JOHANNES GUTENBERG UNIVERSITÄT MAINZ

Interdisciplinary Public Policy Mainz

IPP

Gutenberg School of Management and Economics

& Research Unit “Interdisciplinary Public Policy”

Discussion Paper Series

Expectations as Reference Points: Field Evidence from Professional Soccer

Björn Bartling, Leif Brandes, Daniel Schunk

April 2014

Discussion paper number 1405

Johannes Gutenberg University Mainz
Gutenberg School of Management and Economics
Jakob-Welder-Weg 9
55128 Mainz
Germany
wiwi.uni-mainz.de

Contact details

Björn Bartling
Department of Economics
University of Zurich
Blümlisalpstrasse 10
8006 Zurich
Swizerland

bjoern.bartling@econ.uzh.ch

Leif Brandes
Warwick Business School
University of Warwick
Coventry
CV4 7AL
United Kingdom

leif.brandes@wbs.ac.uk

Daniel Schunk
Department of Economics
University of Mainz
Saarstrasse 21
55099 Mainz
Germany

daniel.schunk@uni-mainz.de

Expectations as Reference Points: Field Evidence from Professional Soccer*

Björn Bartling† Leif Brandes‡ Daniel Schunk§

April 17, 2014

Abstract

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 pre-play 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 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.

Keywords: reference points, expectations, experience, high stakes, competition
JEL classification: C23, D03, D81, D84

*We would like to thank excellent referees, the associate editor, the department editor, and seminar and conference participants at the University of Zurich, the Economic Science Association World Meeting in Copenhagen 2010, the Nordic Conference on Behavioral and Experimental Economics in Helsinki 2010, the International Meeting on Experimental and Behavioral Economics in Barcelona 2011, the Royal Economic Society Meeting in London 2011, the Thurgau Experimental Economics Meeting on reference-dependent preferences in Kreuzlingen 2013 for very helpful comments and suggestions. Tizoc José Bachmann, Nicolai Grüter, and Stefan Schmid provided excellent research assistance.

†Björn Bartling, Department of Economics, University of Zurich, Blümlisalpstrasse 10, 8006 Zurich, Switzerland, e-mail: bjoern.bartling@econ.uzh.ch

‡Leif Brandes, Warwick Business School, University of Warwick, Coventry, CV4 7AL, UK, e-mail: leif.brandes@wbs.ac.uk

§Daniel Schunk, Department of Economics, University of Mainz, Saarstrasse 21, 55099 Mainz, Germany, e-mail: daniel.schunk@uni-mainz.de

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), Köszegi 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 relative to when they win. Ockenfels et al. (forthcoming) 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,

[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. Marzilli Ericson and Fuster (2011) provide evidence for expectation-based reference points in exchange and valuation experiments. Gill and Prowse (2012) show that subjects

we use a data set from two leading soccer leagues, the German Bundesliga and the British 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' pre-play 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" that are shown for irregular behavior to individual players by highly trained, impartial referees. Our second behavioral outcome variable is the coaches' strategic adjustments that are implemented by means of player substitutions during a match.

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 pre-play 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 pre-play 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 percent 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, again controlling for the state of the match. 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.

The assignment of a card reflects a breach of the rules of the game by a player. The underlying reasons for irregular behavior can be manifold. Cards may reflect a more risky or aggressive way of playing, increased effort, or it may be that players engage in sabotage of the opponent's effort. Offensive strategy adjustments by way of player substitutions may reflect risk taking behavior by coaches. Substituting, say, a defender with a striker increases the probability of scoring a goal but also increase the probability of receiving one.

have reference points given by their expected monetary payoff in tournaments. Fehr et al. (2011) and Bartling and Schmidt (forthcoming) provide evidence that contracts serve as reference points.

Importantly, it may be the case that players of unexpectedly losing teams *should* play in a way that leads to more cards and that their coaches *should* implement a more offensive strategy of play. The reason is that it may be productive for favorite teams, i.e., for relatively stronger teams, to engage in these kinds of behaviors when they are behind in score. In other words, non-reference-dependent reasons might drive the observed behavior of favorite teams. However, our data reveal that for favorite teams, both receiving more cards and substituting players in an offensive way while being behind expectations *decrease* the likelihood of changing the ultimate match outcome for the better. This shows that our data do not reflect an entirely rational response to falling behind. Rather, this latter finding is consistent with a model of reference-dependent preferences where being behind expectations is "psychologically different" from not being behind expectations, in the sense of feeling pressured and stressed, which can manifest itself in a deviation from fully 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 an NFL football team, on domestic violence. They find that a 10 percent increase in the rate of at-home violence by men against their women results when their team loses a match while it was predicted to win by some margin. Similar to our paper, Card and Dahl use betting market data to infer expected match outcomes. Our paper is however 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, while Card and Dahl analyze violent and futile reactions to unchangeable facts.

Also related to our paper is Pope and Schweitzer (2011) who analyze professional golfers' performance.[2] They find that golfers are significantly 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, while par (or the average score on a hole, which might differ from par) not necessarily coincides with an individual golfer's expectation in a given tournament.[3]

[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).

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

2 Data

Our data contains information on all 3'672 matches in the German Bundesliga (henceforth BL) in the 12 seasons from 1998/99 to 2009/10 and on all 4'560 matches in the English Premier League (henceforth PL) in the 12 seasons from 2000/01 to 2011/12.[4] For each match, we have detailed minute-by-minute information on goals, cards, and substitutions. For cards, we do not only know 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 goal keepers. Strikers are the most offensive type of player, so we assign them a value of 4. Midfielder, defenders, and goal keepers 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 I 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. Altogether, 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, about 1.1 of these 5 substitutions are offensive and about 0.8 are defensive. On the minute and team

[4] Background information on soccer and on the two leagues is provided in Appendix A.

[5] The data for the BL and PL is 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 (www.bundesliga-datenbank.de/en) for the BL and from Press Association Sport (www.pressassociation.com/sport) for the PL. We could not get the two most recent seasons of the BL because from the season 2010/11 onwards the Deutsche Fussball Liga GmbH, which organizes and markets the professional soccer in Germany, is the official data provider and we were informed that they do not share their data for statistical analysis.

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.

