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Experimental Evidence on Forecaster (anti-) Herding in Sports Markets

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Experimental evidence on forecaster (anti-)herding in sports markets

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Abstract

We experimentally analyzed whether (anti-)herding behavior of forecasters in sport-betting markets is influenced by the incentive structure of the market (winner-takes-all vs. equal payment of most accurate forecasts) and by personal traits of forecasters. We found evidence of anti-herding in forecasts of the German Bundesliga. Self-reported knowledge and, more surprisingly, winner-takes-all incentives reduced anti-herding. On average, forecasts were less accurate with stronger anti-herding. Winner-takes-all incentives and self-reported knowledge improved forecasts.

Keywords: (Anti-)Herding, Sports forecasting, Experiment, Survey data

1. Introduction

In recent years, several researchers have studied forecasting efficiency in sports markets. Leitner et al. (2010), e.g., report that the bookmaker consensus model correctly predicted that the final of the UEFA European Championship in 2008 would be Spain vs. Germany. Inefficient sports-betting markets lead to enormous welfare losses: The global sports-betting and gaming group GVC (including Bwin) announces revenues of nearly 3 billion £ and a gross profit of over £ 2 billion in 2018[1]. Analyzing the Betfair betting market (revenue of £ 475.6 million £), Deutscher et al. (2017) find evidence for match-fixing in the German Bundesliga from 2010 to 2015 – a phenomenon that is more likely to occur in inefficient betting-markets.

One potential source of inefficiencies is (anti-)herding behavior of forecasters. Deschamps and Gergaud (2008) observe that French tipsters' forecasts of horse races are excessively original, exaggerated, distant from public information, and thus inefficient. They show that most tipsters try to "anti-herd". In the same vein, Spann and Skiera (2009) show that prediction markets and betting odds both strongly outperform the accuracy of tipsters' forecasts for the Bundesliga. Whereas Dixon and Pope (2004) calculate that published odds in the UK soccer betting markets are inefficient, Forrest et al. (2005) argue that experts' forecasts of English soccer games, measured by odds, are efficient over 5 years. For English and Scottish soccer matches, Forrest and Simmons (2000) report that three newspaper tipsters

[1] see GVC, 2019.

outperform the accuracy of random forecasting methods and that a consensus of the three tipsters is more precise than any single forecast.

In the general forecasting literature, there is an ongoing debate on whether evidence of clustering of forecasts around a consensus forecast indicates herding behavior or rather reflects influences like correlated information, market-wide shocks, or systematic optimism/pessimism of analysts[2]. Controlling for such influences, Bernhardt et al. (2006) find evidence of anti-herding of stock-market analysts[3]. Similarly, Pierdzioch and Rülke (2012), using the U.S. Livingston survey data, report evidence of anti-herding of stock-market forecasters. Forecaster anti-herding has also been observed for forecasts of metal prices[4], exchange-rate forecasts[5], forecasts of inflation rates[6], and business-cycle forecasts[7].

In general, evidence of forecaster herding is likely to depend on how a researcher models the information set available to a forecaster at the time a forecast is being made[8] because the information set defines the consensus forecast that may anchor a forecast. Controlling for a forecaster's information set is possible in an experimental setting.

Meub et al. (2015) conduct a lab experiment on strategic coordination in a neutral forecasting task. In their experimental design, they introduce (monetary) incentives for coordination and indeed observe herding-behavior. Meub et al. (2015) conclude that opposite incentive structures might foster anti-herding. In a large online experiment, Drehman et al. (2007) also use treatments with payoff externalities that should trigger coordination ("Network" and "Follower") on the one hand, and discoordination ("Early Bird" and "Hipster") on the other hand. In Network (Follower), subjects receive additional payment for every group member (every follower) with the same forecast. In Early Bird, subjects had to pay for every predecessor with the same forecast, and Hipster was a combination of Early Bird and Follower. Drehman et al. (2007) observe extreme herding behavior in Network, herding in Follower, and anti-herding in Early Bird and Hipster. Thus, the incentive structure of the market is highly likely to influence herding or anti-herding behavior. In our experiment, we introduce winner-takes-all incentives vs. equal payment of most accurate forecasts. According to the results of Meub et al. (2015) and Drehmen et al. (2007), winner-takes-all incentives should foster anti-herding.

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[2] see Bernhardt, Campello & Kusoati, 2006; for models of forecaster (anti-)herding, see Scharfstein & Stein, 1990; Laster, Bennet & Geoum, 1999.
[3] for earnings forcecasts of German analysts, see Naujoks, Aretz,, Kerl & Walter, 2009.
[4] see Pierdzioch, Rülke & Stadtmann, 2013.
[5] see Pierdzioch, Rülke & Stadtmann, 2012.
[6] see Pierdzioch & Rülke, 2013.
[7] see Rülke, Silgoner & Wörz, 2016.
[8] e.g., Pierdzioch, Reid & Gupta, 2016.

Our study aims to contribute to recent experimental research on forecaster (anti-) herding. In doing so, we combine methods of the general forecasting literature[9] with experimental methods[10]. This is new in both streams of the literature and important: Fildes (2015), e.g., argue that an interdisciplinary research, including an experimental approach, is needed for any decomposition of a forecast error (e.g., into psychological and organizational factors).

In our online-experiment, we found evidence of anti-herding in forecasts of the German Bundesliga. We show that the anti-herding behavior of forecasters in sport-betting markets is influenced by the incentive structure of the market and by personal traits of forecasters. These results are likely also relevant in other markets where herding or anti-herding can be observed.

2. Experiment

2.1. Procedure

The participants were recruited online via university mailing lists several weeks before the start of the 2015/2016 Bundesliga season. The list of participants consisted of students and academic staff. Participants were informed about the betting game itself, its rules and its course over the first eight matchdays of the season. They were guaranteed anonymity, given an individual ID number, and assured that the generated data would only be used for scientific purposes.

The game comprised eight match days, which were equal to the first eight matchdays of the Bundesliga. We chose the first eight matchdays because at the beginning of the season, as opposed to the end of the season, there are a lot of changes in the ranking of the teams. We sent out a notification e-mail to the participants every Wednesday morning, asking them to give their predictions by Friday noon, several hours before the start of the match day. Participants had to answer questions regarding the expected position in the ranking of all eighteen teams after the current (short-term forecasts) and after the eighth matchday (longer-term forecasts). Both questions were set up as drag-and-drop questions. All eighteen teams of the Bundesliga were displayed on the left side of the screen in random order to avoid order effects. They could be dragged over to the right side and put in the order anticipated by the participant. At the bottom of the screen, the participants were then additionally asked to state their confidence level on a scale from 0 to 100. The experiment was implemented using the free online survey SoSci Survey[11].

We implemented four different treatments during the eight matchdays. An overview is given in Table 1. Initially, we provided no additional information, neither within the

[9] see Bernhardt et al., 2006; Pierdzioch et al., 2012.

[10] see Drehmann, Oechssler & Roider, 2007; Meub, Proeger, Bizer, Spiwoks, 2015.

