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Going with your Gut: The (In)accuracy of Forecast Revisions in a Football Score Prediction Game*

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Abstract

This paper studies 150 individuals who each chose to forecast the outcome of 380 fixed events, namely all football matches during the 2017/18 season of the English Premier League. The focus is on whether revisions to these forecasts before the matches began improved the likelihood of predicting correct scorelines and results. Against what theory might expect, we show how these revisions tended towards significantly worse forecasting performance, suggesting that individuals should have stuck with their initial judgements, or their ‘gut instincts’. This result is robust to both differences in the average forecasting ability of individuals and the predictability of matches. We find evidence this is because revisions to the forecast number of goals scored in football matches are generally excessive, especially when these forecasts were increased rather than decreased.

Keywords: Sports forecasting, Fixed-event forecasts, Judgement revision

JEL codes: C53, C23, D84, Z2

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1 Introduction

Sports fans get pleasure from successfully judging the outcomes of events in advance, in addition to possibly earning financial rewards if they choose to back these judgements at a betting exchange. For the most prominent and prestigious events, this is evidenced by the ready supply of expert opinion in the media beforehand, which must be meeting a demand for insight on what is about to take place.

In this paper, we analyse the judgement forecasts of 150 individuals who chose to play an online football score prediction game for all 380 matches in the 2017/18 season of the English Premier League (EPL), unquestionably the most watched domestic sports league in the world. The forecasts were of exact score outcomes, for example Manchester United to draw 1-1 playing at home against Liverpool. We also observe if, how and when the game players revised these forecasts before each match began. This allows us to ask an important question, the answer of which could apply to wider economic and social contexts: when forecasting the outcome of fixed events based primarily on judgement alone, do revisions or updates improve those forecasts? Or in other words, should individuals stick with their gut instincts? This is a question that has been addressed before in the laboratory (e.g. [O'Connor et al., 1993, 2000](#); [Lim and O'Connor, 1995](#)). It has also been addressed in the field in the context of company sales forecasting ([Lawrence and O'Connor, 2000](#)). But, to the best of our knowledge, it has never been addressed in a context where large numbers of individuals voluntarily choose to make purely judgement-based forecasts and revisions (or not) at a time of their own choosing for many fixed events.

A reasonable working hypothesis would be that revising football scoreline forecasts as the match kick-off approaches should lead to improved forecast accuracy. There are numerous sources of information which become available to the forecaster over time and which are relevant to football match outcomes: not least betting odds (e.g. [Forrest et al., 2005](#)), other tipsters (e.g. [Forrest and Simmons, 2000](#); [Spann and Skiera, 2009](#)) and the so-called 'wisdom of crowds' (e.g. [Brown et al., 2018](#); [Brown and Reade, 2018](#); [Peeters, 2018](#)). Furthermore, there are pre-match shocks which can significantly affect a team's abilities, like an injury to the star goalscorer.¹ However, there are also plausible reasons why revisions to judgement forecasts can lead to worse accuracy. First, there is evidence of bias among forecasts of football match results, such as the 'favourite-longshot' bias (e.g. [Cain et al., 2000](#); [Deschamps and Gergaud, 2007](#) and 'wishful-thinking' ([Massey et al., 2011](#)).² It is unknown and an outstanding empirical question, which we do

¹Perhaps the most infamous example in recent sporting history occurred just 72 minutes before the 1998 World Cup final. The leading goalscorer in the tournament, Ronaldo, was inexplicably omitted from the starting lineup of Brazil. He was eventually reinstated and started the match, but was clearly not fully fit. Brazil went on to lose the match.

²Favourite-longshot bias is the tendency to observe in betting markets insufficient money backing the favourites to win, and too much backing the long-shots. Wishful-thinking bias refers to individuals

not shed any direct light on here, whether these biases weigh more heavily on initial judgement forecasts or subsequent revisions. Second, individuals may anchor on their previous forecast when making a revision, such that revisions are just white noise in the absence of relevant news (Clements, 1997). Third, the forecasting responses to salient new information can be excessive (Kahneman and Tversky, 1973; Tversky and Kahneman, 1974), overshooting and potentially even worsening the forecast, even if they are in the right direction towards the eventual outcome (De Bondt and Thaler, 1985, 1990; O'Connor et al., 1993; Lawrence and O'Connor, 2000).

We consider three main measures of forecast accuracy for football match scorelines: the percentage of correct scores and results, and the score achieved in the predictor game. Each game player revises at least one match forecast during the season and overall 6.3% of the 57,000 forecasts are ever revised, with two-thirds of these only being done so once. Against all three measures, the overall forecast performance is worse in cases when the players ever revised their judgements compared with never. 9.2% of final scoreline forecasts actually happened, compared with 7.7% when that scoreline forecast had been revised at least once. In these cases that were revised, the initial forecasts would have gotten 9.2% of scores correct. Therefore, there is descriptive evidence suggesting that the game players would have been better off sticking with their first judgements rather than ever revising. We also use regression analysis and the panel structure of the data to confirm this result is robust, controlling for the time when forecasts and revisions are made relative to the events taking place, unobserved player forecasting ability and the predictability of each match. We find that scoreline forecasts that were revised had around 80% as great a likelihood of predicting a correct scoreline compared with those that weren't revised, and the players would have done better had they stuck with their original judgements. When match results were revised as well as scorelines, players were only 60-80% as likely to predict a correct result compared with cases where no revisions were made. We also look at the goals scored forecast errors made by the players. There is significant evidence that positive revisions (decreasing the number of goals scored by teams) are generally in the right direction and improve on these errors. However, negative revisions lead to significantly greater forecast errors.

Beyond that already mentioned, this paper contributes to the wider literature on judgemental forecasting (see for a summary Lawrence et al., 2006). In particular, it provides further evidence that new judgements may not improve on old ones when forecasters make revisions for fixed events. However, here the context is forecasting discrete and relatively low probability outcomes, as opposed to the continuous company sales forecasts or macroeconomic time series previously studied. This paper also adds to the growing list of studies which have used crowd-based data to analyse forecasting

backing the team to win with whom they have the greater affinity. Massey et al. (2011) looked at this in the context of a different brand of football: the US National Football League.

behaviour. Unlike the studies of [Brown et al. \(2018\)](#) and [Peeters \(2018\)](#), the members of the crowd we study are themselves directly making forecasts.

