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Normality Bias in the Field: Evidence from Panel Data

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ABSTRACT

Scenario studies in social psychology have shown that more negative feelings are attributed to negative outcomes following abnormal behavior than to the same negative outcomes caused by normal behavior. This study employs field data to test whether individuals avoid unconventional behavior in order to reduce anticipated negative affections. Using panel data from professional German soccer, we find evidence that after a positive game result, soccer coaches follow the "never change a winning team" heuristic, whereas after a lost game, coaches become more active and change the starting lineup. This effect is robust to the inclusion of potential confounders such as injuries, suspensions, and unobserved heterogeneity of the coaches and the teams and cannot be explained by increased subsequent team performance.

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1. Introduction

Various scenario studies in social psychology have shown that individuals tend to follow norms because dissatisfaction from a certain negative outcome is higher when it was caused by an abnormal action than by a normal one (Miller and McFarland 1986; Macrae 1992; Ritov and Baron 1994; Turley, Sanna and Reiter 1995; Prentice and Koehler 2002; Zeelenberg et al. 2002). The norm theory of Kahneman and Miller (1986) explains that the more easily the imagined counterfactual of what might have been can be compared to reality, the more intense are feelings like frustration and regret in the case of a negative outcome. Potentially bad outcomes resulting from abnormal behavior are perceived as worse than the same outcomes resulting from common behavior, as it is easier to mentally undo abnormal behavior. Counterfactuals of abnormal actions are more easily available than the counterfactuals of normal actions. Kahneman and Miller (1986), therefore, reason that people tend to avoid unconventional actions.

From an economic perspective, the normality bias is an example of non-standard decision-making, because decisions are not only affected by own payoffs but by emotions as well. However, the application of methods from other social sciences—particularly psychology—to economics is rather common, as the rising behavioral economics literature proves (Shiller 2005). So far the empirical literature on normality bias has largely relied on survey data of hypothetical scenario experiments (Miller and McFarland 1986; Macrae 1992; Ritov and Baron 1994; Turley, Sanna, and Reiter 1995; Prentice and Koehler 2002). Turley et al. (1995), for example, presented one scenario in which a woman walks home via the usual route and is raped, and another scenario in which a woman takes an unusual route home and is raped. After reading the scenarios, participants answered a set of questions assessing their reactions to the described events. The results

of Turley et al. (1995) show that participants believed that the victim in the unusual condition would feel more regret than the victim in the usual condition. Since individuals are likely to take anticipated regret into account before they decide, theory predicts that individuals are biased towards conventional behavior (Janis and Mann 1977; Bell 1982; Loomes and Sudgen 1982; Zeelenberg and Pieters 2007).

This paper empirically tests whether the normality bias that was discovered in psychological scenario studies has behavioral consequences in reality. In doing so, we use a real-world setting in which the agents have strong financial incentives to avoid biased decisions and in which the ultimate consequences of the decisions are easily identified due to the availability of accurate outcome measures, namely in professional sports. More precisely, we analyze the decisions of professional soccer team coaches on how many players of the starting lineup they change between two matches. Even though the average roster size is approximately twenty-five players, only eleven players are eligible to play on the field. As the rules of the game limit the number of substitutes to three players, the selection of the starting lineup is a critical and important decision the coach has to take before a competition game. We argue that the norm regarding the "turnover" of the starting lineup depends on the previous result of the team. If the team won the last match, the coaches should—according to the "never change a winning team" heuristic—field the same players in the next game again. If the team lost the previous game, the coach is expected to become more active, which means changing the starting lineup in this context. The scenario study of Zellenberg et al. (2002) provides evidence that students attribute lower levels of responsibility and regret to soccer coaches for a negative game outcome if they follow the abovementioned norm, compared to the situation in which soccer coaches did not follow the norm and achieved an identical negative result.

Using longitudinal match-level data of all team compositions and results during seven seasons of the highest German soccer league, we find evidence that coaches who lost their last game change significantly *more* players and that coaches who won the last game change significantly *less* players of the starting lineup than coaches who tied the last game. This result is robust to the inclusion of potential confounders such as injuries, suspensions, unobserved team and coach heterogeneity, and the team performance of the subsequent game. Thus, the different behavioral reaction of soccer coaches depending on the last game's result can neither be explained by unwanted drivers of the starting lineup's "turnover," like injuries, nor by sportive reasons. From a standard economic perspective, coaches should maximize the team's winning, as this maximizes their material payoffs and minimizes the likelihood of being dismissed (e.g. Frick, Barros, and Prinz 2009; Dios Tena and Forrest 2007). We show that professional soccer coaches are also guided by regret avoidance when deciding about the "turnover" of the starting lineup. This implies that the coach does not only consider the simple winning probability but also how winning comes about.

