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Expectations as Reference Points: Field Evidence from Professional Soccer

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We show that professional soccer players and their coaches exhibit reference-dependent behavior during matches. Controlling for the state of the match and for unobserved heterogeneity, we show on a minute-by-minute basis that players breach the rules of the game, measured by the referee's assignment of cards, significantly more often if their teams are behind the expected match outcome, measured by preplay betting odds of large professional bookmakers. We further show that coaches implement significantly more offensive substitutions if their teams are behind expectations. Both types of behaviors impair the expected ultimate match outcome of the team, which shows that our findings do not simply reflect fully rational responses to reference-dependent incentive schemes of favorite teams to falling behind. We derive these results in a data set that contains more than 8,200 matches from 12 seasons of the German Bundesliga and 12 seasons of the English Premier League.

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1. Introduction

Understanding the determinants and behavioral effects of reference points is an active area of research. The key idea is that a person's assessment of an outcome is determined not only by the outcome itself but also by how the outcome compares to a reference point (Kahneman and Tversky 1979). An important open question in the literature is what determines the reference point. A growing number of theoretical contributions (e.g., Bell 1985; Loomes and Sugden 1986; Gul 1991; Kőszegi and Rabin 2006, 2007, 2009) model reference points as shaped by expectations. Direct tests of these ideas using field data are, however, difficult because "expectations are hard to observe in the field" (Abeler et al. 2011, p. 470). In this paper, we report on a unique and large panel field data set that allows exactly this: to observe (i) an exact quantitative measure of people's ex ante expectations, (ii) the current state of the world relative to the ex ante expectation, and (iii) objective measures of behavior over time.

Empirical evidence on reference points and their behavioral consequences is of value for economics in general and for managerial decision making in particular. Consider the impact of reference points on worker morale and effort choices. Bewley (1999) provides evidence from interviews with business executives, labor leaders, and professional recruiters that workers compare current earnings to previous earnings and that wage cuts undermine work morale. This suggests that previous earnings serve as an expectation-based reference point for current earnings and that workers dislike falling short of this reference point. Analyzing the relationship between pay raises, expectations, and performance, Mas (2006) finds that, in the months after New Jersey police officers lose in final-offer arbitration over salary demands, arrest rates and average sentence length decline and crime reports rise, compared to when they win. Ockenfels et al. (2015) investigate how bonus payments affect managers' satisfaction and performance in a large, multinational company. They show that bonus payments falling short of individually assigned bonus targets—a likely expectation-based reference point—reduce work satisfaction and performance.

Despite the importance of reference points in the literature, field evidence on the determinants of reference points and on their influence on behavior is still relatively scarce.[1] In this paper, we use a data set from two leading soccer leagues, the German Bundesliga and the English Premier League, to show that the behavior of professional soccer players and coaches during matches depends significantly on whether or not their team is behind the expected match outcome. Professional bookmakers' preplay betting odds on match outcomes allow us to construct a measure of expectations. Our first behavioral outcome variable is the players' breaches of the rules of the game, such as fouling a player of the opposing team, measured by "cards," which are shown for irregular behavior to individual players by highly trained, impartial referees. The underlying motivations for such irregular behavior can be manifold: cards may reflect a riskier or more aggressive way of playing or a player's increased effort, or it may be that players engage in sabotage of the opponent's effort. Our second behavioral outcome variable is the coaches' strategic adjustments that are implemented by means of player substitutions during a match. Such adjustments may reflect risk-taking behavior by coaches, because substituting, say, a defender with a striker increases the probability of scoring a goal but also increases the probability of receiving one.

We show that players receive significantly more cards per minute if their team is behind expectations (e.g., the team is behind by one goal but the preplay expectation was to win the match) than if their team is not behind expectations (e.g., the team is behind by one goal and the preplay expectation was indeed to be defeated). This finding holds while we control for the state of the match (e.g., the goal difference and the minute of play) as well as for unobserved match- and team-specific heterogeneity. The size of the effect is considerable: players of a team that is behind the expected match outcome receive 14% more cards per minute than players of a team that is not behind expectations. Moreover, we show that coaches implement offensive strategy adjustments by means of substitutions (they substitute, say, a midfielder with a striker rather than a midfielder with another midfielder) significantly more often if their teams are behind expectations than if their teams are not behind expectations, controlling for the state of the match as well as for match- and team-specific effects. The size of the effect is again large: the probability of an offensive substitution in a given minute more than doubles. These findings lend support to the idea that expectations shape reference points and that people's behavior depends on how a given outcome contrasts with this reference point.

Importantly, we conduct a productivity analysis to address the possibility that our findings simply reflect fully rational responses to reference-dependent incentive schemes of favorite teams to falling behind. If this were the case, players of unexpectedly losing teams *should* play in a way that leads to more cards, and their coaches *should* implement a more offensive strategy of play. However, we find that both receiving more cards and substituting players in an offensive way while being behind expectations *worsen* the expected ultimate match outcome. Moreover, we analyze the reasons for card assignments and find that reasons related to overreaction and aggression, such as "violent conduct," account for a much larger share in the loss frame (i.e., when a team is behind expectations) than out of the loss frame. This latter finding provides additional evidence that the observed behavioral pattern is not entirely driven by rational responses of favorite teams to being behind.

Overall, our study thus provides evidence for a model of reference-dependent preferences where being in a loss frame is "psychologically different" from not being in a loss frame. In particular, players and coaches might feel pressure or frustration when being behind expectations, which can manifest itself in different and potentially not entirely rational behaviors.

A much-related paper is Card and Dahl (2011), who show the effect of unexpected emotional cues, such as the unexpected loss of a team in the National Football League, on domestic violence. They find that a 10% increase in the rate of at-home violence by men against the women with whom they live results when their team loses a match that it was predicted to win by some margin. Similar to our paper, the work of Card and Dahl uses betting market data to infer expected match outcomes. Our paper, however, is different in that we analyze behavior by players and coaches during matches, i.e., behavior that can influence the state of being in a loss frame, whereas Card and Dahl analyze violent and futile reactions to unchangeable facts.

Also related to our paper is the work of Pope and Schweitzer (2011), who analyze professional golfers' performance.[2] They find that golfers are significantly

[1] Recent laboratory studies showing the importance of expectation-based reference points include Abeler et al. (2011), who exogenously influence subjects' earnings expectations. They show that if expectations are high, subjects work longer and earn more money than if expectations are low. Ericson and Fuster (2011) provide evidence for expectation-based reference points in exchange and valuation experiments. Gill and Prowse (2012) show that subjects have reference points given by their expected monetary payoff in tournaments. Fehr et al. (2011) and Bartling and Schmidt (2015) provide evidence that contracts serve as reference points.

[2] One reason for the increasing usage of sports data sets in economic research is that they provide statistics that "are much more detailed and accurate than typical microdata samples" (Kahn 2000, p. 75). Other examples include Walker and Wooders (2001), Chiappori et al. (2002), Garicano et al. (2005), and Kocher et al. (2012).

influenced by the reference point that is provided by "par," the typical number of strokes that a professional golfer takes to complete a hole. Our paper is different because the betting odds data provide a measure of every single team's expectation in every single match, whereas par (or the average score on a hole, which might differ from par) does not necessarily coincide with an individual golfer's expectation in a given tournament.[3]

2. Data

Our data contain information on all 3,672 matches in the German Bundesliga (henceforth BL) in the 12 seasons from 1998–1999 to 2009–2010 and on all 4,560 matches in the English Premier League (henceforth PL) in the 12 seasons from 2000–2001 to 2011–2012.[4] For each match, we have detailed minute-by-minute information on goals, cards, and substitutions. For cards, we know not only the team and minute but also the reason, such as, e.g., "violent conduct" or "deliberate handball." For substitutions, the data contain not only the team and minute but also the strategic component, i.e., whether, say, a midfielder was substituted with a midfielder (strategically neutral substitution) or with a striker (offensive substitution).[5]

To quantify the offensiveness of substitutions, we construct a *strategy adjustment measure*. In soccer, there exist four categories of players: strikers, midfielders, defenders, and goalkeepers. Strikers are the most offensive type of player, so we assign them a value of 4. Midfielder, defenders, and goalkeepers are assigned the values 3, 2, and 1, respectively. We define our strategy adjustment measure as the category value of the incoming player minus the category value of the outgoing player. For example, the measure takes on value 0 if a striker comes for another striker, it is +1 if a midfielder comes for a defender, and it is −2 if a defender comes for a striker. A substitution is thus classified as "offensive" if and only if the measure is strictly positive, and the higher the measure, the higher the offensiveness of a substitution.

