UCL Journal of Economics

Article (Explore Econ Popular Vote)

Score! What is it Good for? Why Football Managers Need to Look Beyond Results

Iain Simmons[1]

[1] Student (BSc Economics with a Placement Year, 2019-23), Dept. of Economics, UCL, UK; iain.simmons.19@ucl.ac.uk

Submission Date: 26th April 2023; Acceptance Date: 7th June 2023; Publication Date: 2nd October 2023

How to cite
Simmons, I. (2023). Score! What is it Good for? Why Football Managers Need to Look Beyond Results. UCL Journal of Economics, vol. 2, pp. 12-17. DOI: https://doi.org/10.14324/111.444.2755-0877.1691

Peer review
This article has been peer-reviewed through the journal's standard double-blind peer review, where both the reviewers and authors are anonymised during review

Open access
UCL Journal of Economics is a peer-reviewed open-access journal

---

Abstract

Outcome bias is a pervasive phenomenon in decision-making, referring to the tendency to evaluate decisions made under identical circumstances as more favourable when it results in the desired outcome. This paper analyses this cognitive bias in the context of top-flight European football, examining whether a Bayesian updating model distorted by a multiplicative outcome bias is valid. Managers make significantly more changes to their strategy following a loss than a win, even having controlled for expected performance, in-game performance, and team and game-specific variation. The results of this paper are consistent with a positive-outcome bias, but not necessarily a multiplicative bias.

Keywords: Outcome Bias, Strategy Selection, Behavioural Economics, Cognitive Biases

A Discontinuity Analysis of Outcome Bias in Strategy Selection

Economic agents regularly participate in repeated scenarios (games) that require them to update their beliefs and evaluate their strategies to achieve the best outcomes possible. Following each instance of a game, agents review their strategy selection, assimilating all new information to evaluate if their decision was optimal (Holmstrom, 1979), and if the state of the game has changed. In situations where principals delegate tasks to their subordinates without perfect observation of their actions (principal-agent problems), principals must also update their beliefs on how agents will act, as well as their capabilities. These evaluations motivate principals to persevere with their strategy or adjust to a new optimal choice.

For these evaluations to consistently improve strategies and outcomes, they must be Bayesian, complete and unbiased. Behavioural studies repeatedly find violations of these assumptions, with individuals struggling with quantitative probability problems (Tversky and Kahneman, 1974a), bounded rationality limiting the number of factors that can be considered (Chetty et al., 2009), and heuristics leading to systematic biases in decision-making (Tversky & Kahneman, 1974b).

Whilst outcomes often provide information regarding the correctness of a decision (Hershey & Baron, 1992), individuals tend to evaluate decisions made under identical circumstances as better when the outcome is more favourable (Baron and Hershey, 1988). If individuals repeatedly make suboptimal evaluations, they will make worse decisions in subsequent games, leading to worse outcomes and significant welfare losses. Whilst in everyday situations marginally worse outcomes may be inconveniencing, incorrect assessments of policy and investment decisions can have generational negative impacts at a large cost to taxpayers and shareholders.

Current studies on outcome bias find principals overweight outcomes when rating their agent’s decision-making and are unwilling to avoid the bias (Brownback and Kuhn, 2019; König-Kersting et al., 2021) originated in laboratory environments with inexperienced actors completing unfamiliar tasks; a stark contrast to policymakers and business leaders, undermining their findings. Sports provide unprecedented access to elite and well- resourced actors, with well-defined contracts making managers in European football particularly well- incentivised to maximise the probability of winning matches instead of maximising profits (Sloane, 1969; Késenne, 2006; Garcia-del Barrio & Szymanski, 2009). This setting allows for a highly generalisable analysis of the outcome bias, with its finding of a significant outcome bias in managers’ strategy adjustments suggesting that the outcome bias is pervasive and likely present in most settings.

Within sports-economics, Lefgren et al. (2015) propose a Bayesian updating model, which focuses on the updating process following a basketball match. Within this setting, they must determine if their strategy selection was optimal ex-ante (state A), having a mean of h or if it was second best (state B), having a mean of l. In both states variance ($\sigma 2$) is constant. Having observed a performance (P) the coach assesses if their initial assumption that they were in state A (with probability $p \geq 0.5$) was correct or if they should adjust their beliefs. There is also an additional probability that the state of the world changes ($\delta \in [0 , 0.5]$).

https://doi.org/10.14324/111.444.2755-0877.1691

The performance is assumed to be normally distributed, and the probability of P is as below.

$$Pr(P|A) = \frac{e^{-\left(\frac{1}{2\sigma^2}\right)(P-h)^2}}{\sqrt{2h} * \sigma}$$

$$Pr(P|B) = \frac{e^{-\left(\frac{1}{2\sigma^2}\right)(P-l)^2}}{\sqrt{2h} * \sigma}$$

Using this new information, the manager updates their belief to a posterior belief $\hat{p} = \delta - \frac{p(1-2\delta)}{p+(1-p)e^{-\left(\frac{1}{2\sigma^2}\right)(h-l)(h+l-2p)}}$. If $\hat{p}$ < 0.5, the manager no longer believes they are in state A, and changes strategies. (Note a team can lose and not see the posterior belief fall below $\hat{p}$=0.5).