[11] see Leiner, 2014.

notification e-mails nor within the online experiment. On match days three to six, we provided additional information, which was available for the participants upon request, i.e., they had to actively follow a link to open the document containing the information. In this way, we were able to track what additional information our subjects used. Five different pieces of additional information were provided:

1. The average predicted Bundesliga ranking of a team on the previous matchday

2. A historical Bundesliga ranking, showing the historical average ranking of a team after the eighth matchday of the season

3. The current ranking of the Bundesliga after the previous match day

4. The ranking of the best single predictions of the previous match day

5. The overall betting game ranking of our subjects

Matchday	Add. Information	Payoff Scheme
1	No	Equal
2	No	Equal
3	Yes	Equal
4	Yes	Equal
5	Yes	Winner-takes-all
6	Yes	Winner-takes-all
7	No	Winner-takes-all
8	No	Winner-takes-all

Table 1: Treatments

We provided information on the overall game ranking and the best single bets of the previous match days because the most successful participants would benefit from a payoff at the end of the game. Participants were only paid out if they participated in every round of the betting game. After the eighth matchday, the most successful participants were given a financial payoff in the form of Amazon gift cards. The first place got € 20, the second place € 15, and the third place € 10. Additionally, the best participants of every match day were rewarded with a voucher(s) for in total € 15: For the first four match days, the amount was equally divided between the three best participants (payoff scheme: equal). For the last four match days, the payoff scheme for the best bets of the current match day was changed to winner-takes-all (, and we paid out only one participant). We calculated the participants' ranking within the betting game by loss points. Each forecaster was assigned a loss-point account based on an individual ID number. Every week, the squared deviation of the predictions from the actual positions of the Bundesliga teams in the ranking was added to the account in the form of loss points. The participant with the fewest loss points led the ranking.

2.2. Descriptive statistics

After the initial recruitment phase, 215 respondents registered for the game. In total, 148 participants started in the first week. The participation decreased over the course of the game reaching its lowest numbers in weeks six and eight (see Figure 1). Throughout the last four weeks, the number of participants remained at around 50. It should be noted that the overall participation does not correspond to those participants who played all rounds of the game. The forecasters were able to skip a week and join in later again, yet they could not receive any payoffs then. 35 participants played all eight rounds. We call them completers.

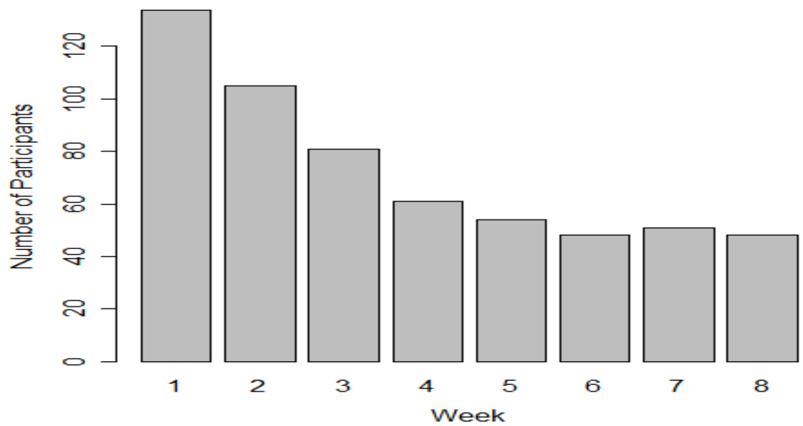


Figure 1:Participation

Table 2 presents the actual Bundesliga ranking over the first eight match days. The sorting of the table is based on the final position after the previous season plus the promoted teams from the 2nd Bundesliga on positions 17 and 18 (Column MD0). Because FC Ingolstadt 04 was playing in the 2015/2016 Bundesliga season for the first time in the Bundesliga, we could not compute the historical Bundesliga ranking for this team and excluded it from our sample for further analyses.

Team	MD 0	MD 1	MD 2	MD 3	MD 4	MD 5	MD 6	MD 7	MD 8	Mean	Median	σ
FC Bayern München	1	1	2	2	2	2	1	1	1	1.50	1.50	0.53
VfL Wolfsburg	2	5	6	3	3	3	4	4	9	4.63	4.00	2.07
Borussia M'gladbach	3	17	18	18	18	18	16	14	13	16.50	17.50	2.00
Bayer 04 Leverkusen	4	5	3	6	13	13	11	5	7	7.88	6.50	3.91
FC Augsburg	5	13	14	15	14	14	14	16	16	14.50	14.00	1.07
FC Schalke 04	6	3	4	9	5	4	3	3	3	4.25	3.50	2.05
Borussia Dortmund	7	2	1	1	1	1	2	2	2	1.50	1.50	0.53
TSG 1899 Hoffenheim	8	11	16	14	15	15	17	15	15	14.75	15.00	1.75
Eintracht Frankfurt	9	11	12	8	4	8	12	11	12	9.75	11.00	2.87
SV Werder Bremen	10	16	15	11	6	9	13	13	14	12.13	13.00	3.31
1. FSV Mainz 05	11	13	8	5	10	7	9	12	8	9.00	8.50	2.62
1. FC Köln	12	4	5	4	8	5	7	7	5	5.63	5.00	1.51
Hannover 96	13	9	12	16	16	16	18	18	17	15.25	16.00	3.15
VfB Stuttgart	14	15	17	17	17	17	15	17	18	16.63	17.00	1.06
Hertha BSC	15	7	7	10	7	11	5	6	4	7.13	7.00	2.36
Hamburger SV	16	18	10	13	12	10	6	10	11	11.25	10.50	3.41
FC Ingolstadt 04	17	7	9	7	9	6	8	8	6	7.50	7.50	1.20
SV Darmstadt 98	18	9	11	12	11	12	10	9	10	10.50	10.50	1.20

Table 2: Actual Bundesliga Ranking

Table 3 shows the median predicted ranking for all eighteen teams after the current (short-term forecasts) match day along with summary statistics. Table 4 summarizes the median predicted ranking and corresponding summary statistics for all eighteen teams after the eighth matchday (longer-term forecasts).

Team	MD 0	MD 1	MD 2	MD 3	MD 4	MD 5	MD 6	MD 7	MD 8	Mean	Median	σ
FC Bayern München	1	1	1	2	2	2	2	1	1	1.50	1.50	0.53
VfL Wolfsburg	2	3	4	5	3	3	4	4	4	3.75	4.00	0.71
Borussia M'gladbach	3	9	10	15	14	18	17	15	14	14.00	14.50	3.12
Bayer 04 Leverkusen	4	4	5	5	4	12	10	6	5	6.38	5.00	2.97
FC Augsburg	5	8	13	10	16	14	14	14	16	13.13	14.00	2.80
FC Schalke 04	6	6	3	6	7	5	3	3	2	4.38	4.00	1.85
Borussia Dortmund	7	6	2	1	1	1	1	2	3	2.13	1.50	1.73
TSG 1899 Hoffenheim	8	14	16	12	14.5	15	16	17	15	14.94	15.00	1.52
Eintracht Frankfurt	9	15	11	13	9.5	6	9	7	10	10.06	9.75	2.96
SV Werder Bremen	10	11	14	15	11	6	9	13	13	11.50	12.00	2.93
1. FSV Mainz 05	11	6	15	7	7	7	8	11	11.5	9.06	7.50	3.12
1. FC Köln	12	11	7	4	5	7	5	6	9	6.75	6.50	2.31
Hannover 96	13	9	12	15	17	16	17	18	18	15.25	16.50	3.20
VfB Stuttgart	14	9	12	15	17	17	16	15	17	14.75	15.50	2.87
Hertha BSC	15	12	7	9	10	9	12	8	6	9.13	9.00	2.17
Hamburger SV	16	18	18	12	14	11	11	8	11	12.88	11.50	3.56
FC Ingolstadt 04	17	14	10	11	8.5	10	6	9	8	9.56	9.50	2.35
SV Darmstadt 98	18	12	13	14	12	12	13	12	9	12.13	12.00	1.46