Finally, this paper relates to the literature on using sports to study the practice of forecasting (see for a summary [Stekler et al., 2010](#)). One novelty here for football is that the game players, or tipsters, are forecasting exact scorelines. Several studies have developed statistical models to predict scorelines, though they have only tended to evaluate these models in terms of then forecasting match results (e.g. [Dixon and Coles, 1997](#); [Karlis and Ntzoufras, 2003](#); [Goddard, 2005](#); [Koopman and Lit, 2015](#); [Boshnakov et al., 2017](#)). However, no studies have yet looked at how successful individuals are at forecasting these relatively low probability and countably infinite variations on the outcomes of football matches.

The rest of the paper proceeds as follows: Section 2 describes the Superbru Premier League Predictor Game and the sample of player forecasts which we analyse; Section 3 measures the forecast accuracy in the game; Section 4 looks at how making revisions relates to subsequent forecast accuracy; Section 5 asks whether players' revisions are excessive; and Section 6 summarises.

2 Data

2.1 The Superbru Premier League Predictor Game

Superbru is an online platform for sports-based predictor and fantasy games. It is trademarked and managed by a South Africa based company, Sport Engage Ltd, who use the platform for marketing purposes. Across all the games on the platform there are over 1.5 million registered users, who each play one or more of the games. These cover multiple sports, including cricket, rugby union, cycling, golf, motorsports and American football, among others. This paper focuses on the English Premier League Predictor Game. As of September 2019, there were 89,000 players of this game. Despite focusing on English football, the players are global, with just over a sixth based in the United Kingdom.³

The game is simple. In advance of each EPL fixture the player submits his forecast for the outcome of the match. There are 380 matches in a season between August and May of consecutive years. The forecasts are in the form of scorelines, for example 2-1, where the first number refers to the number of goals forecast to be scored by the team playing at home (their own stadium), and the second refers to the goals forecast for the opposition, who are playing away from home. There are 20 teams in the EPL, and each team plays all the others twice, home and away. All games end in regular time and there

³Statistics obtained from www.superbru.com.

are three possible result outcomes: a home win, an away win or a draw. The aim of the game is to accumulate points through accurate forecasts of scorelines and results. Each forecast is awarded one of four possible amounts of points:

- 0 points: result is incorrect
- 1 point: result is correct
- 1.5 points: result is correct and forecast has a ‘closeness’ score ≤ 1.5 (see below)
- 3 points: scoreline is correct (and implies that result is correct too).

A forecast is determined to be close to the actual outcome of a match using Superbru’s own metric of ‘closeness’, given by:

$$closeness_{ij} = |gd_j - \widetilde{gd}_{ij}| + \frac{|gs_j - \widetilde{gs}_{ij}|}{2}, \quad (1)$$

where i denotes a game player and j denotes a match. gd_j refers to the goal difference outcome of the match, measured as the home minus the away goals scored, and gs_j refers to the actual outcome sum of goals scored by both teams. The equivalent accented terms refer to the values implied by player i ’s forecast. In practice, a player will earn 1.5 closeness points if they forecast the correct result and the predicted scoreline has one goal more or less for one or both teams than the actual outcome of the match.

Players of the predictor game have several possible incentives to make accurate forecasts. First, there is a game leaderboard for each season. After each round of matches (typically 10), a player receives their global and nation rankings, both for that particular round and for the season as a whole up to that point. These are expressed in absolute terms and as percentiles. The player can also earn eighteen different badges, corresponding to achievements in the game, such as for accuracy, streaks of correct results or scores and achieving a globally high rank at any point. Players can also organise themselves into their own pools or leagues, perhaps competing against friends and family. Finally, there are cash prizes on offer for the number of correct scores achieved in a round.⁴

In practice, playing the game works as follows. Users access their game accounts and are immediately asked for forecasts of the upcoming round of EPL fixtures. Each match forecast is keyed in numerically and saved automatically after both the home and away goals are inputted. A user does not have to provide predictions on all the fixtures in a round. They can also make forecasts from the present day right up to the end of the season, for all future fixtures. No information is revealed to a player about what other players have forecast for a match unless they ‘lock’ their prediction. Locking a prediction prevents a player from further revising it, but they are then given information on the distribution of other players’ predictions over possible scorelines for that match. If a

⁴The number of correct scoreline forecasts in a round, out of 10, earns the following prizes: 6, a Premier League jersey (cash value £50+); 7, £500; 8, £1,000; 9, £10,000; 10, £50,000.

prediction is not locked, then it can be revised at any point up to the start of the match. After each round, players are sent an email update on their forecast accuracy, their game scores and relative rankings. Email reminders are also sent a couple of days before each round of matches, reminding players to make forecasts. The online game is available on PC and as an app for mobile devices. From our own experience, the process of making new forecasts for each round of fixtures is relatively costless, taking no more than a minute on a mobile phone, perhaps after being prompted by a reminder email. Revising those forecasts is similarly not time intensive. We presume that the game players are not using statistical modelling to make forecasts and are generally applying their best judgements, affected by whatever personal biases they might have.

2.2 A sample of game players

The administrators of the online prediction game provided us with all the forecasts made during the 2017/18 season by 150 players. These players were randomly sampled from the population of Superbru users who ‘completed’ the game, i.e who made forecasts for all 380 Premier League matches that season. We can distinguish the order in which players made multiple forecasts (revisions) for any particular match. To the nearest minute we observe the time at which each forecast was made. The 150 players are otherwise completely anonymous, and we have no information, for example, on team affiliations (which EPL club they are a fan of), ages or nationalities.

Table 1 shows some descriptive statistics for the sample of 57,000 final match forecasts in the sample, as well as for the actual outcomes of the 380 matches during the EPL 2017/18 season. For home goals scored forecasts, the players are more conservative than reality, though the average actual number of away goals scored reflects their forecasts closely. Overall, the mean total number of goals forecast to be scored by both teams in a match is 2.58, 0.1 goals lower than what occurred. The final forecast number of goals shows less variation across matches than in the outcomes. Looking at the frequency of scoreline forecasts, the game players tend to predict lower-scoring matches with one exception: only 1.5% of forecasts were for no goals in a game, compared with 8.4% of matches ending this way. This difference also accounts for why the game players forecast fewer draws, 18.9%, compared with among outcomes, 26.1%. Taking account of this under-prediction of draws, there does not seem to be any clear bias in the forecasts for the team playing at home to win as opposed to the away team. The average time between the final scoreline forecast and the kick-off of a match is 81 hours, and the median is 55 hours. Some forecasts were made weeks or even months before the match took place.⁵ In general, the game players are not waiting until right before kick-off to make

⁵We do not have data on when players were sent email summaries of their forecasting performance or reminders to make forecasts. From playing the game ourselves, reminders are sent around 2-3 days ahead of a round of fixtures (e.g. on a Wednesday or Thursday for matches on a Saturday to Monday), which is consistent with the timing patterns we observe.

their forecasts. This would frequently lead them to ignore what could be considered important information relating to match outcomes, such as which of a team’s footballers are available for selection (typically announced 48-72 hours before a match) or even which footballers will take to the field (typically announced less than 1 hour before kick-off).

