Any time (III)**	**Any time (IV)**
probstart	0.008***	0.008***	0.008***	0.008***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)
equalizer	−0.004	−0.003	−0.002	0.050**
	(0.005)	(0.005)	(0.005)	(0.020)
minute	0.002***	0.002***	0.002***	0.003***
	(0.0002)	(0.0002)	(0.0002)	(0.001)
minute^2	− 0.00004***	− 0.00004***	− 0.00004***	− 0.0001***
	(0.00000)	(0.00000)	(0.00000)	(0.00001)
redcarddiff	− 0.168***	− 0.442***	− 0.442***	− 0.458***
	(0.017)	(0.028)	(0.028)	(0.031)
minute · *redcarddiff*		0.006***	0.006***	0.007***
		(0.001)	(0.001)	(0.001)
minute^2 · *redcarddiff*		− 0.00003**	− 0.00003**	− 0.00003**
		(0.00001)	(0.00001)	(0.00001)
prob · *equalizer*			−0.00004	−0.00004
			(0.0001)	(0.0001)
minute · *equalizer*				− 0.002**
				(0.001)
minute^2 · *equalizer*				0.00002**
				(0.00001)
Constant	0.059***	0.058***	0.058***	0.032***
	(0.007)	(0.007)	(0.008)	(0.012)
N of matches	431	431	431	431
N of observations	862	862	862	862
R^2	0.900	0.906	0.906	0.907

Note: Estimates of Equation (2) with added control variables and interactions. See Table 3.

***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses that account for match-level clustering.

TABLE A3 Robustness checks on "Do bettors follow the apparent momentum?".

	Timing of equalizer for 1-1				
	Any time (3 min after equalizer) (I)	**Any time (II)**	**Any time (III)**	**Any time (IV)**	**Any time (V)**
probstart	0.002***	0.002**	0.002**	0.002*	0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
equalizer	0.198***	0.191***	0.191***	0.157***	−0.030
	(0.012)	(0.014)	(0.014)	(0.016)	(0.067)
minute	− 0.001***	0.003***	0.003***	0.003***	−0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
minute^2		− 0.00004***	− 0.00004***	− 0.00004***	− 0.00002***
		(0.000)	(0.000)	(0.000)	(0.000)
redcarddiff	− 0.196***	− 0.224***	−0.066	−0.064	0.002
	(0.039)	(0.051)	(0.377)	(0.377)	(0.373)
prerelstake	0.637***	0.617***	0.568***	0.578***	0.580***
	(0.033)	(0.042)	(0.065)	(0.066)	(0.065)
prerelstake^2			0.052	0.041	0.036
			(0.051)	(0.052)	(0.051)
minute · *redcarddiff*			−0.006	−0.006	−0.008
			(0.014)	(0.014)	(0.014)
minute^2 · *redcarddiff*			0.00004***	0.00005***	0.0001***
			(0.000)	(0.000)	(0.000)
probstart · *equalizer*				0.001***	0.001***
				(0.000)	(0.000)
minute · *equalizer*					0.007**
					(0.003)
minute^2 · *equalizer*					− 0.0001***
					(0.000)
Constant	0.005	− 0.052***	− 0.045**	−0.029	0.064*
	(0.013)	(0.018)	(0.018)	(0.019)	(0.039)
N of matches	400	429	429	429	429
N of observations	800	858	858	858	858
R^2	0.764	0.672	0.673	0.674	0.681

Note: Estimates of Equation (3) with added control variables and interactions. See Table 4.

***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses that account for match-level clustering. The samples contain 429 instead of 431 matches since in two matches no stakes were placed in the next minute after the 1-1 equalizer. In the first column, which refers to the stakes placed in the next 3 min after an equalizer, the sample size is slightly smaller as other major events (further goals or red cards) occurred during the next 3 min in 15 matches.

TABLE A4 Do bookmaker odds-implied probabilities for the win reflect momentum? without normalization.