Table 1 Summary Statistics

Variable	Mean	Std. dev.	Min	Max
Per match (N = 8,232)				
Goals	2.728	1.679	0	11
Cards	3.728	2.102	0	15
Yellow cards	3.632	2.049	0	13
Red cards	0.096	0.324	0	3
Substitutions	5.146	1.019	0	6
Offensive substitutions	1.096	0.894	0	5
Defensive substitutions	0.782	0.816	0	5
Strategy adjustment measure	0.362	1.429	−6	7
Per minute and team (N = 1,569,478)				
Goals	0.014	0.119	0	2
Cards	0.020	0.140	0	3
Yellow cards	0.019	0.138	0	3
Red cards	0.001	0.023	0	2
Substitutions	0.027	0.173	0	3
Offensive substitutions	0.006	0.077	0	3
Defensive substitutions	0.004	0.064	0	2
Strategy adjustment measure	0.002	0.119	−3	4

Table 1 contains summary statistics for goals, cards (yellow and red cards combined), yellow cards, red cards, substitutions, and the strategy adjustment measure; all statistics are reported on the match level and on the minute and team level. All together, 22,460 goals were scored, 30,694 cards were shown, and 42,359 substitutions were made. The average number of goals per match is 2.73, which corresponds to 0.014 goals per minute per team. We find red cards to be very rare events relative to yellow cards. On the match level, the average number of yellow and red cards is 3.63 and 0.10, respectively. The average number of substitutions per match is 5.15. On average, approximately 1.1 of these 5 substitutions are offensive and approximately 0.8 are defensive. On the minute and team level, this corresponds to 0.027 substitutions, of which 0.006 are offensive and 0.004 are defensive. The average values of the strategic adjustment measure are 0.362 on the match level and 0.002 on the minute and team level; i.e., coaches tend to implement a more offensive strategy over the course of a match on average.

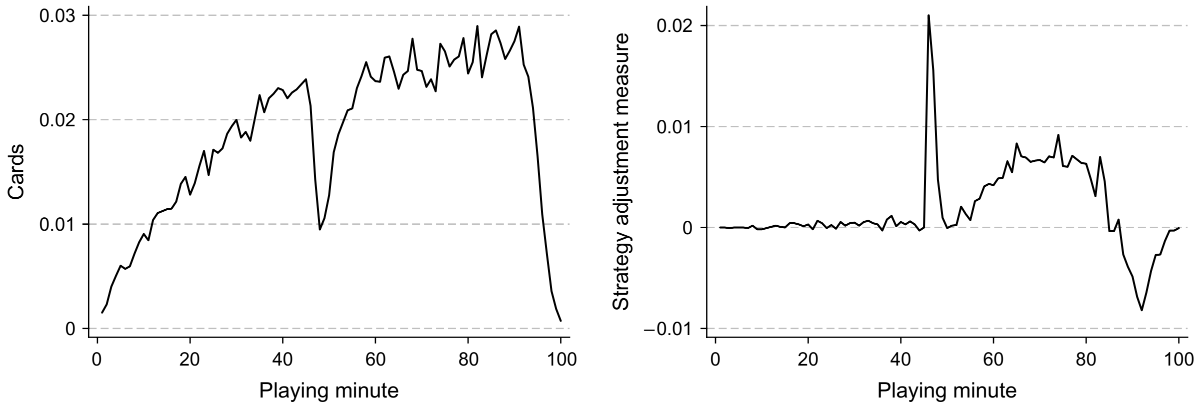
Our two behavioral outcome variables are the cards that players receive and the strategy adjustment measure that is determined by the substitutions that coaches implement. Figure 1 shows the dynamics of the per-minute average of these two outcome variables over the course of the match. The left panel shows the average number of cards per minute over time. It can be seen that the number of cards substantially increases over the course of a match. However, there is a pronounced dip around halftime. Also, the frequency of cards per minute drops to almost

[3] Further related papers on reference-dependent behavior in the field include Camerer et al. (1997), Farber (2005, 2008), Fehr and Goette (2007), Crawford and Meng (2011), and Gneezy et al. (2014).

[4] Background information on soccer and on the two leagues is provided in §A.1 of the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mnsc.2014.2048).

[5] The data for the BL and PL are partly freely available on the Internet (apart from, e.g., injury time and the assignment of goals, cards, and substitutions to specific minutes in the injury time). The full data set is proprietary, and we purchased it from the commercial data providers Impire (http://www.bundesliga-datenbank.de/en) for the BL and from Press Association (http://www.pressassociation.com/sport) for the PL. We could not get the two most recent seasons of the BL because, from the season 2010–2011 onward, the Deutsche Fußball Liga GmbH, which organizes and markets professional soccer in Germany, is the official data provider, and we were informed that they do not share their data for statistical analysis.

Figure 1 **Dynamics of Cards and Strategy Adjustment Measure**



Notes. The left panel shows the average number of cards per minute over time. The right panel shows the average of the strategy adjustment measure per minute over time.

zero in the final minutes of matches with very long injury time. There are relatively few observations for matches with very long injury time. Only 16% of matches last longer than 97 minutes, 7% last longer than 98 minutes, and 3% last longer than 99 minutes.

The right panel of Figure 1 shows the average of the strategy adjustment measure per minute over time. It can be seen that, on average, virtually no strategy adjustments are made in the first half of the match. However, coaches tend to make offensive substitutions right after the break, a natural point in time where many substitutions are made in general. The second half then sees a tendency toward a more offensive strategy, followed by a pronounced shift toward a more defensive strategy as the end of the match approaches.

In addition to our data on match events, we collected preplay betting odds from professional bookmakers for each match in our sample. These data allow us to derive ex ante expectations of match outcomes. For the BL, we (mainly) use the betting odds of the German bookmaker ODDSET, one of the largest state-run betting providers in Europe. For the PL, we (mainly) use the betting odds of Interwetten, one of the leading providers of online betting worldwide.[6] As an example, consider the match between Hannover 96 and Mainz 05 on November 5, 2005. The odds from ODDSET for Hannover 96 winning, Mainz 05 winning, and a tie were 1.70, 3.50, and 2.70, respectively. Placing 1 euro on, say, Hannover 96 winning results in receiving 1.70 euros if Hannover 96 wins but in losing the euro otherwise. The odds allow constructing probabilities for each possible match outcome. The implicit probability of Hannover 96 winning is 0.47 in this example.[7]

3. Hypothesis and Estimation Method

3.1. The Loss Frame

We derive the ex ante expectations of match outcomes as follows. For each match, we collect the betting odds for all three possible match outcomes (home team win, tie, and guest team win), which imply a probability for each match outcome. We then take the most likely match outcome as the teams' ex ante expectation and thus as the reference point in our regression analysis below. We refer to a team that expects to win as the "favorite team" (or simply the "favorite").[8]

We view a team as being in a *loss frame* whenever (i) it is behind its reference point and (ii) at least one goal has been scored in the match. If we did not impose the condition that at least one goal has to be scored in a match, the favorite team would be considered to be in a loss frame right at the beginning of a match, which starts with a tie at 0:0. However, not even a clear favorite will feel to be in a loss frame if it is not ahead after a few minutes of play. Indeed, in matches with at least one goal, the first goal is not scored

[6] We obtained the betting odds for the BL upon request directly from ODDSET (http://www.oddset.de). ODDSET betting odds are, however, unavailable for the 1998–1999 season, and we used betting odds from the BetExplorer website (http://www.betexplorer.com) instead for this season. The betting odds of Interwetten for the PL can be retrieved from Football-Data.co.uk (http://www.football-data.co.uk/). The Interwetten betting odds are missing for 17 matches, and the website allows us to fill the gap by providing the betting odds for these matches from Gamebookers, another large bookmaker.

[7] The sum of the inverses of the odds is 1.244, reflecting the bookmaker's margin. Adjusting the inverse of the odds for Hannover 96 winning, $1/1.7 = 0.588$ for this margin, results in an implicit probability of 0.47.

[8] In 3.9% of all matches (321 of 8,232), both teams were equally likely to win, and these were the most likely match outcomes. In one single match, a tie and the guest team winning were jointly the most likely match outcomes. In these 322 cases, we adopted the assumption that the expectation was a tie. A tie was only twice the single most likely match outcome in our data.

until the 33rd minute of play on average, i.e., after more than a third of the regular playing time is over. Hence, we exclude the possibility that the favorite is in a loss frame when the state of the match is 0:0, and we adopt the assumption that the favorite is in a loss frame only if an event occurs that goes against expectations. This is the case if the opposing team scores and gains the lead or if the state of the match is a tie other than 0:0.[9] A team that expects to tie is in a loss frame when the opposing team gains the lead. A team that expects to lose (the "underdog") can never be in a loss frame.[10] On average, teams are in a loss frame in approximately 14% of the minutes.[11]

3.2. Hypothesis

We employ two objective measures of behavior—assigned cards and strategy adjustments by way of player substitutions—to test the following null hypothesis.