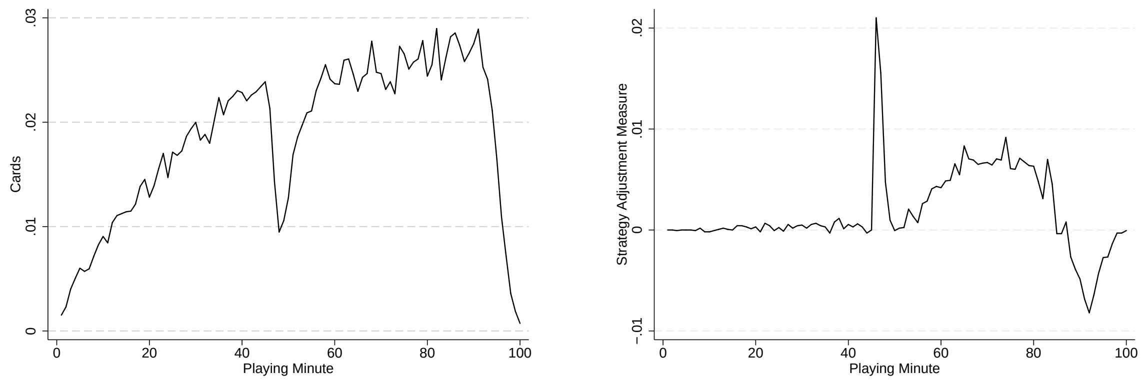
Table I: Summary statistics

variable	**mean**	**std.dev.**	**min**	**max**	**N**
per match:					
goals	2.728	1.679	0	11	8’232
cards	3.728	2.102	0	15	8’232
yellow cards	3.632	2.049	0	13	8’232
red cards	0.096	0.324	0	3	8’232
substitutions	5.146	1.019	0	6	8’232
offensive substitutions	1.096	0.894	0	5	8’232
defensive substitutions	0.782	0.816	0	5	8’232
strategy adjustment measure	0.362	1.429	-6	7	8’232
per minute and team:					
goals	0.014	0.119	0	2	1’569’478
cards	0.020	0.140	0	3	1’569’478
yellow cards	0.019	0.138	0	3	1’569’478
red cards	0.001	0.023	0	2	1’569’478
substitutions	0.027	0.173	0	3	1’569’478
offensive substitutions	0.006	0.077	0	3	1’569’478
defensive substitutions	0.004	0.064	0	2	1’569’478
strategy adjustment measure	0.002	0.119	-3	4	1’569’478

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 I 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. Only around half-time there is a pronounced dip. Also, the frequency of cards per minute drops to almost zero in the final minutes of matches with very much injury time. There are relatively few observations for matches with very long injury time. Only 16 percent of matches last longer than 97 minutes, 7 percent last longer than 98 minutes, and 3 percent last longer than 99 minutes.

The right panel of Figure I 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

Figure I: Dynamics of "Cards" and the "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.

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 towards a more offensive strategy, followed by a pronounced shift towards a more defensive strategy as the end of the match approaches.

In addition to our data on match events, we collected pre-play 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* from November 5, 2005. The odds from ODDSET for *Hannover 96* winning, *Mainz 05* winning, and tie, were 1.70, 3.50, and 2.70, respectively. Placing 1 Euro on, say, *Hannover 96* winning results in receiving 1.70 Euro 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]

[6]We obtained the betting odds for the BL upon request directly from ODDSET (www.oddset.de). ODDSET betting odds are however unavailable for the 1998/1999 season, and we used betting odds from the website www.betexplorer.com instead for this season. The betting odds of Interwetten for the PL can be retrieved on www.football-data.co.uk/. The Interwetten betting odds are missing for 17 matches and the website allows 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.

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 wins, tie, guest team wins), 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 the team is not ahead after a few minutes of play. Indeed, in matches with at least one goal, the first goal is not scored 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 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 about 14 percent of the minutes.[11]

[8] In 3.9 percent of all matches (321 out 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.

[9] Note that this approach has the drawback that a favorite team is assumed not to be in a loss frame even towards 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, while only 7.6 percent of matches end at 0:0. In Section 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 Section 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 they are behind (as it never occurred that the probability of loosing is 1) and that they 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 we cannot observe such possible adjustments, we assume that the ex-ante expectations determine reference point for the entire match.

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 their team is in a loss frame or not, 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 reference-dependent behavior that, in our context, the number of assigned cards that players receive and the strategy adjustments that coaches implement is influenced by whether their team is in a loss frame or not.[12]

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 of team t receive in minute m.[13] 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 of 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 of team t in minute m. Minutes with multiple cards in a given minute however account for less than 1 percent of minutes.[14]

Second, the dependent variable $strategy\,adjustment_{itm}$ is a function of the strategic adjustment measure (see Section 2) in match i of team t in minute m. In one specification, where we estimate a linear probability model, $strategy\,adjustment_{itm}$ 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

[12] Loss aversion and diminishing sensitivity to losses and gains are additional predictions of many models of reference-dependent behavior (leaving the question of the determinants of the reference point aside). Note that in this paper we only test the central prediction that behavior is reference-dependent, but we neither address loss aversion—in the sense of losses looming larger than gains—nor diminishing sensitivity. See however our discussion in Appendix D, where we address behavioral differences in our data between being in a loss frame and being in a gain frame.

[13] See Appendix B 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.

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

minute m of match i (i.e., the strategy adjustment measure is positive). In our other specifications, $strategy\,adjustment_{itm}$ 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.[15]

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 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:

$$card_{itm} = c + lossframe_{itm} \times \beta_1 + X^{'}_{itm} \times \beta_2 + \epsilon_{itm} \tag{1}$$

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 II, III, and IV below.[16] In addition, we always control for the state of the match by including dummy variables on exact goal differences.

In estimation equation (1), unobserved factors such as contestedness, weather conditions, audience size, referees, location, or 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 in 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

[15] 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.

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

error component model for the disturbances ϵ_{itm}, with

$$\epsilon_{itm} = \alpha_{it} + u_{itm} \tag{2}$$

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 estimation equation

$$card_{itm} = c + lossframe_{itm} \times \beta_1 + X'_{itm} \times \beta_2 + \alpha_{it} + u_{itm} \tag{3}$$

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

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

$$strategy\,adjustment_{itm} = \tilde{c} + lossframe_{itm} \times \tilde{\beta}_1 + X'_{itm} \times \tilde{\beta}_2 + \tilde{\alpha}_{it} + \tilde{u}_{itm} \tag{4}$$

Note that, since 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) do not only account for match 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.

3.4 Discussion of Identifying Assumptions

Our data allows us to compare teams that are unexpectedly behind (i.e., teams that are in a loss frame) to teams that are expectedly behind. We assume that the 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 non-favorite teams when being behind in score for reasons other than reference-dependence.[17] However, by definition, a favorite team is behind expectations if the team

[17] 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.

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 with one goal behind.[18] 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 expectations on the behavior of favorite teams. With non-experimental field data it is however impossible to randomly assign expectations.

Our strategy to address this limitation is to further analyze the nature of the behavioral changes that we observe in our data. Why would a favorite team behave differently than a non-favorite team when being behind in score? As the relatively stronger team, it may be productive for favorite teams to play in a way that leads to more cards and to implement a more offensive strategy of play when being behind in score, compared to non-favorite teams being 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. With reference-dependent preferences, to the contrary, it can be the case that players and coaches do not behave fully rational. The model that we have in mind is that being in a loss frame is “psychologically different” from not being in a loss frame and that this manifests itself in different and potentially not fully rational behavior by players and coaches. In particular, players and coaches might feel increased pressure or stress, be nervous, or even frustrated when being 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 (applies to players and coaches), or it could lead to a “loss of control” (see Card and Dahl (2011)), i.e., to overreaction and aggression (applies to players). All these behaviors would result in a less successful match outcome.