TABLE 1: Sample descriptive statistics

	Final predictions					Actual outcomes				
	Mean	Med.	Min.	Max.	St. dev.	Mean	Med.	Min.	Max.	St. dev.
Home goals	1.42	1	0	9	0.96	1.53	1	0	7	1.34
Away goals	1.15	1	0	6	0.97	1.15	1	0	6	1.18
Match goals	2.58	3	0	11	1.09	2.68	3	0	9	1.66
Hours to k-off	81.4	55.3	-0.0	3677	151.5					
<i>Result (%)</i> :										
Home win			48.17					45.33		
Away win			32.94					28.42		
Draw			18.90					26.05		
<i>Scores (%)</i> :										
0-0			1.5					8.4		
1-0			10.1					11.6		
2-0			10.7					7.1		
0-1			5.1					6.1		
0-2			6.0					3.9		
1-1			13.8					11.8		
2-1			15.1					8.4		
1-2			12.7					6.3		
other			25.0					36.3		
Players - n					150					
Matches - m					380					
Total - N					57,000					

Notes: author calculations using a sample of Superbru user data from 2017/18.

2.3 Forecast revisions in the game

Game players can revise their forecasts as many times as they like and at any point before a match kicks off. We define these goals revisions by:

$$r_{ijk} = f'_{ijk} - f_{ijk}, \quad (2)$$

where $k \in \{h, a\}$ denotes whether the revision is made to the home or away goals scored. f_{ijk} denotes the new forecast following a revision and f'_{ijk} refers to some previous forecast. The vast majority of scoreline predictions by the players are never revised. Before describing this relatively small number of revisions, first we consider the possibility that some observed revisions are simply mistakes (palpable errors or ‘typos’) made when players submit their forecasts. Appendix Table A1 shows the extent of all

home and away goals revisions made in the sample between first and final scoreline predictions. There is suggestive evidence that some revisions are just players correcting their mistakes. For example, of the 3,781 forecasts ever revised, 31 revisions are by players decreasing the away goals scored forecast by 8 goals. As you can see from Table 1, the away team never actually scored 8 goals during the season, neither did any player predict they would score 8 with their final forecast. This compares with only single instances where players decreased their away goals forecasts by 7 and 9 goals. This would be consistent with mistakes made when submitting forecasts on the Superbru platform from a mobile device using the ITU E 1.161 layout for a numbers keypad (i.e. with the 8 key above the 0). If in some cases players are correcting palpable forecast errors rather than making true revisions, and we are unable to distinguish these from one another, then we would anticipate estimating an improvement in forecast accuracy following an observed revision which is biased upwards. To partially address this, we arbitrarily label as ‘mistakes’ any scoreline revisions which involved the forecast number of home or away goals being revised by more than two goals, in either direction. This relabels 199 forecast cases as never having been revised. Tables 2-4 describe the remaining 3,582 forecasts which were revised.

Table 2 presents statistics on the frequency of revisions over game players and matches. Every player makes at least one revision during the season. The average number of forecasts revised by players is 25, with the median number being 15 (4%). Conditional on revising the scoreline, players might also revise the result. A player did this on average 12 times during the season. We could expect that some matches are less likely to have forecasts revised than others. This could be due to the timing of a match kick-off or any especially pertinent new information, for example an injury during the warm-up to one team’s goalkeeper or primary goal scorer. There is some variation across matches in the extent to which scorelines and results are revised, with a standard deviation of 3 forecasts for both. We know when revisions were made. Typically, the time between the final and first forecast is around a minute. However, the mean time between is almost two days, accounted for by a small number of players who revised their predictions after a long period of time. The average home goals revision and the average away goals revision are a decrease of 0.15 and 0.13, respectively. As shown by Table 3, the clear majority (86%) of forecasts which are revised only involve the player revising either the home or away goals, with a slightly greater tendency to revise the away goals, and a tendency to make more conservative final forecasts. Table 4 also reflects this, showing if and how results were revised, with revisions tending more towards a win by the away side than the home. There is also evidence that players’ first scoreline forecasts tend to favour draws more than after they are revised.

TABLE 2: Forecast revision descriptive statistics

	Mean	Med.	Min.	Max.	St. dev.
<i>Number of forecasts revised per player:</i>					
Score	23.86	15	1	215	28.73
Result	11.80	7	0	113	14.21
<i>Number of forecasts revised per match:</i>					
Score	9.43	9	2	22	3.37
Result	4.67	4	0	15	3.41
Hours between final and first forecast	45.97	0.02	0	1699	157.66
Home goals revision - r_{ijh}	-0.15	0	-2	2	0.84
Away goals revision - r_{ija}	-0.13	0	-2	2	0.91
<i>Total number of forecasts revised:</i>					
Score	3,582 (6.31%)				
Result	1,722 (3.12%)				

Notes: author calculations using a sample of Superbru user data from 2017/18.

TABLE 3: Goals revisions, $> |2|$ excluded: first forecast minus final

		Away - r_{ija}					Total
		-2	-1	0	1	2	
Home - r_{ijh}	-2	9	22	70	16	3	120
	-1	19	229	748	143	15	1,154
	0	108	797	N/A	542	59	1,651
	1	23	120	446	146	7	742
	2	9	10	28	8	5	60
	Total	168	1,178	1,437	855	89	3,582

Notes: author calculations using a sample of Superbru user data from 2017/18. See Appendix Table A1 for all user revisions.

TABLE 4: Updated result forecasts following goals revisions

		Away	Updated Draw	Home	Total
Original	Away	670	306	121	1,097
	Draw	370	127	451	948
	Home	177	347	1,013	1,537
	Total	1,217	780	1,585	3,582

Notes: author calculations using a sample of Superbru user data from 2017/18. Follows from Table 3 in so far as any score revisions by $> |2|$ away or home goals are excluded from the sample of forecast updates.

3 Forecast accuracy in the game

We consider four measures of forecast accuracy. Assuming that the players are playing the game to win and achieve a high ranking, we use the number of points awarded to each forecast in the game, which we simply refer to as the ‘Superbru’ measure. Related, we measure the ‘closeness’ of forecasts, as defined by Equation (1), and where a lower score implies a more accurate forecast. We also look at the percentage of correct scoreline and result forecasts.