Table 3: Median Predicted Bundesliga Ranking – Short-Term Forecasts

Team	MD 0	MD 1	MD 2	MD 3	MD 4	MD 5	MD 6	MD 7	Mean	Median	σ
FC Bayern München	1	1	1	1	1	1	1	1	1.00	1.00	0.00
VfL Wolfsburg	2	3	3	4	3	3	3	4	3.29	3.00	0.49
Borussia M'gladbach	3	5	6	9	11	15	16	15	11.00	11.00	4.51
Bayer 04 Leverkusen	4	4	5	3	4	7	7	6	5.14	5.00	1.57
FC Augsburg	5	10	11	12	14	14	13.5	14	12.64	13.50	1.65
FC Schalke 04	6	6	4	4	6	4	4	3	4.43	4.00	1.13
Borussia Dortmund	7	4	2	2	2	2	2	2	2.29	2.00	0.76
TSG 1899 Hoffenheim	8	10	11	12	13	16	16	16	13.43	13.00	2.57
Eintracht Frankfurt	9	11	10	12	9	6	8	7	9.00	9.00	2.16
SV Werder Bremen	10	10	12	13	10	6.5	9	13	10.50	10.00	2.36
1. FSV Mainz 05	11	9.5	13	9	8	9	8	10	9.50	9.00	1.71
1. FC Köln	12	12	9	7	6	8	6	7	7.86	7.00	2.12
Hannover 96	13	13	14	14	17	17	17	18	15.71	17.00	1.98
VfB Stuttgart	14	12	12	12	16	16.5	16	15	14.21	15.00	2.12
Hertha BSC	15	13	10	10	11	10	12	8	10.57	10.00	1.62
Hamburger SV	16	16	17	15	15	11	11	8	13.29	15.00	3.30
FC Ingolstadt 04	17	17	13	14	12	12	9	10	12.43	12.00	2.64
SV Darmstadt 98	18	16	16	16	15	13	13.5	12	14.50	15.00	1.66

Table 4: Median Predicted Bundesliga Ranking - Longer-Term Forecasts

3. Testing for (anti-)herding

3.1. The herding statistic

We implemented a test developed by Bernhardt et al. (2006) to study whether the participants of our experiment (anti-)herd. The test measures the position of a forecast relative to the consensus forecast. We measured the consensus forecast in two ways. First, in a benchmark scenario, when we did not provide participants with any additional information on the forecasts of other participants, then we used the position of a team in the league table after the previous match day to measure the consensus forecast. This information was always in the information set of every participant, and it represents a scenario in which the best forecast of a team's future position in the league table is a team's current position. Second, when we provided additional information, and a participant inspected this information (we kept track of this), we measured the consensus forecast using the average forecast - of the position of a team in the league table after the previous match day - from all participants (made before the previous matchday).

To explain how the test works[12], we start by defining as a benchmark a situation in which a participant forms a median-unbiased private forecast of a team's position in the league table. The probability that such an unbiased forecast overshoots (undershoots) the actual position of a team in the league table after the next match day should be equal to 0.5, irrespective of the consensus forecast.[13] Similarly, the conditional probability that a forecast above (below) the consensus forecast overshoots (undershoots) a team's position in the league table after the next match day should be 0.5.

A constituent feature of herding is that a published forecast is biased towards the consensus forecast. Accordingly, if the biased published forecast exceeds the consensus forecast then the probability that the forecast overshoots a team's position in the league table after the next match day should be less than 0.5. By the same token, if the biased published forecast is less than the consensus forecast then the probability that the forecast undershoots a team's position in the league table after the next match day also should be less than 0.5. In contrast, a constituent feature of anti-herding is that participants try to differentiate their forecasts from the forecasts of others. Hence, in the case of anti-herding, the consensus forecast "repels" forecasts, and the over- and undershooting probabilities should exceed 0.5.

The herding statistic, S, proposed by Bernhardt et al. (2006), is computed as the average of the sample estimates of the overshooting and undershooting probabilities. Accordingly, the S statistic is 0.5 for unbiased forecasts, the S statistic is smaller than 0.5 in the case of forecaster herding, and the S statistic exceeds 0.5 in

[12] for a detailed description, see also Rülke et al., 2016.

[13] This is not true for teams being first or last in the league table (see next subsection).

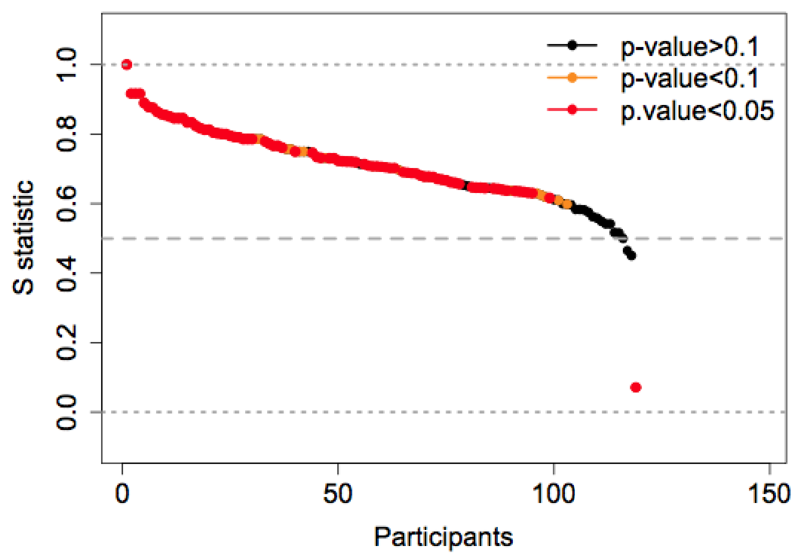
case of forecaster anti-herding. Averaging the two probabilities makes the herding statistic robust to various forms of "misspecification". For example, averaging the two probabilities implies that the statistic does not depend on whether participants target the median or the mean of a potentially asymmetric distribution over a team's position in the league table after the next match day. The herding statistic has an asymptotic normal distribution. The null hypothesis is that participants form unbiased forecasts. Hence, under the null hypothesis, we have S=0.5. Bernhardt et al. (2006) show that the variance of the herding statistic attains a maximum under the null hypothesis. In other words, the herding statistic is conservative in the sense that, under the null hypothesis, we maximize the difficulty to reject unbiasedness of forecasts.