The normality bias we find for soccer coaches is likely to apply to other agents as well. Politicians or chairmen of central banks, for example, may be tempted to launch an economic stimulus package in times of crises even though the benefits of such a plan are unlikely to outweigh the costs. They simply do so because action is considered more normal following a bad outcome. On the other hand, if the economy is flourishing, the same people tend to lean back although changes could possibly improve the economy even further.

The remainder of this paper is structured as follows: First, we survey the related theoretical and empirical literature on the normality bias. In section three, we motivate

our hypotheses. The empirical setup and the results are discussed in section four. Finally, we conclude and illustrate implications for theory and practice.

2. Related Literature

The normality bias rests upon the norm theory outlined by Kahneman and Miller (1986). They argue that an outcome that follows exceptional action causes stronger affective reactions than the same outcome elicited by routine action. Kahneman and Miller (1986) use the concept of counterfactual thinking to explain the different affective reactions. It is easier to generate counterfactual alternatives for exceptional than routine actions. Unlike unconventional behavior, it is relatively hard to mentally "undo" routine behavior. As a consequence, thoughts of "what might have happened, if only" are less prevalent after normal actions, reducing feelings like regret and blame.

The predictions of the norm theory have received support by several scenario studies. Miller and McFarland (1986) present a scenario in which a victim lost the use of his arm as a result of a gunshot wound following a shooting in a convenience store. In the scenario in which the victim visited the store just for a "change of pace," the victim was awarded significantly greater compensation than in the scenario in which the victim visited the store very frequently. Macrae (1992) finds that greater financial compensation was awarded if food poisoning happened in a restaurant never visited before than in a restaurant to which the victim has regularly gone. Turley et al. (1995) perform scenario experiments in which they vary whether a woman walked home via an unusual versus a usual route before being raped. They show that the victims who were raped on the unusual route provoked higher prison sentences for the offender than those being given to the perpetrators in the normal condition. In addition, participants believed that the victim

would feel more responsibility and regret when the rape happened on the unusual route. Prentice and Koehler (2002) use a scenario in which two doctors with similar education and experience choose a course of treatment for a patient and the patient received similarly bad results. They show that the doctor who chose an unconventional treatment is judged more harshly than the doctor who chose a conventional treatment. In a second experiment, jurors had to make a judgment regarding the punishment for a financial advisor whose portfolio dropped by 70%. Prentice and Koehler (2002) show that the abnormality influences the punishment decisions of the jurors. If the advisor invested in "widely owned conventional stocks," he was punished less than in the scenario in which he invested in a portfolio of "less widely owned, unconventional stocks."

Whereas in the abovementioned studies the scenarios clearly state the "normal behavior," in the following studies normality results from the context in which action happens. Ritov and Baron (1994) present different scenarios, all of which concern a train that is rolling down a hill towards a tree that lies on the tracks. In all the cases, someone is injured so that the person spends a week in the hospital but otherwise fully recovers. Their results show that higher compensation was awarded to the injured person in the scenario in which the engineer decides not to stop the train compared to the injured person in the scenario in which the engineer stops the train so quickly that the person is injured. Ritov and Baron (1994) explain their result with the fact that the engineer is expected to stop the train in order to prevent the accident. And adverse outcomes of unexpected behavior are judged worse than the same negative outcome following expected actions. Zeelenberg et al. (2002) show that negative affections such as regret are more intense after abnormal decisions than after normal decisions. They use a setting in which the expected behavior is dependent on prior outcomes: the decision of a soccer

coach regarding whether part of the starting lineup should be replaced for the next game. If the team won the last game, participants report that the coach who changed the starting lineup would feel more regret than the coach who did not change the starting lineup, even though the team loses the game in both scenarios. However, if the previous game was lost, participants indicate that the coach who acted and changed part of the starting lineup would feel less regret from losing again than would the coach who did not act.