Hypothesis. *Controlling for the state of the match, the behavior of players and coaches does not depend on whether or not their team is in a loss frame, with the loss frame being determined by the team's standing relative to an expectation-based reference point.*

In contrast to the null hypothesis, it is a central prediction of models of expectation-based, reference-dependent behavior that, in our context, the number of assigned cards that players receive and the strategy adjustments that coaches implement are influenced by whether or not their team is in the loss frame. The focus of this paper is to address this central prediction. The particular model that we have in mind is that being in a loss frame is psychologically different from not being in a loss frame. Specifically, players and coaches might feel increased pressure or stress, be nervous, or even be frustrated when behind expectations. These states of mind can lead to a reduced ability to always apply the best judgment and always opt for the best course of play (applicable to players and coaches), or they can lead to a "loss of control" (see Card and Dahl 2011), i.e., to overreaction and aggression (applicable to players). We aim to capture these behavioral changes with the two outcome measures at hand.

3.3. Estimation Equation

We construct two dependent variables. First, the dependent variable $Card_{itm}$ is a function of the number of cards in match i that players on team t receive in minute m.[12] In one specification, where we estimate a linear probability model, $Card_{itm}$ is a binary variable that takes on value 0 if no card was assigned and value 1 if at least one card was assigned in match i to a player on team t in minute m. In our other specifications, $Card_{itm}$ is the exact number of cards that were assigned in match i to a player on team t in minute m. However, minutes in which multiple cards were given account for less than 1% of minutes.[13]

Second, the dependent variable $StrategyAdjustment_{itm}$ is a function of the strategy adjustment measure (see §2) in match i of team t in minute m. In one specification, where we estimate a linear probability model, $StrategyAdjustment_{itm}$ is a binary variable that takes on value 0 if no offensive substitution was implemented (i.e., the strategy adjustment measure is negative or zero) and value 1 if the coach of team t implements an offensive strategy adjustment in minute m of match i (i.e., the strategy adjustment measure is positive). In our other specifications, $StrategyAdjustment_{itm}$ is the exact value of the strategy adjustment measure of team t in minute m of match i. If there is more than one substitution in the same minute for the same team, we calculate the net change of the strategy adjustment measure that results from all substitutions. That is, multiple substitutions of a team in the same minute are treated as a single event.[14]

To estimate the influence of being in a loss frame on players' and coaches' behaviors, we specify two estimation equations, one for cards per minute and

[9] Note that this approach has the drawback that a favorite team is assumed not to be in a loss frame even toward the end of a match that results in a 0:0 tie. Empirically, however, this problem is less important because each match starts at 0:0, whereas only 7.6% of matches end at 0:0. In §4.3 we provide a robustness check and show that our results hold if we drop the assumption that the favorite is not in a loss frame at 0:0.

[10] In §4.3 we provide another robustness check in which we use a team's ex ante expected number of points as an alternative reference point and show that our results also hold under this specification. Note, however, that this specification has the undesirable feature that the underdog team is always in a loss frame if it is behind (as it never occurs that the probability of losing is 1) and that it can even be in a loss frame at a tie (if the expected number of points exceeds 1).

[11] Our hypothesis that players and coaches are influenced by the in-play loss frame (and not only by the realized outcome once the match is over) parallels a well-established literature in finance, showing that investors exhibit loss aversion with respect to "paper gains and losses" (Odean 1998). Note also that players and coaches might update their expectations over the course of a match. Since our data do not allow us to observe such possible adjustments, we assume that the ex ante expectations determine the reference point for the entire match.

[12] See §A.2 in the online appendix for the details of the data preparation, e.g., how we dealt with several events within the same minute and how we determined whether a given card or substitution occurred in or out of the loss frame.

[13] We observe 223 minutes in which two cards were assigned and 2 minutes in which three cards were assigned.

[14] Two substitutions by a team in the same minute are observed relatively often: 2,637 minutes in our sample fall into this group. Three substitutions are, however, very rare: only 87 minutes fall into this group.

one for strategy adjustments per minute. We model the number of cards that the players of team t receive in minute m of match i as follows:

$$Card_{itm} = c + LossFrame_{itm} \times \beta_1 + X'_{itm} \times \beta_2 + \epsilon_{itm}, \quad (1)$$

where c is an intercept, $LossFrame_{itm}$ is an indicator variable that denotes whether team t was in a loss frame in match i in minute m, and X_{itm} contains a set of control variables, such as, e.g., minute-of-play dummy variables or previous match events, as specified for each regression in Tables 2, 3, and 4.[15] In addition, we always control for the state of the match by including dummy variables on exact goal differences.

In the estimation equation (1), unobserved factors such as contestedness, weather conditions, audience size, referees, location, and season could influence both the loss frame and the number of cards received. One can think of many different mechanisms by which third factors could have a joint effect on the loss frame and the extent to which players breach the rules of the game. For example, bad weather conditions could add randomness to the course of the game (say, because it is difficult to control the ball), meaning that the team that is expected to win might be in a loss frame for a larger part of the match than usual. At the same time, bad weather conditions could lead to a large number of assigned cards (say, because it is more difficult not to breach the rules of the game while trying to win a tackle), thus creating a correlation between occurrences of the loss frame and cards. Our panel data allow us to control for these unobserved factors. To do so, we utilize a one-way error component model for the disturbances, ϵ_{itm}, with

$$\epsilon_{itm} = \alpha_{it} + u_{itm}. \quad (2)$$

In Equation (2), α_{it} denotes a match-specific effect for each team (later referred to as "team–match fixed effects"). Inserting Equation (2) into (1) leads to the estimation equation

$$Card_{itm} = c + LossFrame_{itm} \times \beta_1 + X'_{itm} \times \beta_2 + \alpha_{it} + u_{itm}, \quad (3)$$

which enables us to consistently estimate β_1, the effect on behavior of being in the loss frame.

The same arguments apply to our second outcome variable, strategy adjustment, which leads to the estimation equation

$$StrategyAdjustment_{itm} = \tilde{c} + LossFrame_{itm} \times \tilde{\beta}_1 + X'_{itm} \times \tilde{\beta}_2 + \tilde{\alpha}_{it} + \tilde{u}_{itm}. \quad (4)$$

[15] We include 109 minute-of-play dummies up to the second-longest match in the sample.

Note that because we are interested in the behavioral responses of the players and coach of a team that is either in a loss frame or not, each match is included twice in our sample: once from the perspective of the home team and once from the perspective of the away team. This also accounts for possible effects of playing at home or away. Hence, Equations (3) and (4) account not only for match-specific but also for team-specific effects. Since this procedure introduces interdependence across match observations, we estimate heteroskedasticity-robust standard errors that are adjusted for clustering on the match level.

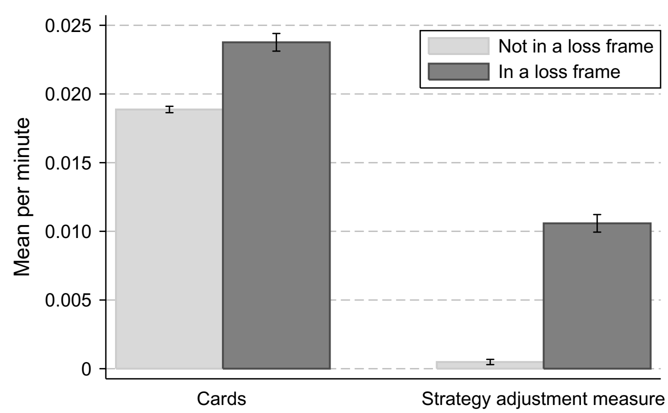
4. Results

4.1. Descriptive Evidence

Figure 2 shows the average number of cards and our strategy adjustment measure for minutes in which a team is not in a loss frame (light grey bars) and for minutes in which a team is in a loss frame (dark grey bars). The error bars show the 95% confidence interval of these averages. It can be seen that both behavioral outcome variables are substantially higher if a team is in a loss frame. Figure 2 thus provides our first piece of evidence that professional players and coaches exhibit reference-dependent behavior.