The first row of Table 5 gives the forecast accuracy for all 57,000 final predictions in the sample of game players. The average Superbru score and closeness was 0.79 and 2.24, respectively. Over the whole season, the best player accumulated 350.5 points, whereas the worst player gained just 208. The median season score was 300.75, with a standard deviation of 19.5 points. Some matches were more ‘predictable’ than others.⁶ There were matches during the season when not a single player forecast the correct scoreline or result. Similarly, there were matches where every player forecast the correct result. Just less than half of the 57,000 forecasts were in line with the actual match result. 9.16% of scorelines were correctly forecast by the players, with the best player achieving 13.42% correct picks, and the worst 5.52%.

TABLE 5: Final forecast accuracy

	Correct (%)		Superbru	
	Score	Result	Game score [†]	Closeness [‡]
Overall/Mean ($N = 57,000$)	9.16	49.55	0.79	2.24
<i>Players ($n = 150$):</i>				
Median	9.21	49.87	300.75	2.23
Min.	5.52	35.53	208	2.00
Max.	13.42	55.00	350.5	2.66
St. dev.	1.56	2.65	19.52	0.12
<i>Matches ($m = 380$):</i>				
Median	4.67	41.67	112.50	1.96
Min.	0.00	0.00	0.00	0.82
Max.	43.33	100.00	318.50	6.32
St. dev.	10.47	34.65	81.48	1.04

[†] Statistics for the the cumulative game score over matches for players and for the cumulative game score over players for matches. The Game score metric is described in Section 2.

[‡] Statistics for the mean value of closeness for players throughout the season and for the mean value of closeness for matches over all players. Closeness for each forecast defined as per equation (1).

Notes: author calculations using a sample of Superbru user data from 2017/18.

⁶Superbru provide players with a measure of ‘predictability’ for matches in their performance summaries after each round.

3.1 Forecast revisions and accuracy

Table 6 summarises the forecast accuracy in the game depending on whether predictions were revised. For comparison, the first row repeats the overall accuracy for final forecasts. The second row looks at the accuracy when either the match scoreline or result forecast were never revised by the player. The accuracy is marginally higher than overall across all four measures considered. The third row of Table 6 describes the accuracy of final forecasts when they had at some point been previously revised by the game players. In these cases, 7.7% of correct scoreline forecasts were made, compared with 9.3% for forecasts which were never revised. Similarly, when results are revised, game players tended to have less forecasting success, and thus the Superbru game scores were also on average lower. However, the fourth row shows that players' first forecasts, i.e. before revision, would have on average achieved the correct score more often than their final forecasts: over 9% correct and at approximately the same rate as forecasts which were never revised. Around a third of the match forecasts where scores were revised saw multiple changes. Therefore, we also look at the accuracy of the forecasts most recent to the final ones, still finding that over 9% of these scoreline picks would have been correct if players had stuck with their earlier judgements. In contrast, in the 1,722 cases where the result forecast was ever revised, corresponding to larger goals revisions, the previous forecasts of players were on average no more accurate than their final forecasts.⁷

TABLE 6: Revisions and forecast accuracy

	Correct (%)		Superbru (Mean)	
	Score	Result	Game score	Closeness
1. All final forecasts (57,000)	9.16	49.55	0.79	2.24
2. Final forecast, never revised (53,418/55,228) [†]	9.26	49.96	0.80	2.24
3. Final forecast, revised (3,582/1,772) [†]	7.71	36.63	0.74	2.28
4. First forecast (3,582/1,772) [†]	9.21	35.16	0.76	2.29
5. Previous to final forecast (3,582/1,772) [†]	9.02	35.21	0.76	2.32

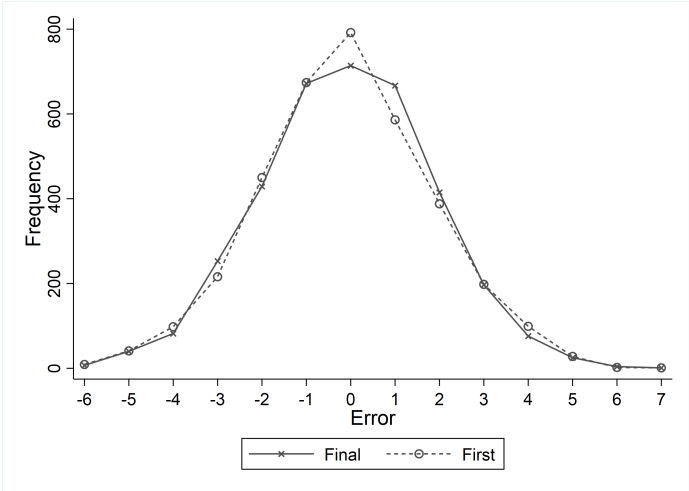
[†] The first and second numbers in parentheses give the number of score and result picks (never) revised, respectively.

Notes: see Table 5, author calculations using a sample of Superbru user data from 2017/18.

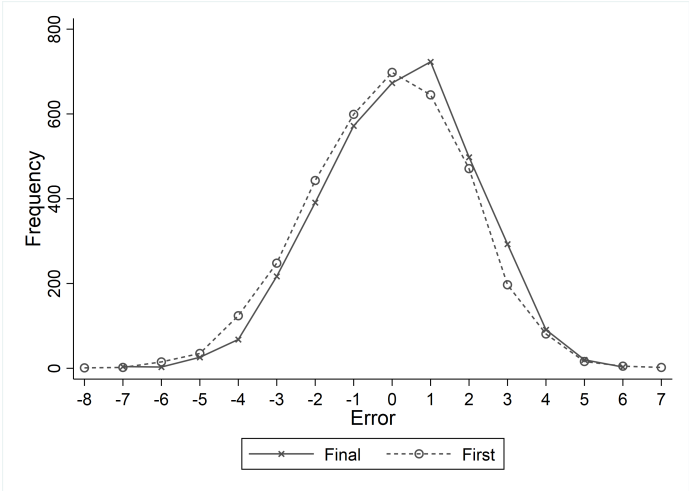
⁷The statistics in Table 6 excluded 'mistakes' from the set of revisions, i.e. scorelines where the home or away goals forecast were revised by more than 2 goals by a player. However, we find qualitatively similar results when we include these other 199 observations. For the percentage of correct scores, for example, we find the following, where the number in parentheses refers to the equivalent row in Table 6: (2), 9.26%; (3), 7.72%; (4), 9.21%; (5), 8.72%.