The consistent results supporting the normality bias in scenario studies are likely to influence behavior, as individuals tend to take anticipated regret into account before they decide (Janis and Mann 1977; Bell 1982; Zeelenberg and Pieters 2007). "The more counterfactual regret an outcome is expected to generate, the more motivated the decision maker is to avoid this outcome." (Miller and Taylor 2002, p. 371). Whereas all the abovementioned studies use *stated preferences,* there are also a few studies employing *revealed preferences* as they observe actual behavior in the field. Bar-Eli et al. (2007) find evidence of a normality bias of professional soccer goalkeepers during penalty kicks.[1] Even though the optimal strategy for goalkeepers would be to stay in the goal's center, goalkeepers almost always jump right or left. The authors explain their finding, as it is the norm to jump. Thus, an identical negative outcome, which in their setting is a goal being scored, is perceived as worse when it follows staying in the center rather than jumping to the right or left. Kruger et al. (2005) show that participants tended to stick with the "first instinct" norm in multiple choice tests, even though they achieved lower test scores than if they had changed their answers more often. The authors explain their

[1] Bar-Eli et al. (2007) label the *normality bias* as *action bias* because taking action by jumping to the right or left is the norm in their context.

finding with anticipated emotions: Switching the answer in a multiple choice test when one should have kept the original answer leads to more counterfactual "if only" self-recriminations than does sticking to one's answer when one should have switched.

3. Testable Hypotheses

We use professional German soccer as field laboratory. Unlike in other industries, (team) performance is easily identified and accurately measured in professional soccer. Feedback cycles are short, which not only provides us with extensive panel data but also makes it more plausible that anticipated affections might influence current decisions.

This paper analyzes the decision of the coach on the number of replacements of the starting lineup between two consecutive matches. German soccer teams compete in one 90-minute match per week. Seventy-five minutes before a match begins, the coach has to announce the eleven players of the starting lineup. As the rules of the game in soccer—unlike in other team sports, like basketball or ice hockey—restrict the maximal number of substitutions during the game to three, the determination of the starting lineup is an important strategic decision. Besides unintentional replacements (e.g., due to injuries or suspensions of core players), the coach also consciously changes the starting lineup as a result of any weak fitness of the usual starters, different tactical strategies or—and this is the focus of our paper—in order to minimize anticipated negative affections such as regret or shame in the case of a negative outcome. The most obvious way to minimize negative emotions is to field the best players, which is perfectly in line with standard economic behavior. The problem, however, is the fact that it is uncertain which combination of players is most likely to succeed. Thus, given the decision under

uncertainty, the coaches are likely to be susceptible to all kinds of heuristics and biases (e.g., Staw and Huang 1995).

This paper examines the potential normality bias. However, what is the norm regarding the number of replacements of the opening team? The experimental results of Zeelenberg et al. (2002) indicate that the norm is likely to depend on the prior game result. If the team won the last game, the "never change a winning team" heuristic applies, and the coach should not alter the starting lineup. But if the team lost the last game, the coach should try to prevent the same thing from happening again by taking action and changing the opening team. The participants of the experiments of Zeelenberg et al. (2002) attributed lower levels of regret to the coach who behaved according to the abovementioned norm and lost the game, compared to the alternative scenario of a coach who did not follow the norm and likewise lost the game. Whereas in the scenario studies the (negative) outcome is predetermined by the researchers, the (varying) outcome in the field has to be "held constant" by including control variables characterizing subsequent team performance. Thus, we conjecture:

H1: A coach replaces significantly more (less) players of the starting lineup if the last game was lost (won) compared to the situation in which the team tied in the last game, holding subsequent team performance constant.

In hypothesis 1 we do not take winning expectations into account. As a second hypothesis, we postulate that expectations moderate the relationship between past game results and the "turnover" of the starting lineup. We expect that the coach will change more players from the starting lineup after a lost last game if his team was treated as

favorite than if it was considered an underdog. On the other hand, if an underdog team managed to succeed, we conjecture that the coach is more likely to follow the "never change a winning team" heuristic than a coach of a favorite team that just did its job. The more unexpected the last game result was, the higher the postulated normality bias should be.

H2: The unexpectedness of the last game's result amplifies the normality bias.

4. Empirical Framework

Sample and Dependent Variable

Our sample consists of match-level observations of all teams appearing in the highest German soccer league, *Bundesliga*, during seven seasons beginning with the 1999/00 season until the 2005/06 season. As the *Bundesliga* consists of 18 teams playing each other twice during the season, the full season includes 306 games, generating 612 team observations. Since due to obvious reasons the number of replacements of the starting lineup is significantly higher in the first match after the transfer periods, we exclude the first match after the summer and after the winter break. Thus, 576 team-match observations per season and 4032 observations in total remain.

The number of replacements of the starting lineup between two consecutive matches of a team serves as the dependent variable. It was calculated from a data set of over 63,000 player-match observations. We did not use the number of replacements of the entire competition team including the substitute players, as the actual score of the game may influence whom and how many players the team substitutes. Teams that are ahead not only substitute more than teams that are behind (Franck and Nüesch 2008); they are

also more likely to exert risk-reducing substitutions by replacing offensive players with defensive ones (Grund and Gürtler 2005). Since we analyze the replacements of the starting lineup, we can exclude such influences.