3.2. Results

Figure 2 summarizes results for the S-statistic estimated on short-term forecasts. To compute the figure, we sorted the S-statistic from left to right in descending order. Panel A summarizes the results that we obtained when we used the position of a team in the Bundesliga league table after the previous match day to approximate the consensus forecast, irrespective of whether a participant used the average predicted Bundesliga ranking of a team on the previous matchday (match days five through eight). In this regard, it should be noted that the historical league table does not necessarily present recent team strength, though the historical league table can be interpreted as a rough summary statistic of past successes of teams and, therefore, their popularity (and perhaps also their recent financial conditions). In any way, given the limitations of the historical league table, we summarize in Panel B the results that we obtained when we used (i) the position of a team in the Bundesliga league table after the previous match day to approximate the consensus forecast when a participant did not use additional information, and, (ii), the average predicted Bundesliga ranking of a team on the previous matchday when a participant made use of this information (match days five through eight).

Two results stand out. First, there is evidence of forecaster anti-herding. While the S-statistic is significantly smaller than its benchmark value of 0.5 at conventional significance levels for only one participant in Panel A and two participants in Panel B, the majority of S-statistics is significantly larger than 0.5. Second, the curve in Panel B showing the S-statistics computed based on a consensus forecast conditional on whether a participant used additional information decreases somewhat faster than the curve in Panel A showing the S-statistics based on a consensus forecast always computed using the position of a team in the Bundesliga league table after the previous matchday. This result mirrors findings reported by Pierdzioch et al. (2016) for forecaster herding. They find that forecaster herding is strong when a forecaster's information set contains no information on the contemporaneous forecasts of others, and that evidence of forecaster herding weakens when they randomly allocate forecasters into a group of early forecasters who can only observe the past forecasts of others and late forecasters who can also observe the contemporaneous forecasters of their predecessors. Correspondingly, our results indicate that forecaster anti-herding tends to weaken when forecasters use information on the consensus forecasts on the previous matchday.

Panel A: Short-term forecasts (consensus based on the historical league table)



Panel B: Short-term forecasts (consensus based on average predicted ranking of a team on the previous matchday if a subject used this information)

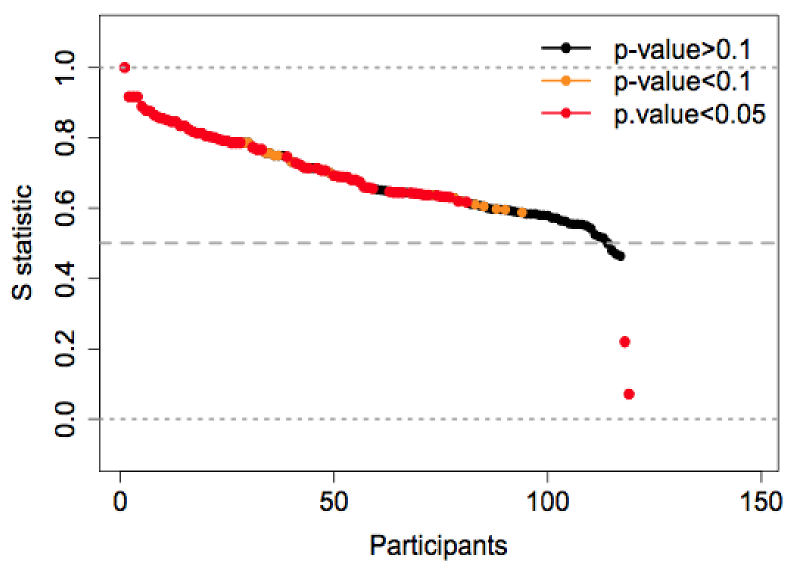


Figure 2: S-Statistic for Short-Term Forecasts

Figure 3 plots the results for longer-term forecasts. We focus on the results that we obtained when we always used the position of a team in the Bundesliga league table after the previous match day to approximate the consensus forecast. The results that we obtained when we used additional information on the average predicted Bundesliga ranking of a team on the previous matchday are similar (available upon request from the authors). The key message to take home from Figure 3 is that, as compared to the results plotted in Figure 2, the evidence of forecaster anti-herding is weaker for longer-term forecasts than for short-term forecasts. The longer-term forecasts reflect expectations of a team's position in the Bundesliga league table after eight match days. A team's position in the league table after eight match days, in turn, to some extent averages out idiosyncratic effects that may arise on individual match days and is likely to reflect to a stronger extent the "fundamental" strength or weaknesses of a team relative to the other teams in the Bundesliga. It is, therefore, not surprising that the incentive to anti-herd is weaker for longer-term than for short-term forecasts.

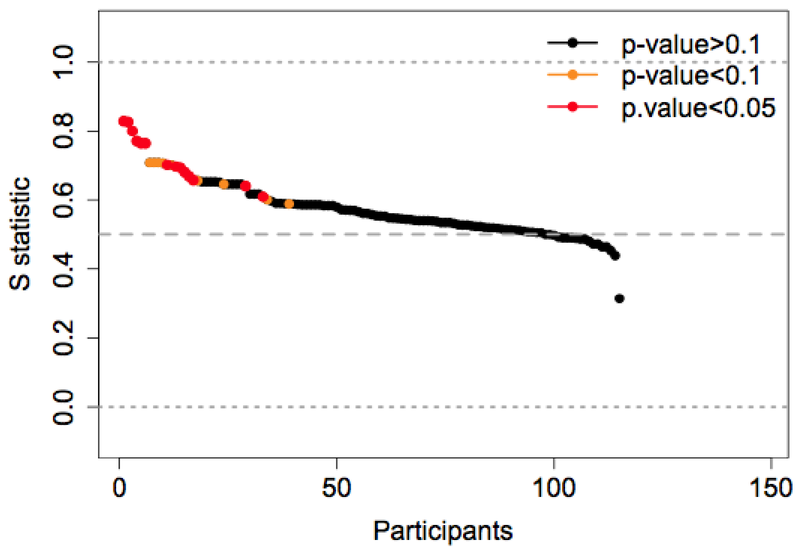


Figure 3: S-Statistics for Longer-Term Forecasts

Figure 4 shows the S-statistic for short-term forecasts for the winner-takes-all payoff scheme, where we computed the consensus forecasts taking into account whether a participant used additional information on the average predicted Bundesliga ranking of a team on the previous matchday. Because we used the winner-takes-all payoff scheme only for match days five through eight, Figure 4 depicts results for fewer participants than Figure 2 (Panel B). When comparing the figures, one should also bear in mind that the figures display the ordered S-statistics, implying that the ordering of the participants along the vertical axis is not identical across figures. Notwithstanding this, eyeballing Figure 4 and comparing it with the S-statistics plotted in Figure 2 (Panel B) shows that a winner-takes-all payoff scheme, surprisingly, tends to lessen the incentive to anti-herd.