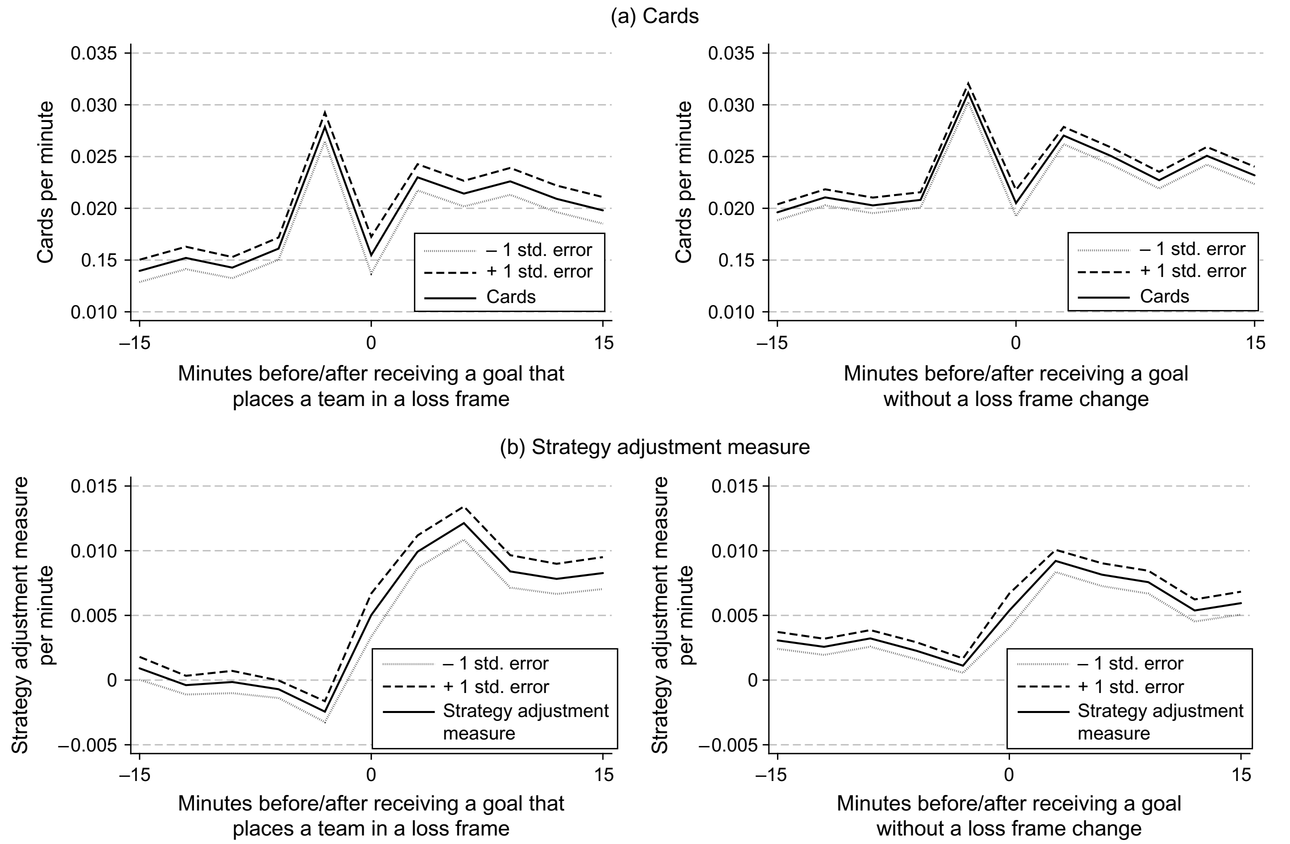
Next, we exploit the timing of events in our data and address the question whether the displayed patterns in Figure 2 are causally related to being in the loss frame. Panel (a) of Figure 3 shows the average number of cards per minute over time. The left graph of panel (a) shows a team's average frequency of cards in the minutes before and after it conceded a goal that placed it in a loss frame. In the 15 minutes before the goal, teams receive approximately

Figure 2 **Cards and Strategy Adjustment Measure per Minute**



Notes. The two left bars show the average number of cards per minute separately for minutes when a team is not in a loss frame (0.0189) and minutes when a team is in a loss frame (0.0238). The two right bars show the respective averages of the strategy adjustment measure (0.0005 and 0.0106, respectively). The error bars show the 95% confidence interval of the averages.

Figure 3 Cards and Strategy Adjustment Measure Before and After Receiving a Goal



Notes. Panel (a) shows the average number of cards per minute as a function of the time before and after conceding a goal that places a team in a loss frame (left) and before and after conceding a goal that does not change the loss frame (right). Panel (b) shows the respective averages of the strategy adjustment measure per minute. For the minutes before and after the goal, the displayed frequencies are averaged over three-minute intervals (– 15 to –12, …, –3 to –1, 1 to 3, 4 to 6, etc.).

0.015 cards per minute. Directly before the goal, however, we see that this average increases sharply to 0.027, most likely because assigned cards are often associated with very good scoring opportunities for the opponent (e.g., penalties and free kicks). In the minute of the goal, the average number of cards drops again to 0.015, most likely because the rules of the game prescribe that a conceded goal results in a kickoff and ball possession for the nonscoring team. Therefore, there is a short break after the goal (while playing time continues) that results in less time for foul play to occur in the minute of the goal. Once the game has been restarted, however, we observe a considerably higher number of cards at a level above 0.020 cards per minute, which corresponds to a 33% increase relative to the pregoal period (excluding the period directly before the goal).

The right graph in panel (a) of Figure 3 is the equivalent graph for teams that concede a goal that does not change the loss frame. Note that this includes, for example, favorites that are already in a loss frame before they concede the current goal. We see that the average number of cards per minute is already somewhat higher, at levels of approximately 0.020 in the minutes before the goal, reflecting the fact that, for example, favorites in the loss frame receive more cards (as observed in the left graph in panel (a)). Again, we observe an increase in cards directly before the goal, followed by a decrease in the minute of the goal. In the 15 minutes after the goal, we observe that the average number of cards per minute rises to levels of approximately 0.025, an increase of about 20%, relative to the pregoal period (again excluding the period directly before the goal).

The two graphs in panel (a) of Figure 3 show that receiving a goal always leads to an increase of the assigned number of cards, which in part reflects the pronounced increasing time trend in card assignments that is displayed in the left panel of Figure 1. Importantly, however, the two graphs in panel (a) reveal that this increase is larger after receiving a goal that places a team in a loss frame.

Panel (b) of Figure 3 shows a similar pattern for our strategy adjustment measure. The left graph of panel (b) shows the coaches' strategy adjustments in the minutes before and after their teams concede a goal that places them in a loss frame. We see that the average strategy adjustment measure per minute is approximately 0 in the 15 minutes before the goal. However, as soon as a goal places a team in a loss frame, we see a clear increase in the offensiveness of substitutions. In contrast to panel (a), we already see a behavioral reaction in the same minute in which the goal was scored. This most likely reflects the fact that the short break in play after a goal is scored provides a natural substitution opportunity. We also see that it takes some time before the level of the strategy adjustment measure reaches its maximum (after approximately five to six minutes after the goal). This might reflect the fact that substitution players typically require some preparation time before they can be brought onto the field. Even 15 minutes after the goal, the average value of the strategy adjustment measure per minute remains at levels of approximately 0.008 and thus orders of magnitude higher than in the pregoal period.

The right graph in panel (b) of Figure 3 shows the strategy adjustment measure for conceded goals that do not change the loss frame. Similar to the right graph in panel (a) for cards, in the right graph of panel (b) we observe that pregoal levels are somewhat higher (approximately 0.003) than in the left graph. Once the goal has been scored against the team, we see an increase in the offensiveness of substitutions that remains at a level of approximately 0.007 even 15 minutes after the goal.

The two graphs in panel (b) of Figure 3 show that receiving a goal always leads to an increase of the strategy adjustment measure. It is important to note, however, the two graphs reveal that this increase is, again, larger after receiving a goal that places a team in a loss frame.