Explanatory Variables[2]

Our main independent variables are related to the result of the last game of the team. To test hypothesis 1, we include two dummy variables, *Last game lost* and *Last game won*, coded 1 if the team lost the last game or won the last game, respectively (and 0 otherwise). The variables *Last game lost* and *Last game won* are not perfectly correlated, as one out of four games in German soccer ends in a draw.

In order to test the second hypothesis regarding whether the unexpectedness of a won or lost game influences the coach's normality bias when deciding on the starting lineup's "turnover," we split the sample into two subsamples depending on the last game's result. The first subsample includes all observations in which the team lost the last game, whereas the second subsample includes all observations in which the team won the last game. In soccer, the bookmaker's (fixed) odds provide a good predictor of the likelihood of certain game outcome. For each possible game outcome $k \in \{HomeWin, Draw, AwayWin\}$, the bookmaker posts decimal odds o_k (e.g., 2.0) that represent the payout ratios for a winning bet. The higher the odds, the less likely this event is expected to occur. We adjusted the odds taken from the bookmaking company *Oddset* by the bookmaker's margin, so that the inverse of the decimal odds, which can be interpreted as the bookmaker's implicit probability of the underlying match outcome

[2] We provide a complete description of variables and data sources in the Appendix.

occurring, sum up to one. The bookmaker's payout ratio for a loss in the last game is defined as the variable *Lag loss unexpected*, whereas the bookmaker's payout ratio for a win in the last game is defined as the variable *Lag win unexpected*. The variable *Lag loss unexpected* is used in the subsample including the observations if the team lost the last game, and the variable *Lag win unexpected* enters the second subsample including the observations if the team won the last game. According to hypothesis 2, the unexpectedness variables should additionally explain variations in the number of replacements of the starting lineup beyond the level effects of having won or lost the last game.

Control Variables

The estimates of a simple model in which the number of replacements is only explained by the result of the previous game may be spurious, as other factors can correlate with both the result of the last game and the dependent variable. We therefore include several control variables in order to reduce potential omitted variable bias. An important aspect we have to consider is the number of suspensions of core players. The rules of the game in professional German soccer state that a player is suspended for one game if he accumulated five yellow cards. If a player receives a second yellow card during the same game, he is sent off the field for the remainder of the game and suspended for the next game. After receiving a red card, the player is not only sent off the field, but he is also suspended for one through five games, depending on the cruelty of misbehavior. Thus it is obvious that the number of red cards increases the replacements of the starting lineup, since the coach has to replace the suspended players. The change of the starting lineup is likely to happen twice: first, when the core player gets suspended

and second, when he is eligible to play again. As players are typically suspended for only one game, we control for the number of red cards in the last and in the next to last game. In addition, we also control for the number of yellow cards in the previous two games, as it makes suspensions more likely due to the five-cards rule. Unfortunately, direct data on player suspensions are not available.

A second factor that increases the number of replacements is injuries of core players who used to play in the starting lineup. Unlike information about red and yellow cards, injury data are not publicly available. We try to proxy the number of injured players at a given point of time by conducting an extensive text analysis of more than 20 different German newspapers at the day of the game and two days after.[3] We marked a player as injured if his name was mentioned less than six words away from the word "injured" (in German "verletzt") together with the full name of the club he was engaged in the corresponding season. Unfortunately, it was impossible to clearly discern from the text analysis whether the player's injury was new, which is more likely to trigger a change of the starting lineup than in the case of long-term injuries.

In addition, we also have to consider possible performance effects of the starting lineup's "turnover." We therefore include a dummy variable *Win* (denoted 1 if the team wins) and a dummy variable *Loss* (denoted 1 if the team loses) in order to control for the performance effects of the number of replacements of the starting lineup. The variables *Win* and *Loss* capture the extent to which "turnover" was needed to increase the winning probability and to decrease the losing probability, respectively. When testing hypothesis

[3] The database we used, *LexisNexis*, contains both quality nationwide newspapers (such as *Frankfurter Allgemeine Zeitung, Süddeutsche Zeitung, Stuttgarter Zeitung, Hamburger Abendblatt, Die Welt, Berliner Morgenpost*) and magazines (including *Der Spiegel, Stern, Bunte*).

2, we no longer assume a uniform relationship between the number of replacements and subsequent team performance, but we allow for different correlations based on the prior game result.