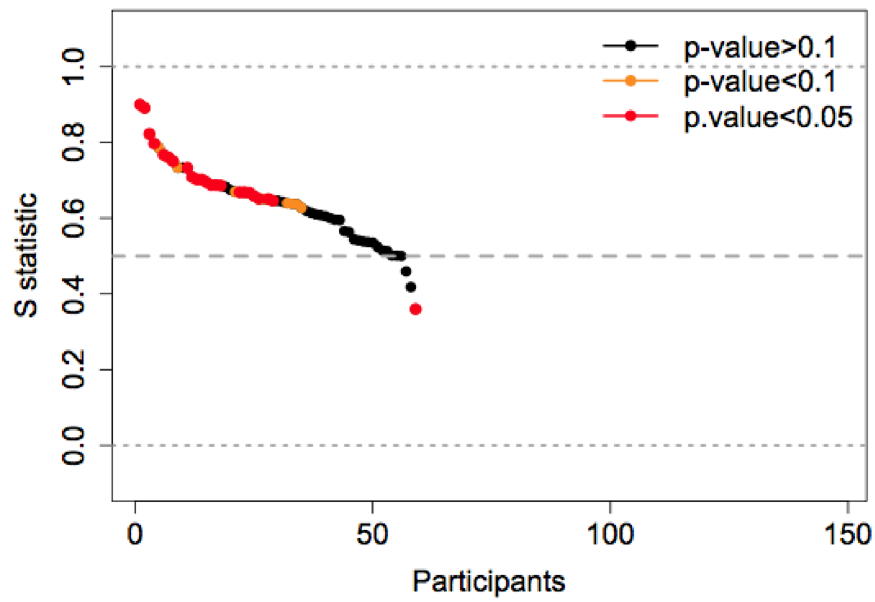
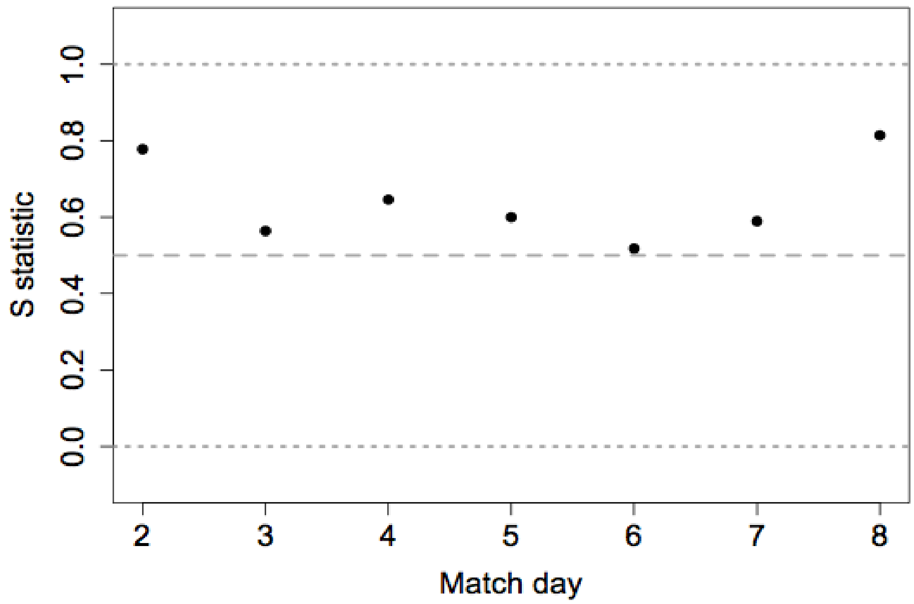


Figure 4: S-Statistic for Short-Term Forecasts (Winner-takes-all Payoff Scheme)

Figure 5 shows how the S-statistic evolves across match days, where the S-statistic was computed taking into account whether a participant used additional information on the average predicted Bundesliga ranking of a team on the previous matchday. The figure shows the average of the S-statistic across participants who submitted forecasts for a match day. As for short-term forecasts (Panel A), the S-statistic starts with a relatively large value of around 0.8. The S-statistic takes values closer to its benchmark of 0.5 at matchday three to six when participants had access to additional information. The S-statistic climbs to a higher level when we again restricted access to additional information, especially at matchday eight. For longer-term forecasts (Panel B), the S-statistic shows a tendency to decrease across match days. It starts with a value of around 0.6 on matchday two and ends at a value of around 0.4 on matchday eight. Figure 5 also illustrates a limitation of our experimental study in that treatment effects are interfered with round effects, especially for longer-term forecasts.

As a robustness check, we studied whether our results are sensitive as to whether we exclude the top teams and the teams often ranked at the lower end of the league table from our sample. For such teams, the probability that an unbiased forecast overshoots (undershoots) the actual position of a team in the league table after the next match day cannot be equal to 0.5. Specifically, we deleted FC Bayern München, Borussia Dortmund, Borussia Mönchengladbach, Hannover 96 and VfB Stuttgart from the sample. Results turned out to be qualitatively similar to the results plotted in Figures 2 to 4 (the results of the robustness check are not reported for the sake of brevity, but are available from the authors upon request).

Panel A: Short term forecasts



Panel B: Longer-term forecasts

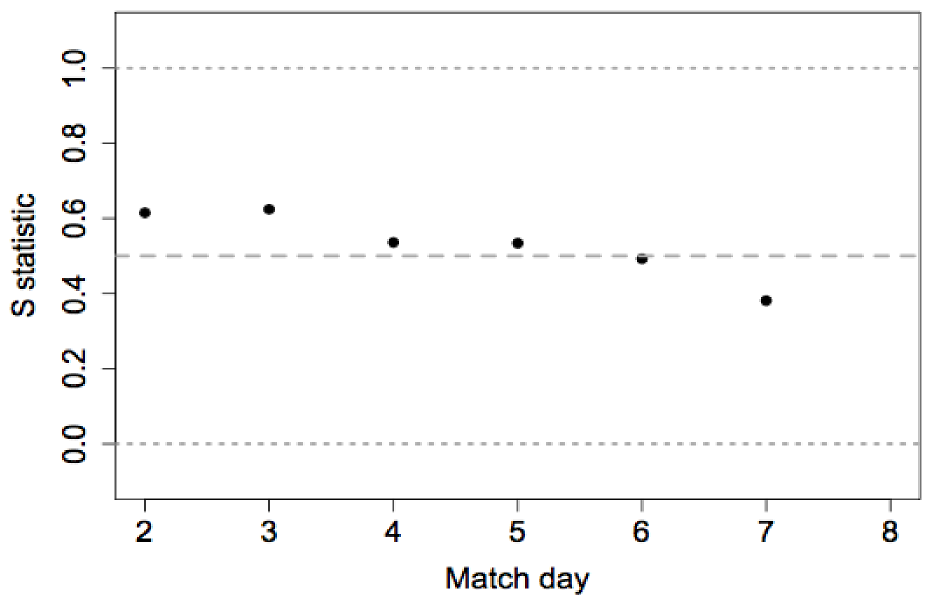


Figure 5: Evolution of the S-Statistic across Match Days

Forecast Horizon	Individual S-Statistic	Obs.	Mean	SD
Short-term forecasts	Consensus based only on historical information	445	0.67	0.18
Short-term forecasts	Consensus based on historical or additional information	448	0.66	0.18
Longer-term forecasts	Consensus based only on historical information	397	0.55	0.13
Longer-term forecasts	Consensus based on historical or additional information	391	0.56	0.13

Individual S-statistics are computed per participants and match day. Additional information = Subject used information on the average predicted Bundesliga ranking of a team on the previous matchday.

Table 5:Descriptive Statistics of Individual (Anti-)Herding Statistics

Table 5 summarizes the descriptive statistics of our individual (anti-)herding statistics computed per round. In line with the figures presented in this subsection, the average of the S-statistics is larger for short-term than for longer-term forecasters and, in the case of the short-term forecasts, when only historical information was used to proxy the consensus forecast.