FIGURE 1: Distributions of final and first forecast errors: scoreline predictions which were ever revised only

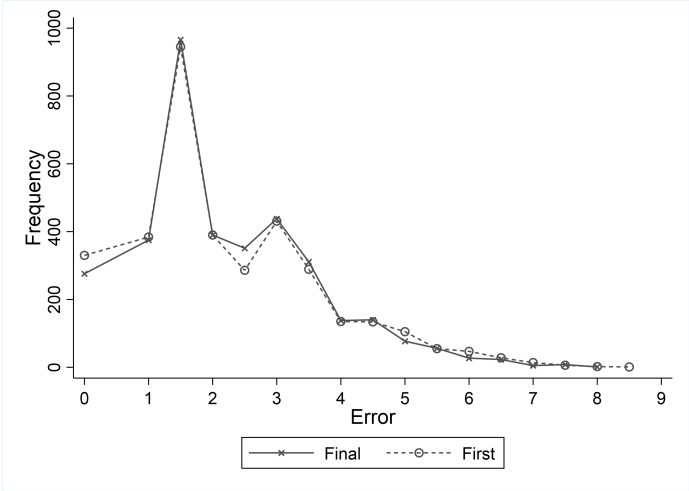
(A) Goal difference (Home minus Away goals)



(B) Total goals scored in a match



(C) Closeness - Equation (1)



Notes.- author calculations using Superbru user data from 2017/18. Goal difference and goals scored forecast errors are computed by subtracting the actual match outcome from the player’s forecast. “Final” refers to the final forecasts ever revised by players. “First” refers to the first forecasts in those cases. Follows from Table 3 in so far as any score revisions by $> |2|$ away or home goals are excluded from the sample of forecast updates displayed here.

Figure 1 plots the magnitude of errors made by players in cases where their forecasts were revised, comparing their final and first predictions. Figure 1A looks at the goal difference in matches. It shows that the number of cases when players achieved the correct goal difference was greater for their first forecasts. Similarly, Figure 1B shows that players generally increased the level of their forecast errors after making revisions, and that the first forecast was marginally more likely to predict the number of goals scored in a match correctly than the final forecast. Finally, Figure 1C plots the distribution of player closeness scores achieved as per Equation (1). This is in effect a weighted average of the forecast errors displayed in A and B, and a closeness score of zero corresponds to a correct scoreline forecast.

The statistics presented so far on forecast accuracy are certainly not causal evidence that when game players revise their judgements they perform worse. They are not even sufficient to descriptively suggest this is the case. First, it is plausible that the players who revise their forecasts more often are also those who tend to be weaker forecasters. Second, as described before, it is a fact that some matches are more difficult to predict than others. If players are more likely to revise their forecasts when matches are difficult to predict, then this could account for why revisions are associated with lower accuracy, as opposed to it mattering whether a forecast was revised at all. Third, there is substantial variation in this sample in terms of how long before the events the players made and revised their forecasts. These temporal differences could explain forecast accuracy and be correlated with whether a pick is revised. We address these issues in the next section.

4 Should players revise their forecasts?

To address whether a game player revising their forecasts is associated with lower accuracy, we estimate a series of regression models, exploiting the panel nature of our sample. For correct score and result forecasts, since the outcome is binary, we estimate logistic regression models. In general, let the outcome of player's i 's final forecast for game j be given by y_{ij} , where in the case of exact scores or results this takes a value of 1 if the forecast was correct and 0 otherwise. We look at logistic regression models of the following general form:

$$y_{ij}^* = \text{revised}_{ij}\lambda + \mathbf{x}'_{ij}\boldsymbol{\beta} + \rho_{L(ij)} + \alpha_i + \mu_j + \epsilon_{ij}, \quad \epsilon_{ij} \sim \text{Logistic}(0, 1), \quad (3)$$

where

$$y_{ij} = \begin{cases} 1; \text{ correct} & \text{if } y_{ij}^* > 0 \\ 0; \text{ incorrect} & \text{otherwise.} \end{cases}$$

In this equation, revised_{ij} takes a value of 1 if the forecast was ever revised, with associated coefficient λ . The vector \mathbf{x}_{ij} contains possible controls, which vary across

players and matches, and β is a vector of coefficients. The set of covariates we can include in \mathbf{x}_{ij} is limited to information derived from the time when forecasts were made. $\rho_{L(ij)}$ gives a set of round fixed effects, where $l = L(ij) = 1, 2, \dots, 38$ and $L(ij)$ is a function indicating that player i made a forecast of match j taking place in round l of the EPL season. Individual player fixed effects are given by α_i . These control for the possibility that some players have higher forecasting ability than others. They also take care of other relevant omitted player-level fixed covariates, such as nationality, age, team affiliation, a player's average tendency to make forecasts a particular amount of time before matches kick-off, and the average extent to which they are a player who ever makes revisions. Similarly, match fixed effects are given by μ_j , which address the characteristics of matches which are common to all players making forecasts, such as the time and date of kick-off, which teams are taking part, the extent to which it was a difficult match to predict the outcome of, and whether players were on average more likely to revise their forecasts. Finally, ϵ_{ij} gives the error term, which is assumed to be logistically distributed. We cannot simultaneously estimate all the coefficients and effects in (3) as it is written above, since the round and match fixed effects would not be identified. Instead, we estimate variations of this regression model via maximum likelihood with player or match cluster robust standard errors.

4.1 Results

Correct score

Table 7 shows our main regression estimates on whether players forecast correct scores with their final predictions. This is based on the full sample of 150 game players, since each makes at least one scoreline revision (Table 2). The results are presented as odds ratios. Column (I) shows the estimates of a standard logistic model based on Equation (3), where the player and match fixed effects are excluded and left in the error term. Covariates are included in the model for the number of days between the final forecast and kick-off, and this value squared.⁸ However, these are not significant, suggesting that when a player makes their final scoreline forecast does not affect the likelihood of it turning out correct. Also included are round fixed effects, which are not displayed but are generally significant, and the number of days between the final forecast and the previous, i.e. the time taken to make a revision. This latter variable does have some significant but very small effect on decreasing forecast accuracy through the longer players take to revise. The main results are given by the first row of Table 7, showing that players are only 83% as likely to forecast a correct scoreline after making revisions relative to when they make no revisions, with this effect being statistically significant at the 1% level. However, this is just a baseline result, consistent with the descriptive results

⁸This is a quasi-continuous variable, since we know to the nearest minute when games kicked-off and forecasts were made.

of sample forecast accuracy described above in Section 3, since we have not yet addressed any unobserved player or match heterogeneity relevant to the accuracy of these forecasts. Without taking these into consideration, there could be plausible omitted variable bias affecting this result.