Furthermore, we account for unobserved time-constant differences between teams and between coaches concerning how they changed the starting lineup depending on the result of the previous match. For example, if the talent pool of a squad is very dispersed, the coach is less likely to consciously alter the starting lineup than in the situation in which he can access a lot of players with very similar talent. Coaches may also have unobserved preferences for either high or low changes of the starting lineup, which may bias our results. Table 1 illustrates the descriptive statistics and the Pearson correlation coefficients.

< Table 1 >

Table 1 reveals that the *Number of replacements of the starting lineup* correlates positively with *Last game lost* and negatively with *Last game won*. The correlation between the *Number of replacements of the starting lineup* and *Win* and *Loss* is almost zero, however. We also see that the serial correlation between the winning and losing probabilities, respectively, are very low. The highest correlations are between *Last game lost* and *last game won* and *Win* and *Loss*, as only one of them can equal 1 in a given match. As the variance inflation factors (VIFs) (not shown in the table) are well below 2 for all regressors, we are not concerned with multicollinearity.

Basic Results

In a first step, we start with some basic results. The average number of replacements of the opening team is 2.12 (n=1519) if the team lost the last game, 1.67 (n=994) if the team tied the last game, and 1.39 (n=1519) if the team won the last game. Mean comparison tests reject the null hypothesis of equal means at the one percent significance level. Figure 1 illustrates the histograms of the number of replacements of the starting lineup depending on the previous game result.

< Figure 1>

Multivariate Analysis

In the following, we proceed with a multivariate analysis in which we control for confounding influences that potentially bias the abovementioned result. As the number of replacements of the starting lineup is a nonnegative count variable with integer values from 0 to 7, we run a Poisson regression model (Winkelmann 2003). Thus, the probability that the dependent variable Y_{it} (*Number of replacements of the starting lineup*) equals the value h, conditional on the vector of explanatory variables x'_{it} is

$$f(Y_{it} = h | x'_{it}\beta) = \frac{exp(-exp(x'_{it}\beta))exp(x'_{it}\beta)^h}{h!}, h = 0, 1, 2, ..., 7.$$

As the Poisson model imposes the assumption that the mean and the variance of the distribution are equal, we performed a goodness-of-fit test. The goodness-of-fit statistic (Chi2=4016.2, p-value=0.29) does not reject the assumption that the replacements of the starting lineup are Poisson distributed. We compute White-heteroskedasticity robust

standard errors adjusted for clustering at the coach-level. In doing so, we allow for serial error-correlation within the observations of the same coach.

< Table 2>

Table 2 illustrates the regression results of the determinants of the number of replacements of the starting lineup. The estimated coefficients of a Poisson regression model have to be interpreted as elasticities. Thus, compared to the situation in which the team tied the last game, the coach increases the number of replacements by 24.3% after having lost the game and decreases turnover by 19.6% if the team succeeded in the last game. Whereas the number of injured players does not significantly increase the number of replacements of the starting lineup,[4] the associations between the number of red cards in the last two games and the number of replacements are significantly positive. The effects of the numbers of yellow cards are also positive but smaller in magnitude. The results in Table 2 also reveal that the number of replacements of the starting lineup does not significantly affect subsequent field performance. Overall, empirical evidence supports hypothesis 1.

< Table 3 >

[4] Since we have to proxy the number of injured players by press reports, measurement error may blur the relationship between injuries and the number of replacements of the starting lineup.

Table 3 illustrates the Poisson estimates of two subsamples: one containing all observations if the last game was lost and the other containing all observations if the last game was won. The results in Table 3 reveal that the number of replacements of the starting lineup is not influenced by the unexpectedness of losing the last game. The variable *Lag loss unexpected* does not exert a significant influence on the dependent variable (first column). Coaches tend to change the starting lineup regardless of whether the bad result was expected or not. The situation is different, however, if the last game was won (second column). Here we find that coaches of underdog teams that managed to succeed against a strong opponent change significantly less players of the starting lineup than coaches of a favorite team that just carried out its duty. Thus, the heuristic of "never changing a winning team" is amplified by the unexpectedness of the last game's result. Underdog winning teams more strongly reduce the starting lineup's "turnover" than favorite winning teams do. As we find no significant relationship between the number of replacements of the opening team and subsequent team performance in both conditions, systematic performance effects cannot explain the coach's opening team selection. Hypothesis 2 is partly confirmed.