As a final piece of descriptive evidence, Figure 4 provides a comparison between the behaviors of favorites and underdogs when being one goal down and when being one goal ahead.[16] The left panel shows that favorites receive many more cards per minute when down by one goal (and thus in a loss frame) than when ahead by one goal. For underdogs, in contrast, the number of cards per minute is not much different when down by one goal (expectedly, and thus not in a loss frame) than when ahead by one goal; it is even slightly higher when they are ahead. The right panel shows that the coaches of favorite teams implement offensive strategy adjustments when down by one goal and defensive strategy adjustments when ahead by one goal. The same pattern emerges for underdogs but, importantly, the extent of offensive strategy adjustments when behind by one goal is smaller for underdogs than for favorites. The extent of defensive strategy adjustments is more comparable when favorites and underdogs are one goal ahead, with slightly more defensive substitutions made by underdogs.[17]

4.2. Main Results

Regressions (1)–(8) in Table 2 display our main results. To test our null hypothesis, all specifications include the dummy variable *LossFrame*, which equals 1 if a team is in a loss frame and 0 otherwise. Panel A shows our regressions with $card_{itm}$ as the dependent variable. The dependent variable is binary (it equals 1 if at least one card was received and 0 otherwise) in regression (1), and it equals the exact number of cards in regressions (2)–(4). The coefficient of the dummy variable *LossFrame* is positive, large, and highly significant in regressions (1)–(4), revealing that the players of a team receive more cards when they are in a loss frame.

Regression (1) in Table 2 is a linear probability model that controls for team–match fixed effects and the exact goal difference. The regression shows that the probability that a player is assigned a card increases by more than 50% if his team is in a loss frame (recall that a team that is not in a loss frame receives 0.0189 cards per minute; see Figure 2). Regression (2) shows that the coefficient is very similar with the total number of cards per minute as the dependent variable. Regression (3) controls additionally for minute fixed effects, and regression (4) also controls for previous match events. In particular, the latter regression controls for the total number of cards assigned in the match so far and for the number of cards squared. Regressions (3) and (4) show that our result is robust to the introduction of controls for in-match time dynamics (recall that the left panel of Figure 1 reveals that there is a clear time trend in the number of cards assigned). The size of the coefficient of the loss frame dummy is 0.0027 in regression (4), implying that the average number of cards per minute increases by more than 14%, even after we control for time effects.

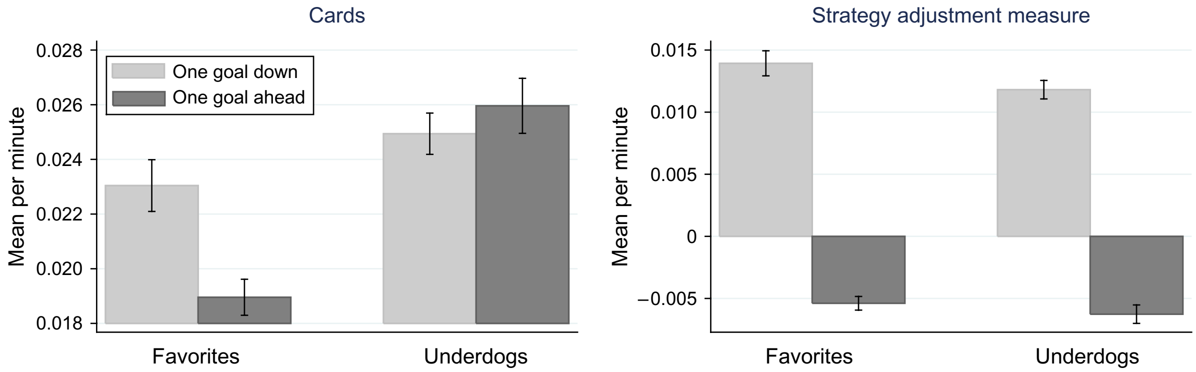
Result 1. Players receive significantly more cards if their teams are in a loss frame. While controlling for the state of the match, being in a loss frame increases the number of cards in a given minute by more than 14%.

Panel B of Table 2 shows our regressions (5)–(8), which are equivalent to regressions (1)–(4) but with

[16] We are grateful to the associate editor for suggesting this particular analysis.

[17] The figure is virtually identical if we include the relatively few cases where a team expects to tie (see Footnote 8) in the category of favorites. Note that these teams are also in a loss frame when they are down by one goal.

Figure 4 Cards and Strategy Adjustment Measure for Favorites and Underdogs



Notes. The left panel shows the average number of cards per minute for favorites and underdogs when one goal behind and when one goal ahead. The right panel shows the average of the strategy adjustment measure per minute for favorites and underdogs when one goal behind and when one goal ahead.

$StrategyAdjustment_{itm}$ as the dependent variable. The dependent variable in regression (5) is a dummy that equals 1 if the strategy adjustment measure is strictly positive, whereas the dependent variable in regressions (6)–(8) is the exact value of the strategy adjustment measure. The previous match events that we control for in regression (8) are the number of previous substitutions and the cumulated strategy adjustment by each team.

Table 2 Expectations as Reference Points: Main Loss Frame

Panel A: Cards per minute				
	LPM (1)	OLS (2)	OLS (3)	OLS (4)
LossFrame	0.0101*** (17.42)	0.0102*** (17.35)	0.0019*** (3.22)	0.0027*** (4.09)
Team–match fixed effects	X	X	X	X
Exact goal difference	X	X	X	X
Minute fixed effects			X	X
Previous match events (cards)				X
Panel B: Strategy adjustment measure per minute				
	LPM (5)	OLS (6)	OLS (7)	OLS (8)
LossFrame	0.0053*** (16.96)	0.0038*** (8.03)	0.0031*** (6.28)	0.0045*** (7.17)
Team–match fixed effects	X	X	X	X
Exact goal difference	X	X	X	X
Minute fixed effects			X	X
Previous match events (substitutions)				X

Notes. N = 1,569,478. t-Statistics are given in parentheses. LPM, linear probability model; OLS, ordinary least squares.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The coefficient of the dummy variable *LossFrame* is again positive, large, and highly significant in all four specifications. This finding reveals that the coach of a team is more likely to implement an offensive substitution and that substitutions are in general more offensive when a team is in a loss frame. Regression (5) shows that the probability of making an offensive substitution more than doubles if a team is in a loss frame (the average *number* of offensive substitutions per minute out of the loss frame is 0.0045). The size of the coefficient of the loss frame dummy is 0.0045 in regression (8), which indicates that the strategy adjustment measure increases by more than 800% (the average value of the strategy adjustment measure per minute out of the loss frame is 0.0005; see Figure 2).[18]

Result 2. Coaches implement significantly more offensive strategy adjustments if their teams are in a loss frame. While controlling for the state of the match, being in a loss frame increases the per-minute average of the strategy adjustment measure by more than 800%.

The above analysis demonstrates that the players' and coaches' behavior depends on whether or not their team is in a loss frame.[19] Results 1 and 2 thus

[18] It could be that favorites have more defensive starting lineups than underdogs and use offensive substitutions to adjust the lineup when they are in a loss frame. To check for this possibility, we calculate the sum of the strategic position values of the teams' starting lineups (recall from §2 that we assigned different values to different positions). The sums are 29.2 and 29.0 for favorites and underdogs, respectively. Judged by this measure, the average starting lineups are very similar; if anything, favorites have a slightly more offensive lineup.

[19] Our data do not allow disentangling if cards reflect the behavior of players or referees, who might also react to the unexpected standing. However, this distinction is of secondary importance for our main result that the behavior of people—be they players or referees—depends on whether or not they are behind the expectation-based reference point.

both reject the null hypothesis that the reference point that is given by the ex ante expected match outcome does not affect behavior.

4.3. Alternative Loss Frame Specifications

To check the robustness of our results, we consider two alternative loss frame specifications. In the first alternative specification, we assume that a team's reference point is given by the expected number of points (instead of the most likely match outcome). Recall that winning a match yields three points, a tie yields one point, and losing yields zero points. The expected number of points is thus calculated as follows: $\textit{expected number of points} = \text{Prob}(\textit{Win}) \cdot 3 + \text{Prob}(\textit{Tie}) \cdot 1 + (1 - \text{Prob}(\textit{Win}) - \text{Prob}(\textit{Tie})) \cdot 0$. We refer to being behind this reference point as being in the *first alternative loss frame*. As in our main specification, we maintain the assumption that a team falls into a loss frame only after it has conceded at least one goal. Although this alternative formulation of the expectation-based reference point uses the betting odds not only in an ordinal but also in a cardinal way, it has three undesirable features. First, it typically yields an expected number of points that is different from the possible match outcomes 0, 1, or 3 points, and it seems implausible that a team's reference point is to get, say, 1.7 points out of a match. Second, using the expected number of points as the reference point typically implies that both teams are simultaneously in a loss frame if the state of the match is a tie (other than 0:0), because in most matches both teams expect to get more than one point. Third, even a clear underdog team is in a loss frame if the team is behind because the expected number of points is always positive; i.e., the betting odds never imply that a team will lose with probability 1. For these reasons, we consider the most likely match outcome to be a more plausible reference point in our context. Teams are, on average, in the first alternative loss frame in approximately 34% of the minutes, which is more than twice as often as in our main specification (14%).