4. Explaining (anti-)herding and forecast performance

To explain individual differences in anti-herding behavior, we used the individual S-values of our subjects per round and regressed them on our two treatments (info vs. no info and winner-takes-all vs. equal payment) as well as on the control variables of our survey (see Appendix). Panel A (Panel B) of Table 6 summarizes the results for short-term (longer-term) forecasts, where we focused on those variables that turned out to be significant in one or the other model. In line with the results reported in the last section, we observed on average anti-herding behavior in our experimental data. Anti-herding behavior tended to be stronger, on average, for short-term than for longer-term forecasts.

According to Models (1) and (3) in Panel A, anti-herding in short-term forecasts was reduced when we provided information and introduced the winner-takes-all rule. Furthermore, women tended to exhibit less anti-herding behavior. Self-reported knowledge of the Bundesliga also reduced anti-herding behavior. When we estimated the regression model on data for those subjects who took part in every round (completers, Models (2) and (4)), we found that knowledge of the Bundesliga was no longer able to explain (anti-)herding behavior in our experiment. A possible reason for this finding is that completers reported on average higher knowledge scores than non-completers according to a two-sided t-test (7.74 vs. 7.36, p=0.06).

The individual S-values in Models (3) and (4) take into account whether a subject used additional information on the average predicted Bundesliga ranking of a team on the previous matchday. The results for these models show that completers exhibited less anti-herding in short-term forecasts if they described themselves as being less risk-averse.

Models (5) to (8) in Panel B look at the longer-term forecasts. Again, winner-takes-all incentives reduced anti-herding. However, providing information strengthened anti-herding behavior in the case of longer-term forecasts. Model (7), which calculates the consensus taking into account whether a subject used information on the average predicted Bundesliga ranking or not, confirms that anti-herding was reduced by being female as well as by self-reported knowledge about the Bundesliga and by being less risk-averse.

Panel A: Short-Term Forecasts

	Model 1		Model 2		Model 3		Model 4	
	S-statistic (Case A)		S-statistic (Case A) (completers only)		S-statistic (Case B)		S-statistic (Case B) (completers only)	
	Coef.	t-test	Coef.	t-test	Coef.	t-test	Coef.	t-test
Info	-0.12***	-8.3	-0.13***	-6.43	-0.16***	-11.36	-0.16***	-8.19
Winner-takes-all	-0.08***	-5-53	-0.86***	-5.01	-0.05***	-3.97	-0.06***	-3.55
Female	-0.06**	-2-30	-0.24	-0.67	-0.05**	-2.36	-0.04	-1.57
Knowledge	-0.01***	-2.85	-0.01	-1.22	-0.01**	-2.58	-0.01	-1.24
Risk-taking	>-0.01	-0.61	-0.01	-1.44	-0.01	-1.28	-0.01**	-2.21
Constant	0.89***	18.14	0.89***	10.99	0.89***	18.62	0.91***	12.28
R^2	0.17		0.18		0.22		0.21	
F-test	27.25***		13.14***		43.97***		24.73***	
Obs.	445		243		448		244	

t-tests were calculated using robust standard errors clustered by subject. *: p<0.1, **: p<0.05, ***: p<0.01.
">" means that a coefficient is absolutely smaller than 0.01. Case A: consensus based on the historical league table. Case B: consensus based on the average predicted ranking of a team on the previous matchday if a subject used this information, and the historical league table otherwise.

Panel B: Longer-Term Forecasts

	Model 5		Model 6		Model 7		Model 8	
	S-statistic (Case A)		S-statistic (Case A) (completers only)		S-statistic (Case B)		S-statistic (Case B) (completers only)	
	Coef.	t-test	Coef.	t-test	Coef.	t-test	Coef.	t-test
Info	0.03***	3.23	0.04***	3.07	0.03***	2.88	0.04***	3.05
Winner-takes-all	-1.14***	-11.85	-0.14***	-8.99	-0.13***	-10.29	-0.13***	-7.84
Female	-0.03*	-1.82	-0.02	-0.99	-0.03**	-2.41	-0.03*	-1.78
Knowledge	-0.01**	-2.39	>-0.01	-0.80	-0.01**	-2.5	>-0.01	-1.00
Risk-taking	>-0.01	-1.53	-0.01	-1.20	-0.01**	-2.17	-0.01	-1.52
Constant	0.67***	19.04	0.63***	10.44	0.68***	20.41	0.65***	11.09
R^2	0.31		0.29		0.27		0.26	
F-test	40.93***		24.52***		33.27***		21.33***	
Obs.	397		210		391		204	

t-tests were calculated using robust standard errors clustered by subject. *: p<0.1, **: p<0.05, ***: p<0.01. ">" means that a coefficient is absolutely smaller than 0.01. Case A: consensus based on the historical league table. Case B: consensus based on the average predicted ranking of a team on the previous matchday if a subject used this information, and the historical league table otherwise.

Table 6: Determinants of (Anti-)Herding Behavior

Table 7 looks at the forecast performance of our subjects. Specification (1) analyzes the sum of gathered loss points in the short- and longer-term forecasts per round. Subjects' forecasts were ceteris paribus better, i.e., they obtained on average fewer loss points, in the winner-takes-all treatment and the information treatment. Moreover, subjects performed better when they were less risk-averse. Additionally, completers (2) performed better when their subjective knowledge of the Bundesliga was higher and when they were optimistic.

	Model 1		Model 2	
	Cumulated loss points		Cumulated loss points (completers only)	
	Coef.	t-test	Coef.	t-test
Info	-195.34***	-9.42	-118.10***	-5.40
Winner-takes-all	-545.05***	-25.15	-500.76***	-25.57
Optimism	-24.40	-1.35	-46.89**	-2.17
Female	-42.82	-0.96	-14.71	-0.30
Knowledge	-7.00	-0.80	-24.71**	-2.10
Risk-taking	-26.01**	-2.53	-27.27*	-1.94
Constant	1399.63***	6.05	1563.86***	5.29
R^2	0.50		0.51	
F-test	183.81***		186.98***	
Obs.	578		280	

t-tests were calculated using robust standard errors clustered by subject. *: p<0.1, **: p<0.05, ***: p<0.01.

Table 7: Determinants of Forecast Performance (Baseline Scenario Without S-Statistic)

Table 8 summarizes the results of an analysis of forecast performance that we obtained when we included the individual S-statistics per round as independent variables in the regression models. In every specification, subjects performed (on average) worse if they exhibited stronger anti-herding behavior. Controlling for the individual S-statistics, we observed that winner-takes-all incentives enhanced short-term forecast performance. The results further show that, when we controlled for additional information in the calculation of the S-statistic, the information treatment worsened short-term forecast performance (Models 3 and 4). Longer-term forecasts, however, were always better in the information and the winner-takes-all scenarios. Again, subjective knowledge as well as completers' optimism and risk-taking improved forecast performance.