In our productivity analysis in Section 4.4 below we show that both receiving more cards and substituting players in an offensive way while being behind expectations indeed impair the expected ultimate match outcome. We also 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

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

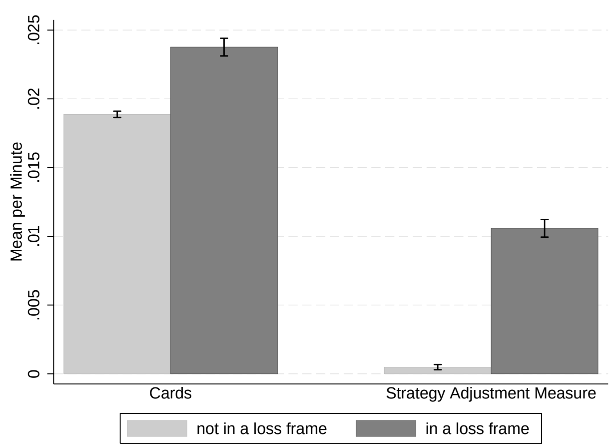
in the loss frame than out of the loss frame. These analyses thus provide support for a model of reference-dependent behavior, where being in a loss frame puts teams under pressure, but they do not support the view that the observed behavior is an entirely rational response of favorite teams to falling behind.

4 Results

4.1 Descriptive Evidence

Figure II 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 II thus provides first evidence that professional players and coaches exhibit reference-dependent behavior.

Figure II: Cards and Strategy Adjustment Measure per Minute



Notes: The two left bars show the average number of cards per minute separately for minutes where a team is not in a loss frame (0.0189) and minutes where 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.

Next, we exploit the timing of events in our data and address the question whether the displayed patterns in Figure II are causally related to being in the loss frame. Panel (a) of Figure III shows the average number of cards per minute over time. The top left graph shows a team's average frequency of cards in the minutes before and after it conceded a goal that places it in a loss frame. In the 15 minutes before the goal, teams receive around 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 kick-off and ball possession for the non-scoring team. Therefore, there is a short break after the goal (while playing time continues) which 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 pre-goal period (excluding the period directly before the goal).

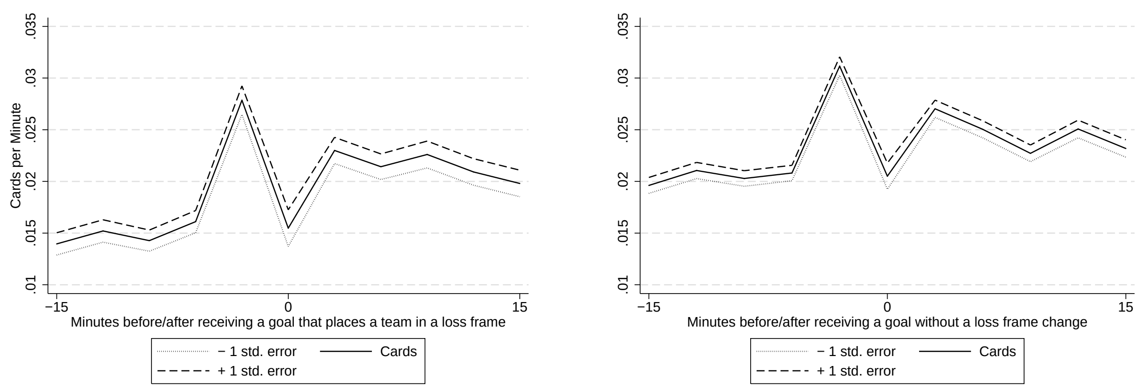
The top right graph in Figure III is the equivalent graph for teams that concede a goal that does not change the loss frame. Note that this includes, for example, favorites that are in a loss frame already before they concede the current goal. We see that the average number of cards per minute is somewhat higher at levels around 0.020 in the minutes before the goal already, reflecting the fact that, for example, favorites in the loss frame receive more cards (as observed in the top left picture). 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 raises to levels around 0.025, an increase of about 20%, relative to the pre-goal period (again excluding the period directly before the goal).

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

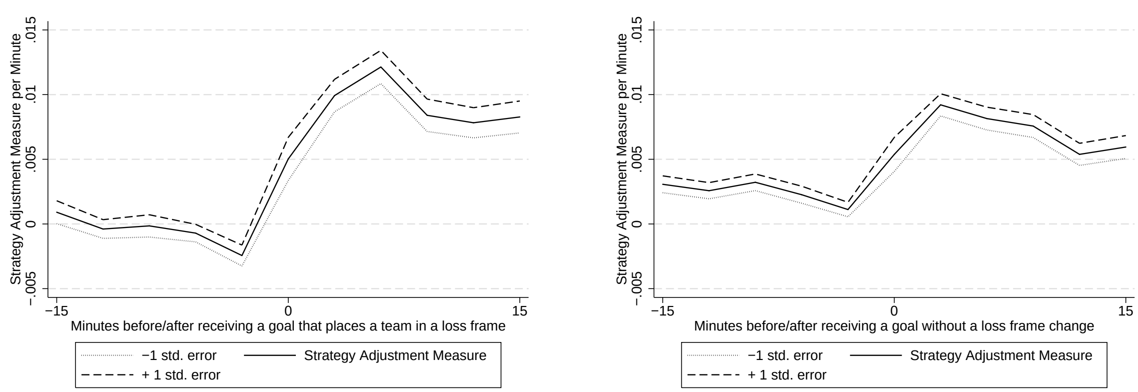
Panel (b) of Figure III shows a similar pattern for our strategy adjustment measure. The lower left picture shows the coaches' strategy adjustments in the minutes before and after their teams concede a goal that places them in a loss frame. We see that the average strategy adjustment measure per minute is around 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 around 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 around 0.008 and thus orders of magnitude higher than in the pre-goal period.

Figure III: Cards and Strategy Adjustment Measure Before and After Receiving a Goal

(a): Cards



(b): Strategy Adjustment Measure



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 (i.e, -15 to -12, ...,.-3 to -1, 1 to 3, 4 to 6, etc.).

The lower right picture in Figure III shows the strategy adjustment measure for conceded goals that do not change the loss frame. Similar to the top right picture for cards, we observe that pre-goal levels are somewhat higher (around 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 about 0.007 even 15 minutes after the goal.