5. Discussion

The norm theory of Kahneman and Miller (1986) conjectures that individuals have stronger feelings of regret and blame associated with outcomes resulting from abnormal behavior than with the same negative outcomes following conventional actions. Individuals tend to minimize anticipated regret and are therefore inclined to favor common behavior in decisions under uncertainty. Unlike the multitude of scenario-based studies, this paper tested a potential normality bias using field data. We find evidence that

the decision of a soccer coach on how many players of the starting lineup he will change between two consecutive matches largely depends on the prior game result, even when potential confounders such as the number of red and yellow cards, injuries, performance effects and unobserved team and coach heterogeneity are held constant. After a lost (won) game coaches change significantly more (less) players than after a tied game. After unexpected winnings the coaches follow the "never change a winning team" heuristic even more strongly, as they replace less players of the starting lineup than coaches of favorite teams that won the last game would do. Even though potential omitted variable bias can never be completed eliminated when using field data, we believe that the normality bias drives our clear results. The different opening team selection decisions of professional soccer coaches depending on the team's previous game result are perfectly in line with the experimental predictions of Zeelenberg et al. (2002) on regret avoidance.

Normality bias must not be confounded with other behavioral biases such as loss aversion or status quo bias. Loss aversion, which states that individuals tend to suffer more from losses than they enjoy comparable gains (Kahneman and Tversky 1984), would suggest that coaches behave in a more risk averse manner when selecting the players for the starting lineup. Thus, one could argue that coaches would reduce the number of replacements of the starting lineup, as this is likely to decrease the uncertainty about the competition team's playing strength. Loss aversion, however, cannot explain why the coach's behavior depends on the prior game result. The status quo bias describes the observation that people prefer to stick to the old (Samuelson and Zeckhauser 1988). Again, according to the status quo bias, the coaches would select the same players regardless of the prior game result.

Could social pressure explain the observed selection behavior? Garicano et al. (2005) show that referees assign substantially more injury time at the end of a soccer game when the home team is one goal behind than when it is one goal ahead. This effect is larger after the introduction of the three points rule (higher stakes) and when match attendance is large (high social pressure). The motive of social pressure is obvious: as the great majority of home team supporters want their team to win, the referee should finish the game when the home team is ahead and extend the playing time when it is behind. The authors found exactly this referee behavior in Spanish soccer. To test if social pressure serves as another explanation of our results, we tested whether match attendance moderates the relationship between the prior game result and the number of replacements of the starting lineup. The interaction terms of the match attendance figures and the prior game results are insignificant throughout, and the other estimates are not changed in any significant way.[5] Hence the intensity of the normality bias does not react to the size of the crowd, which makes the social pressure explanation implausible. In our context, the motive of social pressure is less evident than concerning injury time. Even though the crowd may have special preferences for being able to watch star players (Brandes, Franck, and Nüesch 2008), resulting social pressure on the coach's selection is unlikely to depend on the prior game result.

The idea that emotions affect decision-making is widely accepted in both psychology (Loewenstein and Lerner 2003) and economics (Elster 1998). However, most of the related empirical literature using field data concentrates on the effect of immediate emotions or visceral factors such as hunger, thirst, sexual desire or moods. Hirshleifer and

[5] The regression results are available from the authors upon request.

Shumway (2003), for example, show that investor mood variation induced by different weather conditions influences stock returns. They find that on cloudy days stock returns are lower, which cannot be explained by the fundamentals. Edmans et al. (2007) use international soccer results as a mood variable and show that a loss of the national team lowers the daily returns of the stock market in the losing country. For further economic field studies of immediate emotions affecting decisions, we refer to the review article of DellaVigna (forthcoming). This study shows that even *anticipated* emotions, in our case anticipated regret of a potentially negative outcome, is likely to affect decision-making.[6]

Even though our results are derived from a context with comparably short feedback cycles and clear output measures, the general finding that anticipated regret may bias actual decisions has implications for all kinds of principal-agent relationships. When contracting a manager, for example, the principal has to consider that the agent's utility is not only influenced by the firm's performance and individual material payoffs, but also by the way these outcomes come about. The normality bias implies that managers tend to avoid adopting unconventional strategies if it is very unclear whether the strategies will succeed. Even though management textbooks would suggest differentiating one's own products and services from those of competitors, in reality firms often follow the same management fashions and fads (Abrahamson 1996). The normality bias sheds a new light on this observation. Given the increasing uncertainty in a modern economy, managers tend to be biased towards "best practices," as this reduces the anticipated regret in the case of a negative outcome.

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[6] The idea that anticipated emotions guide individuals in their behavior is more common in the theoretical literature (see, e.g., Loomes and Sugden 1982; Kräkel 2008).