Panel A: Short-Term Forecasts

	Model 1		Model 2		Model 3		Model 4	
	Short term loss points (Case A)		Short term loss points (Case A) (completers only)		Short term loss points (Case B)		Short term loss points (Case B) (completers only)	
	Coef.	t-test	Coef.	t-test	Coef.	t-test	Coef.	t-test
Info	12.17	0.97	18.73	1.35	27.42*	1.94	32.18**	2.06
Winner-takes- all	-123.62***	-7.92	-107.07***	-6.71	-127.57***	-8.73	-108.75***	-7.53
Optimism	-14.89	-1.40	-25.20**	-1.93	-15.12	-1.45	-24.96*	-1.97
Female	-22.84	-0.86	-3.47	-0.12	-22.36	-0.84	2.67	0.09
Risk-taking	-3.52	-0.76	-11.28*	-1.72	-2.50	-0.56	-9.99	-1.61
Knowledge	-15.73**	-2.61	-12.50	-1.49	-15.89***	-2.71	-12.11	-1.50
S-statistic	279.65***	4.84	208.31***	3.19	312.99***	5.60	257.01***	3.95
Constant	331.1***	3.02	442.11***	3.03	302.80***	3.06	391.40***	3.01
R^2	0.42		0.49		0.43		0.51	
F-test	50.61***		54.70***		59.24***		71.68***	
Obs.	445		243		448		244	

t-tests were calculated using robust standard errors clustered by subject. *: p<0.1, **: p<0.05, ***: p<0.01.
">" means that a coefficient is absolutely smaller than 0.01. Case A: consensus based on the historical league table. Case B: consensus based on the average predicted ranking of a team on the previous matchday if a subject used this information, and the historical league table otherwise.

To be cont.

cont.

Panel B: Longer-Term Forecasts

	Model 5		Model 6		Model 7		Model 8	
	Longer-term loss points (Case A)		Longer-term loss points (Case A) (completers only)		Longer-term loss points (Case B)		Longer-term loss points (Case B) (completers only)	
	Coef.	t-test	Coef.	t-test	Coef.	t-test	Coef.	t-test
Info	-69.80***	-6.67	-56.57***	-4.96	-68.99***	-6.64	-60.15***	-5.30
Winner-takes-all	-90.22***	-4.61	-86.95***	-4.36	-98.54***	-5.19	-87.71***	-4.73
Optimism	-9.08	-0.91	-20.58**	-2.04	-10.45	-1.02	-21.65**	-2.13
Female	-13.88	-0.52	-10.03	-0.33	-10.63	-0.40	-1.67	-0.05
Risk-taking	-3.55	-0.84	-12.55**	-2.12	-1.79	-0.41	-10.55*	-1.74
Knowledge	-12.20***	-2.46	-15.97**	-2.47	-12.36**	-2.46	-15.39**	-2.41
S-statistic	610.67***	7.04	582.78***	5.71	582.31***	7.08	599.07***	6.21
Constant	290.20***	3.28	442.80***	5.04	308.87***	3.44	426.51***	4.85
R^2	0.49		0.56		0.49		0.58	
F-test	64.68***		31.94***		72.31***		32.57***	
Obs.	397		210		391		204	

t-tests were calculated using robust standard errors clustered by subject. *: p<0.1, **: p<0.05, ***: p<0.01. ">" means that a coefficient is absolutely smaller than 0.01. Case A: consensus based on the historical league table. Case B: consensus based on the average predicted ranking of a team on the previous matchday if a subject used this information, and the historical league table otherwise.

Table 8: Determinants of Forecast Performance (Including S-Statistic)

5. Discussion and conclusion

We analyzed forecasts of the team rankings in the German Bundesliga in an experimental setting. We found evidence of anti-herding behavior for short-term forecasts. Evidence of anti-herding behavior is weaker for longer-term forecasts. Providing information on the average predicted Bundesliga ranking of a team on the previous matchday reduced (increases) anti-herding for the short-term (longer-term) forecasts. Winner-takes-all incentives reduced anti-herding for both forecasts.

On average, forecasts were less accurate the stronger the anti-herding behavior of subjects. When we controlled for (anti-)herding behavior, winner-takes-all incentives improved the quality of forecasts compared to the equal payoff scheme for both types of forecasts. Providing information improved the performance of longer-term forecasts. However, it worsened the performance of short-term forecasts when we considered whether participants clicked on the information in calculating the (anti-)herding statistic.

Although the winner-takes-all payoff (€ 15 for the single winner) does not differ much from the equal payoff treatment (€ 5 for thee bettors), we observe significant treatment effects in our experiment. Future experiments could try to vary the incentive schemes: e.g., by increasing the payoffs to make the difference between the winner-takes-all and equal payoffs larger. The within-subject design of our experiment can be seen as a limitation: Participants likely learned from round to round. Two aspects of the design of our experiment may have re-enforced this learning effect: i) successful participants in early rounds were perhaps more likely to continue the experiment to the end to get their payoffs, and, ii) forecasting in later rounds perhaps was easier than in earlier rounds because the variation of possible rankings decreased and more information became available. Thus, our treatment (and herding) effects may interfere with round effects. Future experiments could try to replicate our findings in a between-subject design.

We combined our experimental data with questionnaire data on personal traits of our subjects that we assessed before the experiment. Self-reported knowledge of the Bundesliga reduced anti-herding and was positively associated with the performance of forecasts in all specifications. Subjects who took part in every match day made better short-term forecasts if they were more optimistic, and better longer-term forecasts if they were less risk-averse.

In sum, our results show that in markets with evidence of anti-herding, forecasters who are more optimistic, less risk-averse, and who claim to know more perform better. Moreover, winner-takes-all incentives are better suited than equal payment schemes to improve the average forecast accuracy if forecasters anti-herd. In future research, further experimental evidence is needed to get an idea of whether our results can be generalized to other settings and markets. For example, football is the most popular sport in Germany. It is, therefore, interesting whether anti-herding and the treatment effects we have documented in this research can also be detected in forecasting experiments in which subjects forecast match outcomes or league rankings of less popular forms of sport like handball and volleyball. It is also interesting to study whether results similar to those we have documented can be found not only for team sports but also for individual sports. The negative correlation of anti-herding behavior and winner-takes-all incentives also deserve special attention in future research - both in experimental and in theoretical research.

Our findings have implications for the uncertainty of outcome literature[14]: We show that behavioral biases, like anti-herding, reduce the accurateness of game outcome predictions by individuals. The differences between objective and subjective forecasts of game outcomes are likely to influence the demand for sports and might explain differences between the practical relevance and the empirical findings of the uncertainty of outcome hypothesis.

[14] see Coates, Humphreys & Zhou, 2014; Pawlowski, Nalbantis & Coates, 2018.

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Appendix
Survey
Procedure and related literature

In addition to our experiment, we conducted an online survey, in which we assessed overconfidence, optimism, herding preferences, trust, risk-taking, competitiveness, experience, and knowledge (besides age and gender).

Measuring the degree of overconfidence is not easy - Michailova and Katter (2014), e.g., developed an 18-item multiple-choice quiz (out of 50 pretested items) and measured the discrepancy between the individual average of 18 stated confidence levels (from 0 to 100) minus the real percentage of right answers. Glaser et al. (2004) provided an even more comprehensive measure of overconfidence with 20 knowledge questions plus (self-)assessments as well as 15 stock market forecasts and trend forecasting with confidence intervals. In a survey of fund managers, Menkhoff et al. (2006) used three items to tackle different aspects of overconfidence: 1) Unrealistically positive self-evaluation, 2) illusion of control, and 3) miscalibration.

We translated the items studied by Menkhoff et al. (2006) in the context of our Bundesliga forecasting experiment and asked our subjects (on a scale from 0: "very much worse" to 10: "very much better") to compare their forecasting performance to other participants (1.) and to indicate (on a scale from 0: "totally agree" to 10: "totally disagree") if they agree with the statement: "The majority of Bundesliga news is not surprising for me." (2.). Furthermore, we asked for confidence intervals when forecasting the rankings of four Bundesliga teams after the 8th match day (3.)[15].