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

4.2 Main Results

Regressions (1) to (8) in Table II display our main results. To test our null hypothesis, all specifications include the dummy variable "Loss frame" that equals 1 if a team is in a loss frame and 0 otherwise. The top panel of Table II shows our regressions with $card_{itm}$ as 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) to (4). The coefficient of the dummy variable "Loss frame" is positive, large, and highly significant in regressions (1) to (4), revealing that the players of a team receive more cards when they are in a loss frame.

Regression (1) 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 over 50 percent 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 II). 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 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 I 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 percent, even after we control for time effects.

Table II: Expectations as Reference Points: Main Lossframe

Panel A: Cards per Minute

	LPM (1)	OLS (2)	OLS (3)	OLS (4)
loss frame	0.0101***	0.0102***	0.0019***	0.0027***
	(17.42)	(17.35)	(3.22)	(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
Observations	1’569’478	1’569’478	1’569’478	1’569’478

Panel B: Strategy Adjustment Measure per Minute

	LPM (5)	OLS (6)	OLS (7)	OLS (8)
loss frame	0.0053***	0.0038***	0.0031***	0.0045***
	(16.96)	(8.03)	(6.28)	(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
Observations	1’569’478	1’569’478	1’569’478	1’569’478

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 percent.*

The bottom panel of Table II shows our regressions (5) to (8), which are equivalent to regressions (1) to (4), but with $strategy\,adjustment_{itm}$ as dependent variable. The dependent variable in regression (5) is a dummy that equals 1 if the strategy adjustment measure is strictly positive, while the dependent variable in regressions (6) to (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.

The coefficient of the dummy variable "Loss frame" 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 percent (the average value of the strategy adjustment measure per minute out of the loss frame is 0.0005; see Figure II).[19]

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 percent.*

The above analysis demonstrates that the players' and coaches' behavior depends on whether or not their team is in a loss frame.[20] Results 1 and 2 thus both reject the null hypothesis that the reference point that is given by the ex-ante expected match outcome does not affect behavior.[21]

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 3 points, a tie 1 point, and losing 0 points. The expected number of points is thus calculated as follows: $\textit{expected number of points} = \textit{prob}(\textit{win}) \cdot 3 + \textit{prob}(\textit{tie}) \cdot 1 + (1 - \textit{prob}(\textit{win}) - \textit{prob}(\textit{tie})) \cdot 0.$

[19] It could be that favorite teams have more defensive starting lineups than non-favorite teams 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 Section 2 that we assigned different values to different positions). The sums are 29.2 and 29.0 for favorite and non-favorite teams, respectively. Judged by this measure, the average starting lineups are very similar; if anything, favorites have a slightly more offensive lineup.

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

[21] In Appendix D, we present the specifications shown in Table II including, in addition, an indicator variable denoting whether team t was in a *gain frame* in match i in minute m. The coefficients of the loss frame dummies remain highly significant in all specifications and change in size only marginally.

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 conceded at least one goal. While this alternative formulation of the expectation-based reference point uses the betting odds not only in an ordinal but 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 1 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 about 34 percent of the time, which is more than twice as often as in our main specification (14 percent).

As a second alternative specification, we again consider the most likely match outcome to be the reference point, but 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 favourite 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 about 32 percent of the minutes.

Tables III and IV show the regression results for the first and second alternative loss frame specification, respectively. Apart from the respective specification of the loss frame, regressions (R1) to (R8) and (RR1) to (RR8) exactly correspond to regressions (1) to (8) in Table II. The coefficients and significance of the loss frame dummy variable in the regressions in Tables III and IV 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 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, while 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. Out of the more than 5 substitutions that take place on average (see Table I), only 0.14 take place in the first half hour of a match.[22]

Table III: Expectations as Reference Points: First Alternative Lossframe

Panel A: Cards per Minute				
	LPM (R1)	**OLS (R2)**	**OLS (R3)**	**OLS (R4)**
1st alternative loss frame	0.0146***	0.0148***	0.0012*	0.0021***
	(25.27)	(25.24)	(1.82)	(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
Observations	1'569'478	1'569'478	1'569'478	1'569'478

Panel B: Strategy Adjustment Measure per Minute				
	LPM (R5)	**OLS (R6)**	**OLS (R7)**	**OLS (R8)**
1st alternative loss frame	0.0073***	0.0025***	0.0015***	0.0018***
	(25.79)	(5.44)	(2.89)	(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
Observations	1'569'478	1'569'478	1'569'478	1'569'478

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Productivity Analysis

In Section 3.4 we discussed the identifying assumptions of our empirical strategy. We addressed the possibility that the behavioral change of favorite teams in the loss frame is driven by fully

[22] As an additional robustness check, we conduct the analyses presented in Tables II-IV for the two leagues separately in Appendix C. The analysis reveals that the loss frame dummy remains significant in the large majority of the specifications in the separate leagues.

Table IV: Expectations as Reference Points: Second Alternative Lossframe

Panel A: Cards per Minute

	LPM (RR1)	OLS (RR2)	OLS (RR3)	OLS (RR4)
2nd alternative loss frame	0.0022***	0.0022***	0.0035***	0.0040***
	(3.01)	(3.03)	(4.89)	(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
Observations	1’569’478	1’569’478	1’569’478	1’569’478

Panel B: Strategy Adjustment Measure per Minute

	LPM (RR5)	OLS (RR6)	OLS (RR7)	OLS (RR8)
2nd alternative loss frame	0.0004	0.0013**	0.0013**	0.0016**
	(1.29)	(2.31)	(2.24)	(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
Observations	1’569’478	1’569’478	1’569’478	1’569’478

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

rational, non-reference-dependent reasons: It might be that favorite teams *should* play in a way that leads to more cards and that their coaches *should* implement a more offensive strategy because these behaviors are productive in the sense of advancing the ultimate match outcome. Reference-dependent preferences would however be consistent with the finding that players and coaches do not behave in a fully rational way when being behind expectations. The model we have in mind is that being in a loss frame means being in a psychologically different state, such as, e.g., feeling pressured, which can lead to mistakes and thus a less successful match outcome. In this section, we therefore analyze if 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.

To determine if cards or offensive substitutions in the loss frame affect a team's final match outcome, we estimate the following two regression models.[23]

$$\begin{aligned} match\, outcome_{it} &= c + cards\, per\, loss\, minute_{it} \times \gamma_1 + cards\, per\, no\, loss\, minute_{it} \times \gamma_2 + \\ &+ X_{it} \times \gamma_3 + \alpha_t + \epsilon_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} match\, outcome_{it} &= c + off.\, substitutions\, (in\, loss\, frame)_{it} \times \tilde{\gamma}_1 \\ &+ off.\, substitutions\, (out\, of\, loss\, frame)_{it} \times \tilde{\gamma}_2 + X_{it} \times \tilde{\gamma}_3 + \tilde{\alpha}_t + \tilde{\epsilon}_{it} \end{aligned} \tag{6}$$

where $match\, outcome_{it}$ 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), $cards\, per\, loss\, minute_{it}$ 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, $cards\, per\, no\, loss\, minute$ 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), $off.\, substitutions\, (in\, loss\, frame)_{it}$ 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 $off.\, substitutions\, (out\, of\, loss\, frame)$ 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 V below. To estimate both equations, we include match observations only from teams that were at some point of the match in the loss frame.[24] If the most likely outcome is a tie, it can happen that both teams in a match are in the

[23] 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 non-scoring team performs a substitution after the goal was 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 non-scoring 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 Appendix B.