	Timing of equalizer for 1-1		
	Any time (I)	**First half (II)**	**Second half (III)**
probstart (λ_1)	0.853***	0.960***	0.729***
	(0.016)	(0.017)	(0.021)
equalizer (λ_2)	−0.481	−0.040	−0.663
	(0.522)	(0.748)	(0.585)
minute (λ_3)	− 0.247***	− 0.085***	− 0.438***
	(0.008)	(0.008)	(0.012)
redcarddiff (λ_4)	− 18.112***	− 33.386***	− 15.447***
	(1.880)	(2.709)	(1.388)
Constant (λ_0)	14.498***	5.301***	31.504***
	(0.840)	(0.900)	(1.046)
N of matches	431	211	220
N of observations	862	422	440
R^2	0.887	0.920	0.896

Note: Estimates of Equation (2). This table shows results from estimating equivalent models as in Table 3, but without normalizing the odds-implied probabilities (that is, the probability variables are simple the inverse of the decimal odds offered by the bookmaker).
***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses that account for match-level clustering.

TABLE A5 Robustness checks on "Do bettors follow the apparent momentum?"—Home advantage.

	Dependent variable:							
	relstake							
	Any time (home) (1)	**Any time (away) (2)**	**Any time (home) (3)**	**Any time (away) (4)**	**First half (home) (5)**	**First half (away) (6)**	**Second half (home) (7)**	**Second half (away) (8)**
probstart (γ_1)	0.009***	0.009***	0.003***	0.002**	0.003***	0.002*	0.004***	0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
equalizer (γ_2)	0.206***	0.188***	0.202***	0.180***	0.178***	0.147***	0.217***	0.212***
	(0.017)	(0.018)	(0.015)	(0.014)	(0.021)	(0.021)	(0.019)	(0.020)
minute (γ_3)	0.0002***	− 0.002***	− 0.001***	− 0.001***	0.002**	− 0.002*	− 0.003***	− 0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
textitprerelstake (γ_4)			0.546***	0.619***	0.601***	0.680***	− 0.244***	− 0.238***
			(0.045)	(0.047)	(0.065)	(0.065)	(0.047)	(0.054)
redcarddiff (γ_5)	− 0.228***	− 0.218***	− 0.234***	− 0.225***	−0.145	−0.112	0.484***	0.558***
	(0.039)	(0.050)	(0.046)	(0.054)	(0.178)	(0.161)	(0.062)	(0.070)
Constant (γ_0)	− 0.073**	0.131***	− 0.044*	0.057**	− 0.109***	0.059*	0.110*	0.175***
	(0.029)	(0.029)	(0.026)	(0.023)	(0.041)	(0.034)	(0.057)	(0.063)

TABLE A5 (Continued)

	Dependent variable: relstake							
	Any time (home) (1)	Any time (away) (2)	Any time (home) (3)	Any time (away) (4)	First half (home) (5)	First half (away) (6)	Second half (home) (7)	Second half (away) (8)
Observations	429	429	429	429	209	209	220	220
R^2	0.541	0.530	0.671	0.684	0.666	0.694		

Note: Estimates of Equations (2) and (3). This table shows results from estimating equivalent models as in Table 3, conducted separately for events where the equalizing goal is scored by home or away teams.

***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses.

TABLE A6 Relative betting activity when the scoreline changes from 2-0 (0-2) to 2-1 (1-2).

	Type of goal			
	Any time (I)	Any time (II)	First half (III)	Second half (IV)
probstart (γ_1)	0.003***	0.0004	−0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Scoring team (γ_2)	0.220***	0.229***	0.345***	0.199***
	(0.026)	(0.026)	(0.055)	(0.028)
minute (γ_3)	−0.004***	−0.005***	−0.002**	−0.006***
	(0.000)	(0.000)	(0.001)	(0.001)
prerelstake (γ_4)		0.289***	0.527***	0.204***
		(0.064)	(0.118)	(0.069)
redcarddiff (γ_5)	0.021	0.137***	0.160**	
	(0.022)	(0.035)	(0.073)	
Constant (γ_0)	0.342***	0.320***	0.125**	0.451***
	(0.035)	(0.035)	(0.063)	(0.047)
N of matches	142	142	26	116
N of observations	284	284	52	232
R^2	0.381	0.430	0.630	0.374

Note: Estimates of Equation (3) for other types of goal events.

***, **, * indicate significance from zero of the model coefficients at the 1%, 5%, and 10% levels, respectively, two-sided tests, with standard errors in parentheses that account for match-level clustering.