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Table 1: Variables, Descriptive Statistics, and Pearson Correlation Coefficients

	Variable	*Mean*	*SD*	1	2	3	4	5	6	7	8	9	10
1	Number of replacements of the starting lineup	1.735	1.289	1.000									
2	Last game lost	0.377		0.232	1.000								
3	Last game won	0.377		-0.206	-0.605	1.000							
4	Number of injured players	0.340	0.672	-0.025	0.011	-0.009	1.000						
5	Number of red cards last game	0.118	0.344	0.151	0.133	-0.128	-0.002	1.000					
6	Number of red cards next to last game	0.114	0.339	0.023	-0.010	0.026	-0.008	-0.020	1.000				
7	Number of red cards last game	2.051	1.255	0.065	0.075	-0.105	-0.017	0.022	-0.015	1.000			
8	Number of red cards next to last game	2.051	1.255	0.064	0.004	0.003	0.007	-0.004	0.024	0.023	1.000		
9	Win	0.375		-0.001	-0.014	0.008	-0.005	0.026	-0.015	0.010	-0.018	1.000	
10	Loss	0.375		0.013	0.007	0.013	-0.020	-0.012	0.010	-0.008	0.012	-0.601	1.000

Notes: 4032 observations (all matches, except the first match after the summer and winter break, played in the highest German soccer league during seven seasons, 1999/00 until 2004/05). The model also includes fixed effects for the team and the coach.

Table 2: Determinants of the Number of Replacements of the Starting Lineup

Variables	*Coef.*		*Std. Err.*
Last game lost	0.243	***	0.031
Last game won	-0.196	***	0.036
Number of injured players	-0.012		0.014
Number of red cards last game	0.199	***	0.023
Number of red cards next to last game	0.053	*	0.030
Number of yellow cards last game	0.016	*	0.009
Number of yellow cards next to last game	0.031	***	0.008
Win	-0.019		0.024
Loss	0.043		0.028
Team fixed effects	yes		
Coach fixed effects	yes		
Log pseudolikelihood	-6216.47		
Observations	4032		

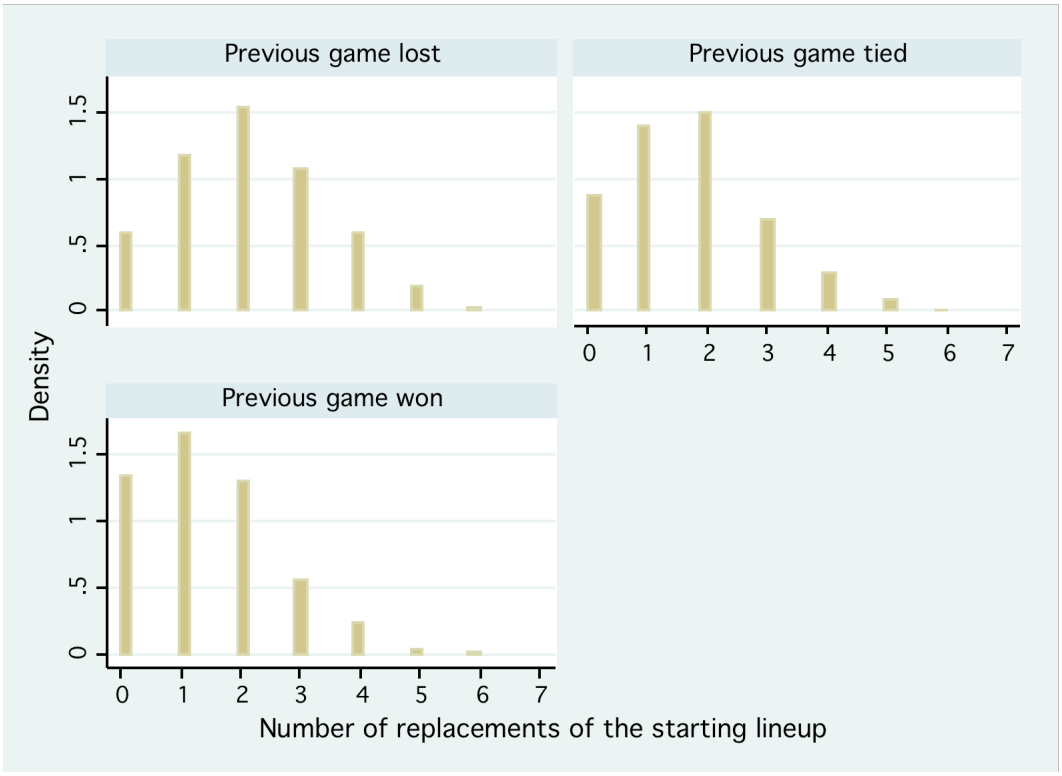
Notes: Poisson regression model. The dependent variable is the number of replacements of the starting lineup between two consecutive matches. The standard errors are White-heteroskedasticity robust adjusted for clustering at the coach-level. Significance levels (one-tailed): * 5%, ** 1%; *** 0.1%.