TABLE 7: Logistic regression estimates for correct score, final forecasts: effects of having revised score (odds ratios)

	(I)	(II)	(III)	(IV)
Revised	0.832***	0.812***	0.802***	0.971
(+1) Days to kick-off	0.998			
(+1) Days to ... squared	1.000			
(+1) Days taken to revise	0.991*	0.989*		
Round fixed effects	Yes	Yes	No	Yes
Player fixed effects	No	Yes	No	Yes
Match fixed effects	No	No	Yes	No
N	57,000	57,000	45,150	57,000

***,**, * indicate significance from one at 1%, 5% and 10% levels, respectively, two-sided tests. Cluster-robust standard errors estimated, with (150) clusters at the player level, except for (III), where (301) clusters are at the match level.

Notes: author calculations using a sample of Superbru user data from 2017/18.

Column (II) of Table 7 extends the model described by Column (I), adding player fixed effects. It is well known that standard logistic regression estimates of models with fixed effects are inconsistent (Chamberlain, 1980). Even though the number of matches forecast within each group (by each player) is relatively large, 380, we nonetheless use conditional likelihood estimation, or what is now generally referred to as just fixed-effects logistic regression. In this model we retain the round effect and time between forecasts covariates but drop those for the time between the final forecast and match kick-off. The estimated negative and significant effect on scoreline accuracy of revising a forecast is then of a similar magnitude, with players 81% as likely to make a correct forecast if they had ever revised it compared with never. However, this result is much stronger than before as it is within player, i.e. it is robust to the possibility that worse forecasters revise more often. In Column (III), we drop the player and round effects and estimate the model with match fixed effects. There were 79 matches during the season with no outcome variation because no player forecast the correct score, and so 11,850 observations are excluded from the estimation. In this case, we also find that revising a forecast is associated with around an 80% likelihood of predicting a correct score relative to revising it. This suggests that the lower predictability of some matches, which may tend towards more revisions being made, is not driving the fact that in these data forecasters perform worse when they do revise than when they don't.

However, none of the above is evidence that the players should not have revised their forecasts. We construct a counterfactual outcome variable to investigate this. Instead of y_{ij} referring to the forecasting outcome of a player's final prediction, we instead look at the forecasting outcome of their first prediction. Column (IV) estimates the equivalent fixed effects logistic model as in Column (II), except that the dependent variable is whether or not the first scoreline forecast made by a player turned out to be correct. The estimated odds ratio relating to whether that forecast was subsequently revised is insignificantly different from 1, implying that the scoreline accuracy of a player's first pick is unrelated to whether it was revised. In other words, players were just as good forecasters with their first judgements independent of whether they subsequently made any revisions. This compares with the finding that player final forecast performance was significantly worse if revisions were made. Taken together, this suggests that players would have performed better if they had stuck with their initial judgements or gut instincts about match scorelines.⁹

Correct result

We also estimate the equivalent regression models for correct result forecast outcomes as for correct scores above. As well as the dependent variable, these models differ in that the *revised_{ij}* now concerns whether the result was ever revised by the player, not just the scoreline. Appendix Table A3 presents these model estimates for 146 of the game players; 4 players made no results revisions throughout the season. We also find for results that revising forecasts is associated with significantly worse accuracy. Without controlling for player or match fixed effects, revisions lead to final forecasts being 59% as likely to be correct (Column I). Conditional on individual players' forecasting abilities, this figure falls marginally to 58% (Column II). However, once we address the possibility that for some matches the result is less predictable than for others, we find that revising forecasts is associated with 83% as much a chance of getting a correct result than without ever having revised them (Column III). This demonstrates how unobserved and relevant heterogeneity in the events being forecast could have led us to overestimate the negative effects of making result revisions through omitted variable bias. We also look at whether the accuracy of a player's first result forecast is related to whether they then subsequently made a revision. Unlike for scoreline forecasts, we find this is significantly the case (Column IV). When it comes to the correct result, game players are just as well off revising their result forecasts than if they don't. This suggests that the optimal strategy for players could be to decide what they think is the most likely result, revise this until they are happy with it, and then forecast the exact scoreline conditional on that result, sticking then with this judgement. However, there is insufficient data here on how individuals play the game to explore this assertion further.

⁹For robustness, Table A2 presents comparable results to Table 7, where the additional 199 cases in which home or away goals scored forecasts were revised by more than 2 goals are re-classified as revisions rather than 'mistakes'. The results are approximately unaffected.

Superbru game score

Finally, we estimate a set of linear regression models, comparable to the logistic ones described above, where the dependent variable is the number of points a final forecast is awarded according to the Superbru EPL Predictor Game. In this case, the variable of interest, $revised_{ij}$, measures whether a scoreline forecast was revised. Appendix Table A3 presents the results. Not controlling for player or match heterogeneity, revising a forecast is associated with achieving a 0.04 points significantly lower game score (Column I). Conditional on the individual players, this effect remains significant and the magnitude of the effect increases to 0.05 points (Column II). The negative effect remains significant also within matches (Column III). Like the accuracy of result forecasts, the counterfactual game score achieved by players' first forecasts, before any possible revisions, is also negatively related to whether that forecast was subsequently revised.

5 Are goals forecast revisions excessive?

To understand our findings from the previous section, we investigate how the magnitude of the goals revisions made by game players relates to their forecast errors. One potential explanation for the fact that revisions in this context do not appear to improve accuracy is that they could in some sense be excessive. This has been found to be the case in laboratory experiments (e.g. O'Connor et al., 1993; Lim and O'Connor, 1995) and in the field among company sales forecasters (Lawrence and O'Connor, 2000). To test whether this is the case here, we estimate variations on the the following model using least squares:

$$e_{ijk} = r_{ijk}\gamma + r_{ij-k}\psi + \mathbf{x}'_{ij}\boldsymbol{\beta} + \rho_{L(ij)} + \alpha_i + \mu_j + \varepsilon_{ijk}, \quad (4)$$

where the dependent variable e_{ijk} is the forecast error made by player i in match j for home or away goals, denoted by k . These errors are computed by subtracting a player's forecast number of goals scored in a match from the actual number scored in the match outcome. The number of goals revised by is r_{ijk} , as defined by (2). We might anticipate some correlation of the revision made to home (away) goals and the away (home) goals forecast error and revisions, and so we also include this in the model, given by r_{ij-k} . As before in the logistic regression models described by Equation (3), we also allow for other covariates in \mathbf{x}_{ij} , round effects and player or match fixed effects. Conditional on the other variables in the model besides r_{ijk} , the coefficient of interest is γ . Note that we can re-write (4) as:

$$e_{ijk} = g e'_{ijk} + z_{ijk},$$

where e'_{ijk} is the error implied by the forecast before revision, $g = \frac{-\gamma}{1-\gamma}$, and $z_{ijk} = \frac{-\gamma}{1-\gamma}(r_{ij-k}\psi + \mathbf{x}'_{ij}\boldsymbol{\beta} + \rho_{L(ij)} + \alpha_i + \mu_j + \varepsilon_{ijk})$ gives some part of the forecast errors accounted for by other factors or randomness. Therefore, if $\gamma \geq 1/2$, then $|g| \geq 1$, and the revised forecasts are on average worse. If $\gamma < 0$, then $0 < g < 1$, and revisions are generally in

the right direction and improve the forecasts. However, if $0 < \gamma < 1/2$, then $-1 < g < 0$ and the revisions are on average in the right direction and improve forecasts, but are excessive, overshooting and reversing the sign of the eventual forecast errors.