[24] The level of observation in the productivity analysis is a team-match pair. Our sample contains 8'232 matches,

loss frame at some point. We thus adjust standard errors for clustering on the match level.

The upper panel of Table V displays the results for estimation equation (5). Regressions (P1) to (P4) consistently show that cards in the loss frame are not productive as 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 points less 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.

The lower panel of Table V displays the results for estimation equation (6). Regressions (P5) to (P8) consistently show that offensive substitutions in a loss frame are not productive, as 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, were falling behind expectations can lead to not entirely rational reactions.[25]

To further analyze the nature of the behavioral change of favorite team in the loss frame, we finally analyze the reasons for which the players are assigned cards.[26] Table VI provides a summary of the different categories and displays their relative share 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.

so we have 16'464 match-team pairs. About 28 percent 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 were a team conceded a goal right in the first minute and stayed in the loss frame thereafter. Accordingly, $cards\,per\,no\,loss\,minute_{it}$ is not defined for these four observations which explains the different number of observations in Panel A and B in Table V.

[25] Note that the results of the productivity analysis do not imply that favorite teams in a loss frame exert less effort than non-favorite teams in a loss frame 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.

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

Table V: Productivity Analysis

Panel A: Are Cards Productive?

	OLS (P1)	OLS (P2)	OLS (P3)	OLS (P4)
Dependent variable:	**goal difference**		**points**	
Cards per Loss-Minute	-3.933***	-3.154***	-3.995***	-3.356***
	(-6.54)	(-5.43)	(-7.17)	(-6.20)
Cards per No-Loss-Minute	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?

	OLS (P5)	OLS (P6)	OLS (P7)	OLS (P8)
Dependent variable:	**goal difference**		**points**	
Offensive Substitutions	-0.300***	-0.302***	-0.298***	-0.301***
in Loss Frame	(-13.58)	(-14.11)	(-16.21)	(-16.82)
Offensive Substitutions	-0.0708	-0.0823	-0.101**	-0.112**
out of Loss Frame	(-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

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table VI: Reasons for Card Assignments

reason	loss frame = 0	loss frame = 1	Difference (%)
Violent conduct	203 (0.8%)	77 (1.5%)	85.52
Serious foul play and abusive language*	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**	1’101 (4.3%)	306 (5.9%)	35.93
Professional foul	179 (0.7%)	44 (0.8%)	20.22
Second bookable offence*	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*	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, touched 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	

* PL only, ** BL only

As an example, take the card reason “violent conduct.” Such cards are assigned to players who deliberately kick or hit an opponent player. A typical situation would be a player hitting his opponent’s face with an elbow. While 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 percent in the loss frame. Cards for “dissent” provide another example. Such cards are usually assigned for players who complain about the referee’s decisions. A typical situation would be the following. A player engages in foul play and the referee assigns a free-kick to the opposing team. The player who committed the foul gets angry about this decision and shows his dissent to the referee who then assigns the player a card for dissent (although the original foul play would not have led to a card). The share of such cards increases by 43 percent if a team is in a loss frame.

The increase of the relative share of reasons for cards like “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, were being behind expectations means being in psychologically worse state of mind, such as "being under pressure."

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 Köszegi (2008)), or optimal contracting (e.g., Hart and Moore (2008), Herweg et al. (2010)). Our paper provides evidence in support of models that assume that peoples' behavior is reference-dependent and that reference points are shaped by expectations.

It is noteworthy that our evidence comes from professional, experienced subjects who act in their natural environment, which is a fiercely competitive industry involving very high stakes. It is sometimes argued (e.g., Levitt and List (2007)) that behavioral "anomalies" observed in laboratory settings, where subjects make decisions in artificial situations and with relatively low stakes, will disappear in real-world contexts with experienced subjects, competition, or high stakes.[27] Our data suggest that the behavioral "anomaly" of reference-dependent behavior neither disappears with experience, competition, nor in a high-stakes environment.

References

Abeler, Johannes, Armin Falk, Lorenz Goette, and David Huffman, "Reference Points and Effort Provision," *American Economic Review*, 2011, *101* (2), 470–92.

Bartling, Björn and Klaus M. Schmidt, "Reference Points, Social Norms, and Fairness in Contract Renegotiations," *Journal of the European Economic Association*, forthcoming.

Bell, David E., "Disappointment in Decision Making under Uncertainty," *Operations Research*, 1985, *33*, 1–27.

Bewley, Truman F., *Why Wages Don't Fall During a Recession*, Harvard University Press, 1999.

[27] See Falk and Heckman (2009) for the comparative advantages of laboratory experiments.

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler, "Labor Supply of New York City Cabdrivers: One Day at a Time," *Quarterly Journal of Economics*, 1997, *112* (2), 407–41.

Card, David and Gordon Dahl, "Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior," *Quarterly Journal of Economics*, 2011, *126* (1), 103–43.

Chiappori, Pierre-Andre, Steven Levitt, and Timothy Groseclose, "Testing Mixed-Strategy Equilibria When Players Are Heterogenous: The Case of Penalty Kicks in Soccer," *American Economic Review*, 2002, *94* (4), 1138–51.

Crawford, Vincent P. and Juanjuan Meng, "New York City Cabdrivers' Labor Supply Revisited: Reference-Dependent Preferences with Rational-Expectations Targets for Hours and Income," *American Economic Review*, 2011, *101* (5), 1912–32.

Deloitte, "Annual Review of Football Finance-Highlights," Technical Report, Deloitte, Sports Business Group 2013.

Ericson, Keith M. Marzilli and Andreas Fuster, "Expectations as Endowments: Evidence on Reference-Dependent Preferences from Exchange and Valuation Experiments," *Quarterly Journal of Economics*, 2011, *126*, 1879–907.

Falk, Armin and James J. Heckman, "Lab Experiments Are a Major Source of Knowledge in the Social Sciences," *Science*, 2009, *326* (5952), 535–38.

Farber, Henry S., "Is Tomorrow another Day? The Labor Supply of New York City Cabdrivers," *Journal of Political Economy*, 2005, *113* (1), 46–82.

_ , "Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers," *American Economic Review*, 2008, *98* (2), 1069–1082.

Fehr, Ernst and Lorenz Goette, "Do Workers Work More if Wages Are High? Evidence from a Randomized Field Experiment," *American Economic Review*, 2007, *97* (1), 298–317.