Table 3: How the Unexpectedness of the Prior Game Result Affects the Number of Replacements

	If last game lost			If last game won		
Variables	*Coef.*		*Std. Err.*	*Coef.*		*Std. Err.*
Lag loss unexpected	0.009		0.048			
Lag win unexpected				-0.094	***	0.026
Number of injured players	-0.002		0.027	-0.044		0.036
Number of red cards last game	0.165	***	0.031	0.322	***	0.072
Number of red cards next to last game	0.051		0.045	0.043		0.044
Number of yellow cards last game	0.019		0.013	0.036	*	0.019
Number of yellow cards next to last game	0.031	**	0.012	0.003		0.019
Win	-0.012		0.047	-0.002		0.048
Loss	0.034		0.050	0.011		0.048
Team fixed effects	yes			yes		
Coach fixed effects	yes			yes		
Log pseudolikelihood	-2479.56			-2158.56		
Observations	1519			1519		

Notes: Poisson regression model. The dependent variable is the number of replacements of the starting lineup between two consecutive matches.The standard errors are White-heteroskedasticity robust adjusted for clustering at the coach-level. Significance levels (one-tailed): * 5%, ** 1%; *** 0.1%.

Figure 1: Histogram of the Number of Replacements of the Starting Lineup Depending on the Prior Game Result



Appendix

Table 4: Data Description and Sources

Variables	Description	Source
Number of replacements of the starting lineup	Our dependent variable denotes the number of replacements of the starting lineup between two consecutive matches of a team	The dependent variable was calculated based on a hand-collected data set of over 63,000 player-match observations. The players on the starting lineup, the corresponding teams, and the match day were collected from *www.kicker.de*
Last game lost	Dummy variable, coded 1 if the team lost the last game (0 otherwise)	Game result data is from *www.fussballdaten.de*
Last game won	Dummy variable, coded 1 if the team won the last game (0 otherwise)	Game result data is from *www.fussballdaten.de*
Lag loss unexpected	Decimal odds (e.g., 2.0) offered by the bookmaker on the team's winning probability in the last game. The higher the odds, the more unexpected the event was expected to occur	The posted odds were bought from *Oddset.* We adjusted the odds by the bookmaker's margin
Lag loss expected	Decimal odds (e.g., 2.0) offered by the bookmaker on the team's losing probability in the last game. The higher the odds, the more unexpected the event was expected to occur	The posted odds were bought from *Oddset.* We adjusted the odds by the bookmaker's margin
Number of injured players	We proxy the number of injured players at a given point of time by conducting an extensive text analysis of more than 20 different German newspapers at the day of the game and two days after. We marked a player as injured if his name was mentioned less than six words away from the word "injured" (in German "verletzt") together with the full name of the club he was engaged in the corresponding season	The text analysis was conducted using the database *LexisNexis*, which contains both quality nationwide newspapers (such as *Frankfurter Allgemeine Zeitung, Süddeutsche Zeitung, Stuttgarter Zeitung, Hamburger Abendblatt, Die Welt, Berliner Morgenpost*) and magazines (including *Der Spiegel, Stern, Bunte*)
Number of red cards last game	*Number of red cards last game* is the number of red cards the players of a given team received in the last game. After receiving a red card, the player is suspended and increases thus the replacements of the starting lineup	Match-level information on yellow cards was taken from the special editions *Sportmagazin Kicker Sonderheft Finale*
Number of red cards next to last game	*Number of red cards next to last game* is the number of red cards the players of a given team received in the next to last game. As players are typically suspended for one game, this variable controls for the change in the starting lineup induced by players who are eligible again	Match-level information on yellow cards was taken from the special editions *Sportmagazin Kicker Sonderheft Finale*
Number of yellow cards last game	*Number of yellow cards last game* is the number of yellow cards the players of a given team received in the last game	Match-level information on yellow cards was taken from the special editions *Sportmagazin Kicker Sonderheft Finale*
Number of yellow cards next to last game	*Number of yellow cards next to last game* is the number of yellow cards the players of a given team received in the next to last game	Match-level information on yellow cards was taken from the special editions *Sportmagazin Kicker Sonderheft Finale*
Win	Dummy variable, coded 1 if the team wins the game (0 otherwise)	Game result data is from *www.fussballdaten.de*
Loss	Dummy variable, coded 1 if the team loses the game (0 otherwise)	Game result data is from *www.fussballdaten.de*