We also look at whether the effects on final forecast errors are symmetric, in practice estimating variations on the following model:

$$e_{ijk} = \{\mathbf{1}_{r_{ijk}>0}\}r_{ijk}\gamma_p + \{\mathbf{1}_{r_{ijk}<0}\}r_{ijk}\gamma_n + r_{ij-k}\psi + \mathbf{x}'_{ij}\boldsymbol{\beta} + \rho_{L(ij)} + \alpha_i + \mu_j + \varepsilon_{ijk}, \quad (5)$$

where γ_p and γ_n now measure the effects of positive and negative revisions, respectively.

5.1 Results

Since the majority of forecasts which are revised are only done so once, we initially regress final forecast errors on the goals revisions since the first forecast of a match. We do so for the 2,076 and 2,290 cases where players made at least a one goal home or away scoreline revision, respectively, i.e. there are no zero values included for the goals revisions in r_{ijk} . Column (I) of Table 8 reports estimates of Equation (4) separately for home and away goals errors, with player fixed effects, but initially omitting the other goals revisions, r_{ij-k} , and the match fixed effects. The first row reports the estimates of γ in each case. The table reports the results of testing whether the coefficient estimate is significantly different from 0 or 1/2. The results do suggest that players' goals revisions are excessive, with values of γ being 0.48 and 0.40 for home and away goals revisions, respectively. Both values are clearly significantly different from zero, but only the away goals coefficient estimate is significantly different from 1/2 at standard levels. From these estimates, we find that goals revisions do in fact reduce the magnitude of errors in the home and away goals forecasts. This is not necessarily inconsistent with our previous finding for correct scores in Section 4, that players would be better off sticking with their first forecasts rather than revising them, since this previous finding was based on a binary outcome and not concerned with the magnitude of the errors being made.

Column (II) of Table 8 reports further results from estimating Equation (5), allowing the effects for positive (revising down) and negative (revising up) goals revisions to differ. We find that γ_p is positive but not significantly different from zero at standard levels of significance, indicating that when players revise down the goals scored by teams this generally improves their forecasts and these revisions are not excessive. However, we find that γ_n is significantly greater than 1/2, indicating that revising up the number of goals scored by teams leads to worse forecasts. Column (III) adds r_{ij-k} to the model but these other goals revisions are insignificant. Column (IV) estimates the model with match fixed effects instead of player and round effects. Qualitatively the result is unchanged; on average home and away positive goals revisions are in the correct

direction, tending to improve the forecast, whereas negative revisions lead to greater forecast errors.

Some players make multiple revisions. But the results on excessive goals revisions described above were based only on payers' first forecasts relative to their last for any given event. Therefore, we also estimate the exact same regression models as before, but now let r_{ijk} and r_{ij-k} refer to the goals revisions between a player's final scoreline forecast and their previous one for each match. The results are shown in Appendix Table A5. Qualitatively, the effects of home and away goals forecast revisions made between the final and previous forecast are the same as for revisions made between the final and first forecasts. On average, positive goals revisions reduce the magnitude of errors but are still generally excessive. However, the overshooting of the actual outcome scoreline is less than for the first forecast, for both home and away goals, conditional on the player or the match concerned. When players increase their goals scored forecasts, making less conservative judgements, the magnitude of forecast errors are generally increased.

6 Summary and further discussion

In this paper, we have analysed the forecasting performance of individuals who each applied their judgement to predict the outcomes of many fixed events. The context of this analysis was the scoreline outcomes of professional football matches. We found that when individuals made revisions their likelihood of predicting a correct scoreline, which they achieved around 9% of the time when never making a revision, significantly decreased. The same applied for forecast revisions to the result outcomes of matches. Not only were these findings robust to unobserved individual forecasting ability and the predictability of events, but also there is evidence that performance would have improved had initial judgements been followed.

As already mentioned, these results have some similarities with those found previously in the behavioural forecasting literature. One explanation could be that game players anchor their beliefs, expectations and consequently their forecasts on past or initial values. However, this behaviour would not be consistent with our finding here that on average forecasters made revisions which not only improved on their errors but were also excessive.

There are several areas for further research, which could be explored with extensions of the dataset used here. First, it appears to be a relatively open question as to how sources of bias among sports forecasters interact with how they make revisions, such as the well-known favourite-longshot bias. Second, players of the forecasting game studied here do reveal which EPL team they have the greatest affinity for, though we are yet to observe this information ourselves. It is an interesting question as to whether any wishful-thinking by the players manifests itself more greatly before or after they

revise their forecasts. Third, an aspect which could be studied from these current data is whether players improve their forecasts over time, and if they learn how to play more to the rules of the game itself, which should lead them to favour more conservative goals forecasts. Finally, our results here suggested one innovation to the game which could improve the crowd's forecasting accuracy and which could be easily tested. Before making forecasts, some of the game players could be prompted with information to the effect that sticking with their initial judgements or gut instincts is likely to improve their performance.

TABLE 8: Linear regression estimates for home or away goals scored forecast errors, final prediction: effects of goals revisions

	(I)		(II)		(III)		(III)	
	Home	Away	Home	Away	Home	Away	Home	Away
Revisions ($\widehat{\gamma}$)	0.48***	0.40***†††						
Revisions, +ve ($\widehat{\gamma}_p$)			0.20 [†]	0.15 ^{†††}	0.20 [†]	0.15 ^{†††}	0.38***†	0.14***†††
Revisions, -ve ($\widehat{\gamma}_n$)			0.74***†	0.63***†	0.74***†	0.64***†	0.55***	0.68***†
Days to kick-off	0.0168	-0.0229*	0.0156	-0.0226*	0.0156	-0.0228*	0.0066	-0.122*
Days to ... squared	-0.0001	0.0004**	-0.0000	0.0004**	-0.0000	0.0004**	-0.0002**	0.0002
Days taken to revise	-0.0228*	-0.0162	-0.0209	-0.0136	-0.0209	-0.0127	-0.0307***	-0.0060
Days taken ... squared	0.0005***	0.0002	0.0004***	0.0002	0.0005***	0.0001	0.0005***	0.0001
Revision, other ($\widehat{\psi}$)					-0.002	0.042	0.025	0.041*
Round fixed effects		Yes	Yes	Yes	Yes	Yes	No	No
Player fixed effects		Yes	Yes	Yes	Yes	Yes	No	No
Match fixed effects		No	No	No	No	No	Yes	Yes
N	2,076	2,290	2,076	2,290	2,076	2,290	2,076	2,290

***, **, * indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Cluster-robust standard errors estimated, with (140/148) clusters at the player level, except for (III), where (379) clusters are at the match level.