_ , Oliver Hart, and Christian Zehnder, "Contracts as Reference Points - Experimental Evidence," *American Economic Review*, 2011, *101* (2), 493–525.

Garicano, Luis, Ignacio Palacios-Huerta, and Canice Prendergast, "Favoritism under Social Pressure," *Review of Economics and Statistics*, 2005, *87* (2), 208–16.

Gill, David and Victoria Prowse, "A Structural Analysis of Disappointment Aversion in Real-Effort Competition," *American Economic Review*, 2012, *102* (1), 469–503.

Gul, Faruk, "A Theory of Disappointment Aversion," *Econometrica*, 1991, *59* (3), 667–86.

Hart, Oliver and John Moore, "Contracts as Reference Points," *Quarterly Journal of Economics*, 2008, *123* (1), 1–48.

Heidhues, Paul and Botond Köszegi, "Competition and Price Variation When Consumers Are Loss Averse," *American Economic Review*, 2008, *98* (4), 1245–68.

Herweg, Fabian, Daniel Müller, and Philipp Weinschenk, "Binary Payment Schemes: Moral Hazard and Loss Aversion," *American Economic Review*, 2010, *100* (5), 2451–77.

Kahn, Lawrence M., "The Sports Business as a Labor Market Laboratory," *Journal of Economic Perspectives*, 2000, *14* (3), 75–94.

Kahneman, Daniel and Amos Tversky, "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 1979, *47* (2), 263–91.

Kocher, Martin G., Marc V. Lenz, and Matthias Sutter, "Psychological Pressure in Competitive Environments: New Evidence from Randomized Natural Experiments," *Management Science*, 2012, *58* (8), 1585–1591.

Köszegi, Botond and Matthew Rabin, "A Model of Reference-Dependent Preferences," *Quarterly Journal of Economics*, 2006, *121* (4), 1133–65.

_ **and** _ , "Reference-Dependent Risk Attitudes," *American Economic Review*, 2007, *97* (4), 1047–73.

_ **and** _ , "Reference-Dependent Consumption Plans," *American Economic Review*, 2009, *99* (3), 909–36.

Levitt, Steven and John A. List, "What Do Laboratory Experiments Measuring Social Preferences Reveal About the Real World?," *Journal of Economic Perspectives*, 2007, *21* (2), 153–74.

Loomes, Graham and Robert Sugden, "Disappointment and Dynamic Consistence in Choice under Uncertainty," *Review of Economic Studies*, 1986, *53* (2), 271–82.

Mas, Alexandre, "Pay, Reference Points and Police Performance," *Quarterly Journal of Economics*, 2006, *121* (3), 783–821.

Ockenfels, Axel, Dirk Sliwka, and Peter Werner, "Bonus Payments and Reference Point Violations," *Management Science*, forthcoming.

Odean, Terrance, "Are Investors Reluctant to Realize Their Losses?," *Journal of Finance*, 1998, *53* (5), 1775–1798.

Pope, Devin G. and Maurice E. Schweitzer, "Is Tiger Woods Loss Averse? Persistent Bias in the Face of Experience, Competition and High-Stakes," *American Economic Review*, 2011, *101* (1), 129–57.

Walker, Marc and John Wooders, "Minimax Play at Wimbledon," *American Economic Review*, 2001, *91* (5), 1521–38.

A Appendix: Institutional Background on Soccer and Leagues

A soccer team consists of 11 players, one of whom must be a goalkeeper. Two teams compete to kick the ball into the other team's goal. The primary rule is that players are not allowed to handle the ball with their hands or arms. The team that has scored more goals at the end of a match is the winner; the match is a tie if both teams have scored an equal number of goals. In order to determine league standings, the winning team receives 3 points; the losing team receives 0 points. If the match is a tie, teams receive 1 point each. A match is officiated by a referee, whose decisions are final. Matches are played in two halves of 45 minutes each, with a 15 minutes break in between, but total playing time regularly exceeds 45 minutes in each half (typically by 1 to 3 minutes) due to the addition of "injury time" by the referee.

A *foul* occurs when a player violates the rules of the game. Most often, a player's misconduct consists of tripping or pushing an opponent. Such misbehavior is sanctioned by the referee with the assignment of a *yellow card* or a *red card*. The first yellow card for a player in a match is a caution, which is shown for a clear offence. The second yellow card for a player in the same match, however, results in being sent off the field - in which case the player's team will continue with only 10 players. Moreover, the sanctioned player is suspended from the next match. A red card is shown for serious foul play such as violent conduct. In these cases, which are very rare, the player must leave the field immediately. Moreover, the sanctioned player is suspended from at least the next match, usually even from two to three matches.

Up to three *substitutions* can be made by the coach of a team per match. A player may be replaced because he is injured, he makes a bad play, or the coach wants to adjust the strategy of play. Importantly, players are typically specialized and play either as a striker, midfielder, defender, or goal keeper, so that the coach can use substitutions to implement strategy adjustments. When he substitutes a defender with a midfielder or striker, or a midfielder with a striker, the coach implements an *offensive substitution*. Substitutions are often made with the only intent to adjust the strategy of play, i.e., they are made even if the replaced player was not injured or unfit.

The German Bundesliga (henceforth BL) is the number one European soccer league in terms of profitability and weekly attendance figures, and it is the second most important league in terms of revenues. The league generated revenues of about 1.9 billion EUR in the 2011/12 season, resulting in profits of about 190 million EUR (Deloitte, 2013). The BL consists of 18 teams that compete with each other for winning the German championship (that is, to become the team with the highest number of points at the end of the season), qualifying for international competitions, such as the UEFA Champions League, and for avoiding relegation. This latter aspect distinguishes many European soccer leagues from most U.S. sports leagues, which are closed leagues. In the BL, for example, the two worst performing teams are directly replaced by the two top teams from the next lower league at the end of each season. Each BL team plays every other team twice every season, where one match is played at the team's home field and the other at the competitor's field. At the end of the season, each team will thus have played 34 matches. The English Premier League (henceforth PL) is the only European soccer league that generates higher revenues than the German BL. In the 2011/12 season, the PL generated revenues of 2.9 billion EUR resulting in profits of 121 million EUR (Deloitte, 2013). The playing schedule in the PL resembles that of the BL, albeit there are 20 teams in the PL. Hence, at the end of the season, each team will have played 38 matches.

B Appendix: Data Preparation

The goal of our empirical strategy is to model the number of cards that the players of a team receive on a minute-by-minute basis as well as the coaches' offensive strategy adjustments as a function of whether or not the team is in the loss frame. For each of our two behavioral outcome variables, we construct a separate data set, and apply the following procedure to determine whether a given card or substitution occurred in or out of the loss frame.