Closely linked to (over)confidence is optimism: We asked subjects for their self-assessment with a single item asking how optimistic they are in general (on a scale from 0: "not optimistic at all" to 10: "totally optimistic")[16].

To assess herding preferences, we also built on Menkhoff et al. (2006) and translated their items on herding behavior to our context. We asked (on scales from 0: "not at all" to 10: "very much") how much subjects talk to others about the Bundesliga and how much they use this information to build their opinion. Further, subjects were supposed to estimate how much they would use convenient strategies (strategies they have tried before) and how much they would use new strategies in our forecasting experiment (both in percent).

Zwiebel (1995) argues that managers who try new actions take relatively greater risks compared to other managers. There is a discussion in the experimental literature of whether trust is a risky decision[17]. At the same time, trusting others'

[15] see Deaves, Lei & Schröder, 2019.
[16] see Kemper, Kovaleva, Beierlein & Rammstedt, 2011.
[17] see Eckel & Wilson, 2004; e.g., Karlan, 2005 vs. Houser, Schunk & Winter, 2010.

opinions could be an argument for herding behavior. To evaluate whether trust and/or risk-taking influences (anti-)herding behavior, we used the scales of the German Socioeconomic Panel: The four trust items of Naef and Schupp (2009) and the single-item for general risk-taking of Dohmen et al. (2005) (on a scale from 0 to 10 to have consistent scales to our other items). Moreover, we added the domain-specific risk-taking (DOSPERT) scales of Blais and Weber (2006) for the domains "gambling" and "investment" (again from 0 to 10).

Furthermore, we integrated the competitive scale of the Flash Eurobarometer Survey on Entrepreneurship 2009 (No. 283) of the European Commission[18] asking (on a scale from 0 to 10) how much subjects like situations in which they compete with others in general and in the domains "professional life", "personal life", and "leisure and sports". High competitive preferences are associated with more risk-taking and status-seeking[19]. Therefore, high competitive preferences are likely to trigger anti-herding.

Lastly, we used questions on experience in soccer, betting games, and the Bundesliga as well as self-assessments on experience and knowledge of the Bundesliga to have further control variables for (anti-)herding. Menkhoff et al. (2006) find, e.g., that herding decreases with experience. Furthermore, we asked for the favorite teams of our subjects (if they have any) to explain possible biases in forecasting behavior.

Descriptive Statistics and Univariate Tests

Table A1 compares the averages and standard deviations of our survey results by subjects that herd (1) and anti-herd (2) with their longer-term forecasts in the specific round of our experiment taking into account if the subject clicked on the average predicted Bundesliga ranking of a team on the previous match in our herding statistic. It can be seen that even in longer-term forecasts around 66% of our forecasts (260 out of 391) tended to exhibit anti-herding. (We choose to present the descriptive results for the longer-term forecasts because in the short-term forecasts very few subjects herd.)

According to two-sided t-tests, forecasters who anti-herd performed on average worse than those who herd – they gathered on average more loss points in the short- ($p<0.01$) and in the longer-term forecasts ($p<0.01$). Furthermore, subjects who anti-herd were, in general, more competitive than subjects who herd ($p=0.043$). A Chi2 test indicates that, on average, women tended to herd and men tended to anti-herd ($p=0.023$). The other survey results do not significantly differ by (anti-)herding behavior. Yet, we found small significantly negative Pearson correlations of individual S-values (less anti-herding) with self-reported knowledge, risk-taking,

[18] see e.g. Bönte, 2015.

[19] see Koedijk, Pwnall & Statman, 2013; see Friedman & Savage, 1948, for the coccection of risk and status

and forecasting performance compared to others as well as with the degree of agreement to the statement that most Bundesliga news is not new to the subject.

Having a look at our experimental treatments, anti-herding in longer-term forecasts was more pronounced in the equal-payment scheme and not in the winner-takes-all scheme (0.59 vs 0.46, $p<0.01$). The sum of loss points for short- and longer-term forecasts was on average lower in the information condition compared to the no information condition ($p<0.01$) and in the winner-takes-all condition compared to the equal-payment scheme ($p<0.01$).

Comparing forecasts of subjects who took part in every round of our experiment (completers) to those who did not complete the whole experiment, we find that completers on average exhibited less anti-herding (in short-term forecasts on average 0.64 vs. 0.70, $p<0.01$, in longer-term forecasts 0.53 vs. 0.57, $p<0.01$) and performed better, i.e., they obtained on average less loss points (for short-term forecasts on average 225.89 vs. 351.04, $p<0.01$, for longer-term forecasts 374.65 vs. 497.83, $p<0.01$).

Variable	Herding					Anti-Herding				
Statistic	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
Loss points short-term	131	136.65	88.55	26	546	260	262.24	172.77	38	1192
Loss points longer-term	131	242.76	108.74	92	644	260	424.06	170.57	96	1430
Sum loss points	131	379.41	178.76	132	1164	260	686.30	319.98	170	2622
Confidence 1	131	40.69	27.14	1	101	260	41.57	25.59	1	101
Confidence 2	131	31.09	23.65	1	101	260	31.10	23.23	1	101
Female	131	1.27	0.44	1	2	260	1.17	0.38	1	2
Age	131	29.44	8.41	20	50	260	28.16	6.56	19	50
Optimism	131	7.60	1.69	1	10	260	7.59	1.94	1	10
Risk taking	131	6.17	1.90	2	9	260	6.27	2.06	1	11
Risk Dospert	131	6.32	1.84	1.75	10.13	260	6.07	1.82	1.63	10.13
Trust	131	6.01	1.66	2.5	9.5	260	5.92	1.58	1	9.5
Competition general	131	6.59	1.85	3	10	260	7.02	2.05	2	11
Competition professional life	131	7.78	1.71	3	11	260	7.76	1.90	2	11
Competition personal life	131	5.45	2.54	1	11	260	5.87	2.53	1	11
Competition leisure and sports	131	7.95	2.19	2	11	260	8.27	2.22	2	11
Knowledge (Bundesliga)	131	7.60	2.44	1	11	260	7.48	2.56	1	11
Experience (Bundesliga)	131	7.56	2.39	2	11	260	7.53	2.48	1	11
Played betting game before	131	0.79	0.41	0	1	260	0.81	0.39	0	1
Experience betting game	104	6.38	2.40	2	11	211	6.46	2.34	2	11
Evaluation of own performance	131	6.16	1.60	3	10	260	6.04	1.85	1	10
Bundesliga news not new for me	131	6.79	2.16	2	11	260	6.50	2.40	1	11
Talk about Bundesliga	131	7.18	2.52	1	11	260	6.97	2.71	1	11
Use of Bundesliga infos of others	131	5.68	2.35	1	10	260	5.87	2.54	1	10
Use of convenient strategies	131	61.57	23.15	0	100	260	57.34	27.21	0	100
Use of new strategies	131	31.56	18.59	0	95	260	32.28	22.50	0	100
Confidence interval	131	5.08	2.72	1.5	14.75	259	4.68	2.13	1.5	14.75

Table A1: Descriptive Statistics by (Anti-)Herding Behavior