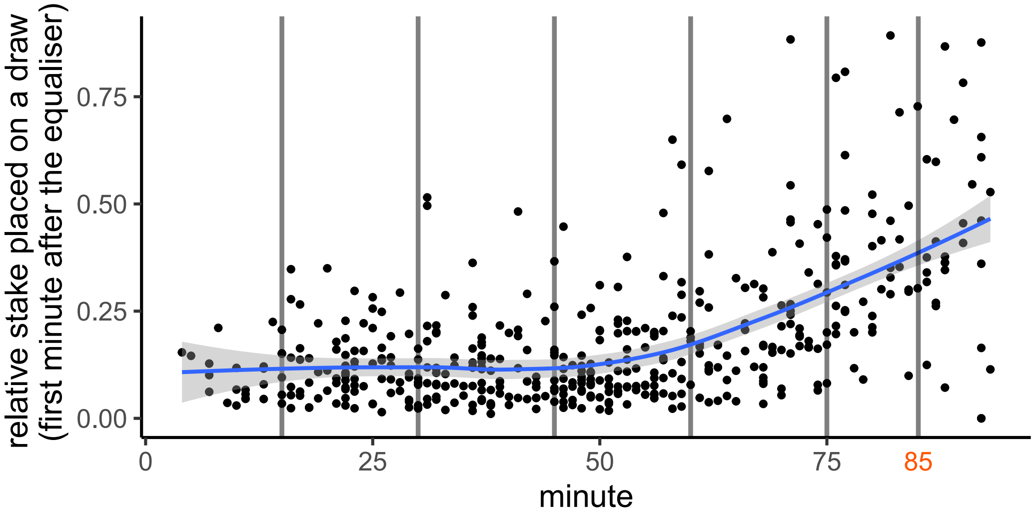

FIGURE A1 Relative stakes placed on the draw outcome in the first minute after each 1-1 equalizer in the estimation sample, according to the minute of the equalizer. The black dots represent each 1-1 equalizer observation in our main estimation samples. The blue line fits a trend line using locally estimated scatterplot smoothing with a 95% confidence interval.

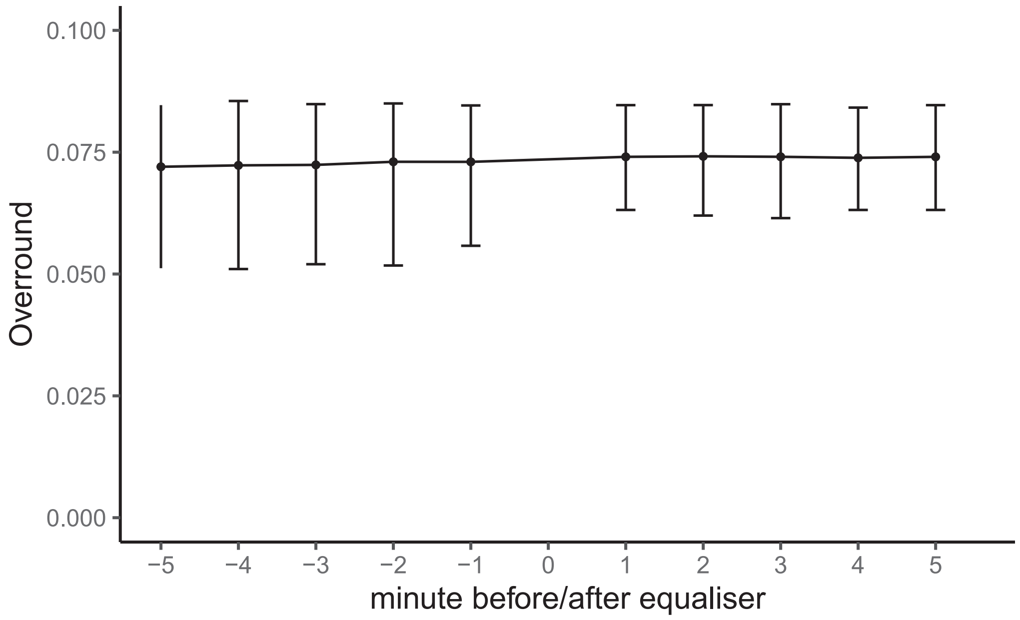

FIGURE A2 Event-study style estimates of the bookmaker's overround for the match result outcome, before and after 1-1 equalizing goals. Estimates from an event-study version regression of Equation (2), using observations 5 min before and after the goal, where the dependent variable is the bookmaker's overround (i.e., the sum of the inverses of odds offered on each potential match outcome, minus one, also sometimes referred to as the "vig"). Dots show the point estimates for dummy variables interacting the minute of the match, relative to the equalizing goal, with $equalizer_{i,m}$. The 95% confidence intervals shown for each point estimate are robust to match-level clustering.