Since we observe the minute of play and a unique time stamp for each goal, card, and substitution, we know the exact chronological order of match events across and within minutes of play. In each minute, we construct the current goal difference from all goals scored in the match so far. We can thus determine whether a team is currently in a loss frame or not. Since we use minutes as units of observation, we have to decide whether to count goals in the very minute in which they are scored, or whether goals should show up from the following minute onwards only. Due to the nature of the obtained data, our procedure differs slightly between PL and BL and we describe this in turn.

Consider first minutes with goals only, that is, without a second event like a card or a substitution. For the PL, we observe an exact time-stamp that relates to in-play match time. This allows us to apply the following rule: if a goal is scored within the first 30 seconds of match minute m, we count the goal for match minute m, but if the goal is scored in the last 30 seconds of a match minute, we count the goal for minute $m + 1$ only. For the BL, in contrast, we separately observe the minute of play, and an exact time stamp that relates to real-time instead of in-play match time. Since we do not observe the exact real-time kick-off, we are able to determine the exact order of multiple events (say, a goal and a card) within a minute, but we are unable to determine whether an event occurred within the first or last 30 seconds within a match minute. Here we apply the rule that goals count for the next minute only. We apply this rule because there is always a short break after a goal is scored. The average number of seconds played in a minute with a goal will thus be lower after the goal was scored than before the goal was scored.

If we have a goal and a card or substitution in a minute, we count the goal for that minute if it precedes the card or substitution, otherwise we count it for the next minute only. This procedure ensures that a card or substitution is accounted for with the correct goal difference. We have however only two observations for minutes in which we first observe a card, then a goal, and then another card. In one case, the team that received the cards was neither in a loss frame before nor after the goal. In the other case, the team that received the cards moved into the loss frame by receiving the goal. In both cases, we do not count the second card for that minute, i.e., we drop one card that was assigned outside the loss frame and one card that was assigned inside the loss frame. We do, however, count both cards to calculate the cumulative number of cards in all subsequent minutes. Multiple substitutions in the same minute for the same team with a goal in-between the substitutions do not occur in our data set.

C Appendix: BL and PL Separately

In this appendix we provide an additional robustness check of our results by reanalyzing the data in the two leagues separately. Table C.1 provides the same summary statistics that are included in Table I in the main text, but now for the two leagues separately. It can be seen, e.g., that fewer goals are scored in the PL compared to the BL (2.63 goals per match compared to 2.85) and fewer cards are assigned (3.26 cards per match compared to 4.31). Also substitutions are rarer in the PL (4.89 per match compared to 5.46) and strategy adjustments tend to be slightly less offensive.

Table C.1: Summary statistics for both leagues separately

	German Bundesliga (BL)					English Premier League (PL)				
variable	**mean**	**s.d.**	**min**	**max**	**N**	**mean**	**s.d.**	**min**	**max**	**N**
per match:										
goals	2.854	1.699	0	11	3'672	2.627	1.657	0	11	4'560
cards	4.308	2.068	0	15	3'672	3.262	2.011	0	12	4'560
yellow cards	4.208	2.004	0	13	3'672	3.168	1.965	0	12	4'560
red cards	0.100	0.330	0	2	3'672	0.094	0.320	0	3	4'560
substitutions	5.459	0.813	1	6	3'672	4.893	1.095	0	6	4'560
off. subst.	0.961	0.841	0	5	3'672	1.204	0.920	0	5	4'560
def. subst.	0.588	0.697	0	4	3'672	0.939	0.870	0	5	4'560
strat. adj. meas.	0.439	1.215	-4	6	3'672	0.299	1.578	-6	7	4'560
per min./team:										
goals	0.015	0.123	0	2	687'674	0.014	0.116	0	2	881'804
cards	0.023	0.151	0	3	687'674	0.017	0.13	0	3	881'804
yellow cards	0.022	0.149	0	3	687'674	0.016	0.128	0	3	881'804
red cards	0.001	0.023	0	1	687'674	0.001	0.022	0	2	881'804
substitutions	0.029	0.179	0	3	687'674	0.025	0.169	0	3	881'804
off. subst.	0.005	0.073	0	2	687'674	0.006	0.080	0	3	881'804
def. subst.	0.003	0.056	0	2	687'674	0.005	0.070	0	2	881'804
strat. adj. meas.	0.002	0.108	-3	3	687'674	0.002	0.127	-3	4	881'804

The regressions in Tables C.2 and C.3 mirror the regressions in Table II in the main text. The results are supportive of our main results. Table C.2 reports the results for the BL. It shows that the coefficients of the loss frame dummy are positive, large, and highly significant in all eight regression models. Table C.3 reports the results for the PL. It shows that the coefficients of the loss frame dummy are again positive, large, and highly significant in six out of the eight regression models. The coefficients however fail to reach statistical significance in regressions (3-PL) and (4-PL), while having a positive sign.

The regressions in Tables C.4 to C.7 mirror the regressions in Tables III and IV. The regressions in Tables C.4 and C.5 report the results for the BL. They show that the coefficients of the alternative loss frame dummies are positive in all regression models and reach at least marginal significance in 13 our of the 16 specifications, except for the specifications in (R7-BL), (R8-BL), and (RR1-BL). Tables C.6 and C.7 report the results for the PL. The coefficients of the alternative loss frame dummies are positive and significant in six of the eight regressions with cards as dependent variable. While the coefficients are negative in regressions (R3-PL) and (R4-PL), they are small and insignificant. The coefficients of the alternative loss frame dummies are always positive in the regressions with the strategy adjustment measure as dependent variable, but fail to reach statistical significance in the second alternative loss frame specification in regressions (RR5-PL) to (RR8-PL).

Table C.2: Expectations as Reference Points: Main Loss frame (Bundesliga)

Panel A: Cards per Minute

	LPM (1-BL)	**OLS (2-BL)**	**OLS (3-BL)**	**OLS (4-BL)**
loss frame	0.0130***	0.0131***	0.0041***	0.0049***
	(13.72)	(13.62)	(4.14)	(4.48)
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
Observations	687'674	687'674	687'674	687'674

Panel B: Strategy Adjustment Measure per Minute

	LPM (5-BL)	**OLS (6-BL)**	**OLS (7-BL)**	**OLS (8-BL)**
loss frame	0.0045***	0.0033***	0.0023***	0.0038***
	(10.31)	(5.29)	(3.41)	(4.44)
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
Observations	687'674	687'674	687'674	687'674

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Expectations as Reference Points: Main Lossframe (Premier League)

Panel A: Cards per Minute

	LPM (1-PL)	**OLS (2-PL)**	**OLS (3-PL)**	**OLS (4-PL)**
loss frame	1.59e-19***	0.0078***	0.0001	0.0006
	(30.86)	(10.83)	(0.10)	(0.72)
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
Observations	881'804	881'804	881'804	881'804