As a second alternative specification, we again consider the most likely match outcome to be the reference point, but we now assume that the favorite is in a loss frame right from the beginning of the match and as long as the team is not ahead. We refer to being behind this reference point as being in the *second alternative loss frame*. The only difference between our main loss frame specification and this second modification is that the favorite is in a loss frame at 0:0 in the latter. Consequently, teams are, on average, more often in the second alternative loss frame in approximately 32% of the minutes.

Tables 3 and 4 show the regression results for the first and second alternative loss frame specifications, respectively. Apart from the respective specification of the loss frame, regressions (R1)–(R8) and (RR1)–(RR8) exactly correspond to regressions (1)–(8) in Table 2. The coefficients and significance of the loss frame dummy variable in the regressions in Tables 3 and 4 show that our main results are generally robust to the above alternative specifications of the loss frame. Only the coefficient of the second alternative loss frame is not even marginally significant in the linear probability model (RR5) with offensive substitutions as the dependent variable. Note, however, that this reference-point specification has the undesirable feature that the favorite team is in a loss frame right at the beginning of a match, although the nature of the game is such that it takes more than 30 minutes on average until the favorite goes ahead (if at all). Player substitutions at the beginning of a match are, however, extremely rare. Of the more than five substitutions that take place on average (see Table 1), only 0.14 take place in the first half hour of a match.[20]

4.4. Productivity Analysis

In our analyses we compared teams that are unexpectedly behind (i.e., teams that are in a loss frame) to teams that are expectedly behind. Our implicit identification assumption was that any behavioral change that we detect is driven by the fact of being behind expectations. Note, however, that it could be that favorite teams behave differently than nonfavorite teams when being behind in score for reasons other than reference dependence.[21] However, by definition, a favorite team is behind expectations if the team is behind in score. We thus cannot separately observe favorite teams that are behind in score and favorite teams that are behind expectations.

This point is exemplified by thinking about the fictitious game "handicap-soccer," in which the favorite team starts the match one goal behind.[22] The favorite team is thus behind by one goal initially, but this is entirely expected. Randomly assigning favorite teams to either handicap-soccer or regular soccer would enable us to observe favorite teams being behind expectations (in case a goal is scored against the favorite team in regular soccer) and favorite teams not being behind expectations (handicap-soccer), while both are behind by one goal. We would then be able to unambiguously identify the effect of being behind

[20] As an additional robustness check, we conduct the analyses presented in Tables 2–4 for the two leagues separately in §A.3 of the online appendix. The analysis reveals that the loss frame dummy remains significant in the large majority of the specifications in the separate leagues.

[21] For simplicity, we refer to teams in the loss frame as favorite teams, without always mentioning that there are also some cases where a team in a loss frame expects to tie and is thus not a favorite; see Footnote 8.

[22] We thank one referee for suggesting this thought experiment.

Table 3 Expectations as Reference Points: First Alternative Loss Frame

Panel A: Cards per minute				
	LPM (R1)	OLS (R2)	OLS (R3)	OLS (R4)
FirstAlternative-LossFrame	0.0146*** (25.27)	0.0148*** (25.24)	0.0012* (1.82)	0.0021*** (2.91)
Team–match fixed effects	X	X	X	X
Exact goal difference	X	X	X	X
Minute fixed effects			X	X
Previous match events (cards)				X

Panel B: Strategy adjustment measure per minute				
	LPM (R5)	OLS (R6)	OLS (R7)	OLS (R8)
FirstAlternative-LossFrame	0.0073*** (25.79)	0.0025*** (5.44)	0.0015*** (2.89)	0.0018*** (2.85)
Team–match fixed effects	X	X	X	X
Exact goal difference	X	X	X	X
Minute fixed effects			X	X
Previous match events (substitutions)				X

Notes. $N = 1{,}569{,}478$. t-Statistics are given in parentheses. LPM, linear probability model; OLS, ordinary least squares.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4 Expectations as Reference Points: Second Alternative Loss Frame

Panel A: Cards per minute				
	LPM (RR1)	OLS (RR2)	OLS (RR3)	OLS (RR4)
SecondAlternative-LossFrame	0.0022*** (3.01)	0.0022*** (3.03)	0.0035*** (4.89)	0.0040*** (4.98)
Team–match fixed effects	X	X	X	X
Exact goal difference	X	X	X	X
Minute fixed effects			X	X
Previous match events (cards)				X

Panel B: Strategy adjustment measure per minute				
	LPM (RR5)	OLS (RR6)	OLS (RR7)	OLS (RR8)
SecondAlternative-LossFrame	0.0004 (1.29)	0.0013** (2.31)	0.0013** (2.24)	0.0016** (2.33)
Team–match fixed effects	X	X	X	X
Exact goal difference	X	X	X	X
Minute fixed effects			X	X
Previous match events (substitutions)				X

Notes. $N = 1{,}569{,}478$. t-Statistics are given in parentheses. LPM, linear probability model; OLS, ordinary least squares.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

expectations on the behavior of favorite teams. With nonexperimental field data it is, however, impossible to randomly assign expectations.

This limitation of our setting poses a potential concern about the interpretation of our previous results. The reason is that it may be productive for the favorite team, as the relatively stronger team, to play in a way that leads to more cards and to implement a more offensive strategy of play when behind in score compared with when the nonfavorite team is behind in score. Fully rational, non-reference-dependent reasons might thus drive the observed behavioral change of favorite teams when they fall behind in score. In contrast, in the model of reference-dependent behavior that we have in mind, being in a loss frame is psychologically different from not being in a loss frame. Importantly, this different state of mind, such as being under pressure or frustrated, can manifest itself in potentially not fully rational behaviors by players and coaches. To distinguish between these alternative explanations, in the following we analyze whether receiving more cards or implementing a more offensive strategy while being behind expectations increases or decreases the likelihood of changing the ultimate match outcome for the better.[23]

To determine whether cards or offensive substitutions in the loss frame affect a team's final match outcome, we estimate the following two regression models:[24]

$$\begin{aligned} &MatchOutcome_{it} \\ &\quad = c + CardsPerLossMinute_{it} \times \gamma_1 \\ &\qquad + CardsPerNoLossMinute_{it} \times \gamma_2 \\ &\qquad + X_{it} \times \gamma_3 + \alpha_t + \epsilon_{it}, \end{aligned} \tag{5}$$

[23] Notice that no such strategic reasons are present in the paper by Card and Dahl (2011) because they analyze behavioral reactions of supporters in the aftermath of matches.

[24] We estimate two separate models because the exact minutes in which a team is in a loss frame can slightly differ for cards and substitutions. An example would be a loss frame-changing goal in the second half of minute m. If the nonscoring team performs a substitution after the goal is scored but still in minute m, then the goal is counted for the goal difference in minute m in the substitution data set. If the nonscoring team does not receive a card in the time span between the goal and the end of minute m, then the goal is counted only for the goal difference in minute $m+1$ in the cards data set. See also our discussion of the data preparation in §A.2 of the online appendix.

$$\begin{aligned}&MatchOutcome_{it}\\&\quad= c + OffSubstitutions\_InLossFrame_{it} \times \tilde{\gamma}_1\\&\qquad + OffSubstitutions\_OutOfLossFrame_{it} \times \tilde{\gamma}_2\\&\qquad + X_{it} \times \tilde{\gamma}_3 + \tilde{\alpha}_t + \tilde{\epsilon}_{it},\end{aligned} \tag{6}$$

where $MatchOutcome_{it}$ is the final match outcome for team t in match i. We use two different measures for the final match outcome: first, a team's final goal difference (i.e., $-8, -7, \ldots, -1, 0, +1, \ldots, +7, +8$) and, second, a team's number of points (i.e., $0, 1, 3$).

In Equation (5), $CardsPerLossMinute_{it}$ is the number of cards that team t received throughout match i while the team was in the loss frame, divided by the total number of minutes that the team spent in the loss frame. Similarly, *CardsPerNoLossMinute* gives the number of cards that the team received while the team was not in the loss frame divided by the total number of minutes that the team spent out of the loss frame. In Equation (6), $OffSubstitutions\_InLossFrame_{it}$ is the number of offensive substitutions that the coach of team t implemented in match i while the team was in the loss frame, and *OffSubstitutions_OutOfLossFrame* is the number of offensive substitutions that the coach of the team implemented while it was not in the loss frame. In both equations, X_{it} contains a set of control variables, such as a linear and a quadratic term for the number of minutes spent in the loss frame ("loss frame duration"), and in some specifications we also include the implicit outcome probabilities; see Table 5. To estimate both equations, we include match observations only from teams that were at some point of the match in the loss frame.[25] If the most likely outcome is a tie, it can happen that both teams in a match are in the loss frame at some point. We thus adjust standard errors for clustering on the match level.