For "Revision", †, ††, ††† indicate significance from one half at 1%, 5% and 10% levels, respectively, two-sided tests.

Notes: author calculations using a sample of Superbru user data from 2017/18.

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Appendix A. Additional tables

TABLE A1: Goals revisions, “mistakes” included: first forecast minus final

		Away goals revision - r_{ija}														Total
		-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	
Home goals revision - r_{ijh}	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
	3	0	0	2	1	7	0	1	1	0	0	0	0	0	0	12
	2	0	0	9	22	70	16	3	2	0	0	0	0	1	0	123
	1	0	4	19	229	748	143	15	2	1	0	0	0	0	0	1,161
	0	2	11	108	797	N/A	542	59	67	6	4	3	1	29	1	1,630
	1	0	3	23	120	446	146	7	3	0	0	0	0	1	0	749
	2	0	0	9	10	28	8	5	1	0	0	0	0	0	0	61
	3	1	1	0	0	18	0	2	1	0	0	0	0	0	0	23
	4	0	0	0	2	3	0	0	0	1	0	0	0	0	0	6
	6	0	0	0	1	2	0	0	0	0	0	0	0	0	0	3
7	0	0	0	0	2	1	0	0	0	0	0	0	0	0	3	
8	0	0	1	3	4	0	0	0	0	0	0	0	0	0	8	
9	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	
Total		3	19	171	1,185	1,329	857	92	77	8	4	3	1	31	1	3,781

Notes: author calculations using a sample of Superbru user data from 2017/18.

TABLE A2: Logistic regression estimates for correct score, final forecasts: effects of having revised score (odds ratios) — all revisions including ‘mistakes’

	(I)	(II)	(III)	(IV)
Revised	0.822***	0.800***	0.802***	0.912
(+1) Days to kick-off	0.998			
(+1) Days to ... squared	1.000			
(+1) Days taken to revise	0.998			
Round fixed effects	Yes	Yes	No	Yes
Player fixed effects	No	Yes	No	Yes
Match fixed effects	No	No	Yes	No
N	57,000	57,000	45,150	57,000

***,**, * indicate significance from one at 1%, 5% and 10% levels, respectively, two-sided tests. Cluster-robust standard errors estimated, with (150) clusters at the player level, except for (III), where (301) clusters are at the match level.

Notes: author calculations using a sample of Superbru user data from 2017/18.

TABLE A3: Logistic regression estimates for correct result, final forecasts: effects of having revised result (odds ratios)

	(I)	(II)	(III)	(IV)
Revised	0.592***	0.577***	0.831**	0.529***
(+1) Days to kick-off	1.000			
(+1) Days to ... squared	1.000			
(+1) Days taken to revise	0.770***	0.825**	0.411***	
Round fixed effects	Yes	Yes	No	Yes
User fixed effects	No	Yes	No	Yes
Match fixed effects	No	No	Yes	No
N	55,480	55,480	50,550	55,480

***,**,* indicate significance from one at 1%, 5% and 10% levels, respectively, two-sided tests. Cluster-robust standard errors estimated, with (146) clusters at the user level, except for (III), where (337) clusters are at the match level.

Notes: author calculations using a sample of Superbru user data from 2017/18.

TABLE A4: Linear regression estimates for Superbru match score: effects of having revised score

	(I)	(II)	(III)	(IV)
Revised	-0.0428***	-0.0487***	-0.0353**	-0.0392**
(+1) Days to kick-off	-0.0002	0.0029**	-0.0015	0.0029***
(+1) Days to ... squared	0.000002	-0.00002**	0.00001	-0.00002***
(+1) Days taken to revise	-0.0051***	-0.0035***	-0.0065***	
Round fixed effects	Yes	Yes	No	Yes
Player fixed effects	No	Yes	No	Yes
Match fixed effects	No	No	Yes	No
N	57,000	57,000	57,000	57,000

***,**,* indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Cluster-robust standard errors estimated, with (150) clusters at the player level, except for (III), where (380) clusters are at the match level.

Notes: author calculations using a sample of Superbru user data from 2017/18.

TABLE A5: Linear regression estimates for home or away goals scored forecast errors, final pick: effects of revisions - since last forecast only

	(I)		(II)		(III)		(III)	
	Home	Away	Home	Away	Home	Away	Home	Away
Revisions ($\widehat{\gamma}$)	0.44***†	0.35***†††						
Revisions, +ve ($\widehat{\gamma}_p$)			0.25	0.07†††	0.25	0.07†††	0.35***	0.03†††
Revisions, -ve ($\widehat{\gamma}_n$)			0.62***	0.70***†††	0.62***	0.70***†††	0.53***	0.77***†††
Days to kick-off	0.0182	-0.0207*	0.0170	-0.0208*	0.0164	-0.0208*	-0.0028	-0.101*
Days to ... squared	-0.0001	0.0003*	-0.0001	0.0003*	-0.0001	0.0003*	-0.0001	0.0001
Days taken to revise	-0.0076	-0.0201	-0.0073	-0.0158	-0.0076	-0.0158	-0.0386***	-0.0094
Days taken ... squared	0.0001	0.0002	0.0001	0.0001	0.0001	0.0002	0.0005***	0.0001
Revision, other ($\widehat{\psi}$)					0.67**	-0.042	-0.01	0.45***
Round fixed effects		Yes	Yes	Yes	Yes	Yes	No	No
Player fixed effects		Yes	Yes	Yes	Yes	Yes	No	No
Match fixed effects		No	No	No	No	No	Yes	Yes
N	1,492	2,093		2,076	2,290	2,290	2,076	2,290

***, **, * indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Cluster-robust standard errors estimated, with (131/148) clusters at the player level, except for (III), where (380) clusters are at the match level.

For "Revision", †, ††, ††† indicate significance from one half at 1%, 5% and 10% levels, respectively, two-sided tests.

Notes: author calculations using a sample of Superbru user data from 2017/18.