Panel B: Strategy Adjustment Measure per Minute

	LPM (5-PL)	**OLS (6-PL)**	**OLS (7-PL)**	**OLS (8-PL)**
loss frame	0.0059***	0.0042***	0.0038***	0.0050***
	(13.46)	(6.04)	(5.28)	(5.58)
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
Observations	881'804	881'804	881'804	881'804

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Expectations as Reference Points: First Alternative Lossframe (Bundesliga)

Panel A: Cards per Minute

	LPM (R1-BL)	OLS (R2-BL)	OLS (R3-BL)	OLS (R4-BL)
1st alternative loss frame	0.0178***	0.0180***	0.0037***	0.0049***
	(19.33)	(19.32)	(3.48)	(4.13)
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
Observations	687'674	687'674	687'674	687'674

Panel B: Strategy Adjustment Measure per Minute

	LPM (R5-BL)	OLS (R6-BL)	OLS (R7-BL)	OLS (R8-BL)
1st alternative loss frame	0.0062***	0.0023***	0.0004	0.0005
	(16.02)	(3.71)	(0.61)	(0.63)
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
Observations	687'674	687'674	687'674	687'674

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Expectations as Reference Points: Second Alternative Lossframe (Bundesliga)

Panel A: Cards per Minute

	LPM (RR1-BL)	**OLS (RR2-BL)**	**OLS (RR3-BL)**	**OLS (RR4-BL)**
2nd alternative loss frame	0.0019	0.0021*	0.0032***	0.0035***
	(1.64)	(1.77)	(2.74)	(2.65)
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
Observations	687'674	687'674	687'674	687'674

Panel B: Strategy Adjustment Measure per Minute

	LPM (RR5-BL)	**OLS (RR6-BL)**	**OLS (RR7-BL)**	**OLS (RR8-BL)**
2nd alternative loss frame	0.0007*	0.0014**	0.0015**	0.0023***
	(1.74)	(1.99)	(2.12)	(2.60)
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
Observations	687'674	687'674	687'674	687'674

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: Expectations as Reference Points: First Alternative Lossframe (Premier League)

Panel A: Cards per Minute

	LPM (R1-PL)	**OLS (R2-PL)**	**OLS (R3-PL)**	**OLS (R4-PL)**
1st alternative loss frame	4.76e-19***	0.0122***	-0.0009	-0.0003
	(35.27)	(16.48)	(-1.05)	(-0.37)
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
Observations	881’804	881’804	881’804	881’804

Panel B: Strategy Adjustment Measure per Minute

	LPM (R5-PL)	**OLS (R6-PL)**	**OLS (R7-PL)**	**OLS (R8-PL)**
1st alternative loss frame	0.0082***	0.0027***	0.0024***	0.0027***
	(20.26)	(4.04)	(3.20)	(3.01)
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
Observations	881’804	881’804	881’804	881’804

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: Expectations as Reference Points: Second Alternative Lossframe (Premier League)

Panel A: Cards per Minute

	LPM (RR1-PL)	**OLS (RR2-PL)**	**OLS (RR3-PL)**	**OLS (RR4-PL)**
2nd alternative loss frame	2.42e-20***	0.0023**	0.0037***	0.0042***
	(6.78)	(2.54)	(4.17)	(4.27)
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
Observations	881’804	881’804	881’804	881’804

Panel B: Strategy Adjustment Measure per Minute

	LPM (RR5-PL)	**OLS (RR6-PL)**	**OLS (RR7-PL)**	**OLS (RR8-PL)**
2nd alternative loss frame	0.0002	0.0012	0.0011	0.0012
	(0.44)	(1.47)	(1.32)	(1.22)
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
Observations	881’804	881’804	881’804	881’804

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Appendix: Gain Frame

In this appendix we present the specifications shown in Table II in the main text including, in addition, an indicator variable denoting whether team t was in a *gain frame* in match i in minute m. Table D.1 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) to (4-GF) with cards as dependent variable, all coefficients of the gain frame indicator are positive and even larger in size than the respective loss frame coefficients; providing further evidence for the existence of a reference point. Importantly, the productivity analysis in Panel A of Table D.2, which mirrors the productivity analysis in Table V in the main text, 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 non-favorite 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 D.3 support this prediction. Specifically, Table D.3 parallels Table VI in the main text 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 being head 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 more often in the loss frame but less often in the gain frame. Hence, while our analyses in the main text 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 data are consistent with the common property of models of reference-dependent behavior that losses and gains are not coded symmetrically.

Regressions (5-GF) to (8-GF) analyze the coaches' substitution decisions. We begin our discussion with regressions (6-GF) to (8-GF), with the strategy adjustment measure as dependent variable. The regressions reveal that coaches implement substitutions that are significantly less offensive in the gain frame relative to the baseline. Indeed, the average value of the strategy adjustment measure of teams in the gain frame is -0.005 (compared to about 0.01 in the gain frame). This shows that teams in the gain frame 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 D.2 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 his is not a productive strategy).

Finally, to mirror the analysis in Table II, the dependent variable in regression (5-GF) 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 the that 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.

Table D.1: 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)**
gain frame	0.0096***	0.0097***	0.0030***	0.0037***
	(16.68)	(16.67)	(4.97)	(5.73)
loss frame	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
Observations	1’569’478	1’569’478	1’569’478	1’569’478

Panel B: Strategy Adjustment Measure per Minute

	LPM (5-GF)	**OLS (6-GF)**	**OLS (7-GF)**	**OLS (8-GF)**
gain frame	0.0024***	-0.0022***	-0.0029***	-0.0035***
	(9.75)	(-4.78)	(-6.21)	(-6.41)
loss frame	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
Observations	1’569’478	1’569’478	1’569’478	1’569’478

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.2: Gain frame: Productivity Analysis

Panel A: Are Cards Productive?

	OLS (P1-GF)	**OLS (P2-GF)**	**OLS (P3-GF)**	**OLS (P4-GF)**
Dependent variable:	**goal difference**		**points**	
Cards per Gain-Minute	0.355	0.631	0.540	0.769*
	(0.87)	(1.60)	(1.22)	(1.79)
Cards per No-Gain-Minute	-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 Offensive Substitutions Productive?

	OLS (P5-GF)	**OLS (P6-GF)**	**OLS (P7-GF)**	**OLS (P8-GF)**
Dependent variable:	**goal difference**		**points**	
Defensive Substitutions in Gain Frame	0.269***	0.260***	0.310***	0.303***
	(10.20)	(10.20)	(11.90)	(11.96)
Defensive Substitutions out of Gain Frame	-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

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.3: Reasons for Card Assignments

reason	**neutral** ("at expectation")	**change (%) if gain frame = 1**	**change (%) if loss frame = 1**
Violent conduct	171 (0.9%)	−34.1	71.5
Serious foul play and abusive language*	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**	804 (4.1%)	30.1	44.5
Professional foul	148 (0.8%)	−26.2	13.3
Second bookable offence*	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*	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, touched 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

* PL only, ** BL only