Panel A of Table 5 displays the results for estimation Equation (5). Regressions (P1)–(P4) consistently show that cards in the loss frame are not productive because they significantly reduce the final goal difference (goals scored minus goals conceded) and points for the team. Increasing the number of cards per loss frame minute by one standard deviation (0.034) reduces the final goal difference by 0.134 goals. Similarly, teams receive 0.135 fewer points from such an increase. Note that we obtain this result while controlling for the time that the team spent in the loss frame. Interestingly, we observe that cards can be productive if they are received out of the loss frame.

Panel B of Table 5 displays the results for estimation Equation (6). Regressions (P5)–(P8) consistently show that offensive substitutions in a loss frame are not productive because they significantly reduce the final goal difference and points for a team. An additional offensive substitution in a loss frame reduces the final goal difference for a team by 0.30. The negative effect on points is almost identical. In contrast, offensive substitutions out of the loss frame seem to be largely inconsequential for the final match outcome measured by the final goal difference; for points, however, these substitutions have a small negative effect, as shown in regressions (P7) and (P8).

Hence, the productivity analysis does not provide support for the view that the observed behavior is an entirely rational response of favorite teams to falling behind. The results are, however, consistent with a model of reference-dependent behavior, where falling behind expectations can lead to not entirely rational reactions.[26]

To further analyze the nature of the behavioral change of favorite teams in the loss frame, we finally study the reasons for which the players are assigned cards.[27] Table 6 provides a summary of the different categories and displays their relative shares among cards in and out of the loss frame. Reading from top to bottom, a clear pattern emerges: reasons that lend themselves to an interpretation of players' overreaction, aggressiveness, and sabotage account for much larger shares in the loss frame than out of the loss frame.

As an example, take the card reason "violent conduct." Such cards are assigned to players who deliberately kick or hit an opponent player. Although such cards are in general relatively rare, we find that they are much more likely if the player's team is in a loss frame. The effect is very large: relative to the share of cards for violent conduct out of the loss frame, the share of such cards increases by about 85% in the loss frame. Cards for "dissent" provide another example. Such cards are usually assigned for players who complain about the referee's decisions. The share of such cards increases by 43% if a team is in a loss frame.

[25] The level of observation in the productivity analysis is a team–match pair. Our sample contains 8,232 matches, so we have 16,464 team–match pairs. Approximately 28% of the teams were in a loss frame at some point during the match, which results in 4,622 team–match observations. Among these, there are four cases where a team conceded a goal in the first minute and stayed in the loss frame thereafter. Accordingly, $CardsPerNoLossMinute_{it}$ is not defined for these four observations, which explains the different number of observations in panels A and B in Table 5.

[26] Note that the results of the productivity analysis do not imply that favorite teams in a loss frame exert less effort than nonfavorite teams or than favorite teams that are not in a loss frame. Rather, it shows that among the favorite teams in the loss frame, those favorites that receive more cards or substitute more offensively are less successful in improving their ultimate score.

[27] These reasons have been assigned by the data-providing companies.

Table 5 Productivity Analysis

Panel A: Are cards productive?

Dependent variable:	*Goal difference*		*Points*	
	OLS (P1)	OLS (P2)	OLS (P3)	OLS (P4)
CardsPerLossMinute	−3.933***	−3.154***	−3.995***	−3.356***
	(−6.54)	(−5.43)	(−7.17)	(−6.20)
CardsPerNoLossMinute	1.030	2.481***	1.934**	3.130***
	(1.09)	(2.70)	(2.38)	(3.93)
Team fixed effects	X	X	X	X
Loss frame duration	X	X	X	X
Implicit outcome probabilities		X		X
Observations	4,618	4,618	4,618	4,618

Panel B: Are offensive substitutions productive?

Dependent variable:	*Goal difference*		*Points*	
	OLS (P5)	OLS (P6)	OLS (P7)	OLS (P8)
OffSubstitutions_InLossFrame	−0.300***	−0.302***	−0.298***	−0.301***
	(−13.58)	(−14.11)	(−16.21)	(−16.82)
OffSubstitutions_OutOfLossFrame	−0.071	−0.082	−0.101**	−0.112**
	(−1.26)	(−1.50)	(−1.97)	(−2.21)
Team fixed effects	X	X	X	X
Loss frame duration	X	X	X	X
Implicit outcome probabilities		X		X
Observations	4,622	4,622	4,622	4,622

Notes. t-Statistics are given in parentheses. OLS, ordinary least squares.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6 Reasons for Card Assignments

Reason	*LossFrame* = 0	*LossFrame* = 1	Difference (%)
Violent conduct	203 (0.8%)	77 (1.5%)	85.52
Serious foul play and abusive language[a]	82 (0.3%)	29 (0.6%)	72.97
Dissent	2,077 (8.2%)	607 (11.7%)	42.94
Leaving or entering field without permission	21 (0.1%)	6 (0.1%)	39.74
Off-the-ball incident[b]	1,101 (4.3%)	306 (5.9%)	35.93
Professional foul	179 (0.7%)	44 (0.8%)	20.22
Second bookable offense[a]	270 (1.1%)	63 (1.2%)	14.12
Not retreating from set play	155 (0.6%)	8 (0.2%)	−74.76
Time wasting	653 (2.6%)	35 (0.7%)	−73.79
Persistent infringement[a]	219 (0.9%)	31 (0.6%)	−30.77
Deliberate handball	333 (1.3%)	53 (1.0%)	−22.16
Not classified	100 (0.4%)	19 (0.4%)	−7.07
Other (spitting, celebrating, diving, touching referee)	257 (1.0%)	49 (0.9%)	−6.75
Unsporting behavior or foul	19,822 (77.8%)	3,881 (74.5%)	−4.24
N	25,472	5,208	

[a]PL only.
[b]BL only.

The increase of the relative share of reasons for cards such as "violent conduct," "serious foul play and abusive language," or "dissent" support the view that cards obtained in a loss frame do not reflect fully rational, productive reactions of favorite teams to being in a loss frame. The reasons for cards are, however, consistent with a model of reference-dependent behavior, where being behind expectations means being in a psychologically worse state of mind, such as feeling under pressure or being frustrated.

4.5. Gain Frame

Many models of reference-dependent behavior assume loss aversion; i.e., they predict that gains and losses are not coded symmetrically. The implications of this additional prediction are not straightforward in our context. One reason is that the underlying behavior for card assignments can be manifold. Cards may reflect a more risky or aggressive playing style, increased effort, or sabotage of the opponent's effort. Whereas some of these behaviors may be more common for unexpectedly losing teams, others may be more common for unexpectedly winning teams. The consequence is that it is not clear that loss aversion would imply, e.g., that teams in a loss frame will receive more cards than teams in a gain frame. Given the particular model that we have in mind, it is perhaps more reasonable to expect (i) that the underlying behavior for cards that players receive in the loss frame is different from the underlying behavior for cards that players receive in the gain frame and (ii) that behavioral changes in the loss frame are less productive than behavioral changes in the gain frame.

To test these two predictions, we include an additional indicator variable, *GainFrame*, denoting whether team t was in a gain frame in match i in minute m in the specifications shown in Table 2. In correspondence with our main loss frame definition, we view a team as being in a gain frame whenever (i) it is ahead of its reference point and (ii) at least one goal has been scored in the match. Table 7 shows that the coefficients of the loss frame indicator remain highly significant in all specifications and change in size only marginally. Moreover, we find that the coefficients of the gain frame indicator are also highly significant in all specifications.

In regressions (1-GF)–(4-GF) in Table 7, with cards as the dependent variable, all coefficients of the gain

Table 7 Expectations as Reference Points: Main Loss Frame and Gain Frame

Panel A: Cards per minute

	LPM (1-GF)	OLS (2-GF)	OLS (3-GF)	OLS (4-GF)
GainFrame	0.0096***	0.0097***	0.0030***	0.0037***
	(16.68)	(16.67)	(4.97)	(5.73)
LossFrame	0.0082***	0.0082***	0.0015***	0.0022***
	(14.24)	(14.18)	(2.59)	(3.44)
Team–match fixed effects	X	X	X	X
Exact goal difference	X	X	X	X
Minute fixed effects			X	X
Previous match events (cards)				X

Panel B: Strategy adjustment measure per minute

	LPM (5-GF)	OLS (6-GF)	OLS (7-GF)	OLS (8-GF)
GainFrame	0.0024***	−0.0022***	−0.0029***	−0.0035***
	(9.75)	(−4.78)	(−6.21)	(−6.41)
LossFrame	0.0048***	0.0042***	0.0035***	0.0049***
	(15.48)	(8.86)	(7.04)	(7.94)
Team–match fixed effects	X	X	X	X
Exact goal difference	X	X	X	X
Minute fixed effects			X	X
Previous match events (substitutions)				X

Notes. N =1,569,478. t-Statistics are given in parentheses. LPM, linear probability model; OLS, ordinary least squares.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8 Productivity Analysis: Gain Frame

Panel A: Are cards productive?

Dependent variable:	*Goal difference*		*Points*	
	OLS (P1-GF)	OLS (P2-GF)	OLS (P3-GF)	OLS (P4-GF)
CardsPerGainMinute	0.355	0.631	0.540	0.769*
	(0.87)	(1.60)	(1.22)	(1.79)
CardsPerNoGainMinute	−7.633***	−6.984***	−7.508***	−6.971***
	(−6.29)	(−6.09)	(−7.71)	(−7.53)
Team fixed effects	X	X	X	X
Gain frame duration	X	X	X	X
Implicit outcome probabilities		X		X
Observations	4,597	4,597	4,597	4,597

Panel B: Are defensive substitutions productive?

Dependent variable:	*Goal difference*		*Points*	
	OLS (P5-GF)	OLS (P6-GF)	OLS (P7-GF)	OLS (P8-GF)
DefSubstitutions_InGainFrame	0.269***	0.260***	0.310***	0.303***
	(10.20)	(10.20)	(11.90)	(11.96)
DefSubstitutions_OutOfGainFrame	−0.289***	−0.269***	−0.194***	−0.177***
	(−4.80)	(−4.71)	(−3.71)	(−3.53)
Team fixed effects	X	X	X	X
Gain frame duration	X	X	X	X
Implicit outcome probabilities		X		X
Observations	4,628	4,628	4,628	4,628

Notes. t-Statistics are given in parentheses. OLS, ordinary least squares.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

frame indicator are positive and even larger in size than the respective loss frame coefficients, thus providing further evidence for the existence of a reference point. It is important to note that the productivity analysis in panel A of Table 8, which mirrors the productivity analysis in Table 5, shows that cards are, if anything, productive when teams are in a gain frame—and clearly not unproductive. Hence, the increase of cards in the gain frame could, potentially, be fully driven by rational responses of nonfavorite teams to being ahead of expectations. If this interpretation were true, we should find that the reasons for (productive) cards that teams receive in the gain frame differ from those for (unproductive) cards that teams receive in the loss frame. Our results in Table 9 support this prediction. Specifically, Table 9 parallels Table 6 and lists the different card reasons and their percentage change in the gain frame and loss frame relative to the baseline of being in a neutral state. On the one hand, we find that strategically reasonable rule violations (when ahead in score), such as "time wasting," are substantially more often observed in the gain frame. On the other hand, we find that reasons such as "violent conduct" or "serious foul play" occur relatively less often in the gain frame, whereas they occur relatively more often in the loss frame. Hence, although our previous analyses are consistent with the idea that being behind expectations puts teams, e.g., under pressure, no such negative psychological state of mind appears to be present in the gain frame. In this sense, our findings are consistent with the common property of models of reference-dependent behavior that losses and gains are not coded symmetrically.

Regressions (5-GF)–(8-GF) in Table 7 analyze the coaches' substitution decisions. We begin our discussion with regressions (6-GF)–(8-GF), with the strategy adjustment measure as the dependent variable. The regressions reveal that coaches implement substitutions that are significantly less offensive in the gain frame relative to the baseline, controlling for the state of the match. Indeed, the average value of the strategy adjustment measure of teams in the gain frame is −0.005 (compared with approximately 0.01 in the loss frame). This shows that teams in the gain frame

Table 9 Reasons for Card Assignments: Gain Frame vs. Loss Frame

Reason	Neutral ("at expectation")	Change (%) if *GainFrame* = 1	Change (%) if *LossFrame* = 1
Violent conduct	171 (0.9%)	−34.1	71.5
Serious foul play and abusive language[a]	69 (0.4%)	−33.6	60.0
Dissent	1,637 (8.3%)	−5.3	41.3
Leaving or entering field without permission	14 (0.1%)	76.1	63.3
Off-the-ball incident[b]	804 (4.1%)	30.1	44.5
Professional foul	148 (0.8%)	−26.2	13.3
Second bookable offense[a]	199 (1.0%)	25.7	20.6
Not retreating from set play	105 (0.5%)	67.7	−71.0
Time wasting	347 (1.8%)	210.6	−61.6
Persistent infringement[a]	171 (0.9%)	−1.14	−30.9
Deliberate handball	260 (1.3%)	−1.1	−22.4
Not classified	78 (0.4%)	−0.7	−7.2
Other (spitting, celebrating, diving, touching referee)	190 (1.0%)	24.2	−1.8
Unsporting behavior or foul	15,646 (78.9%)	−6.0	−5.5
N	19,839	5,633	5,208

[a]PL only.
[b]BL only.

implement defensive strategy adjustments, on average. Accordingly, we conduct a separate productivity analysis for the defensive substitutions of teams in the gain frame. Panel B of Table 8 shows that such defensive substitutions are productive. Hence, the analysis of the strategy adjustment measure in the gain frame is again consistent with the prediction that losses and gains are not coded symmetrically. Indeed, the data suggest that coaches act more risk averse when their teams are ahead of expectations (and that this is a productive strategy) but that they act more risk seeking when their teams are behind expectations (and that this is not a productive strategy).

Finally, to mirror the analysis in Table 2, the dependent variable in regression (5-GF) in Table 7 is an indicator that takes on value 1 if an offensive substitution was conducted in a given minute. The regression reveals that offensive substitutions take place more often in the loss frame, as well as in the gain frame. Combined with our earlier findings, this suggests a generally higher propensity to conduct substitutions compared to the baseline of being "at expectation." A corresponding regression with an indicator that takes on value 1 if a *defensive* substitution was conducted in a given minute (not reported in the table) reveals that the coefficient of the gain frame dummy is highly significant and amounts to 0.0040. The size of the coefficient is thus much larger than the respective value in regression (5-GF), which is consistent with the finding that substitutions are on average defensive if a team is in the gain frame.

5. Conclusion

Understanding the determinants and behavioral effects of reference points is important for many fields in economics, such as worker morale and effort choices (e.g., Bewley 1999), consumer goods pricing (e.g., Heidhues and Kőszegi 2008), and optimal contracting (e.g., Hart and Moore 2008, Herweg et al. 2010). Our paper provides evidence in support of models assuming that people's behavior is reference dependent and that reference points are shaped by expectations. The ability to observe team-specific ex ante expectations about the final match outcome and the availability of objective, behavioral measures for professional, experienced soccer players and coaches who act in their natural environment is what enabled us to draw this inference. Still, some caveats remain.

In particular, our data do not allow distinguishing favorite teams that are behind in score from favorite teams that are behind expectations. This is a potential concern because favorite teams are, by definition, the relatively stronger teams and might thus have rational reasons to play in a way that leads to more cards (Result 1) and to implement a more offensive strategy of play (Result 2) when behind in score compared with underdogs behind in score. Our productivity analysis, however, does not support the possibility that players and coaches act in a fully rational way: receiving more cards or substituting in an offensive way while being in a loss frame impairs the ultimate match outcome. Also, our analysis of the reasons for card assignments, which shows that reasons such as "violent conduct" or "serious foul play" occur relatively more often in the loss frame, supports the interpretation that people's behavior is reference dependent rather than fully rational.

Finally, we would like to point out that soccer players can react to being in a loss frame in multiple ways, many of which are unobservable in our data. For example, there could be a positive interaction effect between cards and running speed in the loss frame. We showed that cards received in a loss frame are unproductive. However, the overall productivity effect could be positive once the interaction effect between running speed and cards is integrated into the analysis. Although such effects neither seem obvious nor first order, they could matter, in principle, but we are unable to address them here. The availability of more sophisticated performance measures of soccer players might render it feasible to address such potential holes in our identification strategy in future research.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2048.

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