The authors then incorporate a multiplicate outcome bias, suggesting a coach overweighs the likelihood of the outcome occurring by a factor ϒ≥1 (ϒ=1 being the unbiased state). This alters their posterior beliefs to $\hat{p} = \delta - \frac{p(1-2\delta)}{p\gamma+(1-p)e^{-\left(\frac{1}{2\sigma^2}\right)(h-l)(h+l-2p)}}$ in wins (P>0)

and the belief $\hat{p} = \delta - \frac{p(1-2\delta)}{p\gamma+(1-p)e^{-\left(\frac{1}{2\sigma^2}\right)(h-l)(h+l-2p)}}$ in losses.

This model yields 4 key predictions:

Firstly, managers are more likely to adjust strategy in losses than victories, with biased managers more likely to adjust in narrow matches than unbiased managers. This results from losing performances being amplified by ϒ.

Secondly, managers with stronger priors can endure larger losses without switching their strategy.

Thirdly, expected performances have no effect on unbiased managers, but may affect biased managers, as expected losses still reduce their posterior belief.

Finally, unbiased managers only switch strategies in response to events directly related to their strategy, whilst biased managers may respond to other factors. In their paper they used free throw shooting percentage, this paper examines crowd attendances.

In this paper, I test this model using line-up data from 7,965 football games in Europe's 'top-five leagues' (England, France, Germany, Italy and Spain) between 2016 and 2022.

Within their model, the authors exclusively consider score differentials. According to the informativeness principle (Holmstrom, 1979), this is an insufficient model of a manager's adjustment process if outcomes are imperfectly informative of an agent's actions. Within football, scores and past points won are not highly predictive of future results, presenting an R2 value of only 0.253 (Brechot and Flepp, 2020). As such, I adapt the model to incorporate the underlying performance metric expected goals (xG) which is shown to have a higher predictive power of points received in

https://doi.org/10.14324/111.444.2755-0877.1691

the next ten games (R2 = 0.320) (Brechot and Flepp, 2020). These findings are corroborated within our sample, as shown in the table below where several metrics are regressed against points gained in the next ten games.

Variable	Coef.	St. Error	p-value	R^2
Points in Last 10 Games	0.549	0.009	0.000	0.296
Score Differential in Last 10 Games	0.382	0.006	0.000	0.325
xG Differential in Last 10 Games	0.518	0.007	0.000	0.388

Table 1: Comparison of Predictive Power

The authors also rarely reference expected results. Betting markets in football are highly calibrated, shown to uphold the efficient market hypothesis (Croxson and Reade, 2014), and are highly accurate in the sample as shown in Figure 1.

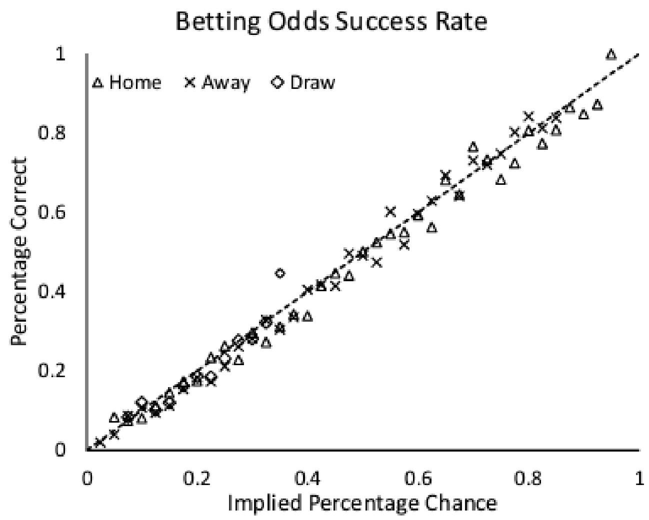

Figure 1: Comparison of implied odds to realised success rate. The dotted line represents perfect predictions, note the strong alignment of the predictions to this line.

Thus, I regress the winning and losing odds against score differentials in the sample to obtain estimates for the ex-ante predicted score differential for each game (draws are possible so there is no perfect collinearity).

Score Differential	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Win Probability	3.574	.308	11.62	0	2.971	4.177	***
Loss Probability	-1.423	.338	-4.21	0	-2.086	-.76	***
Constant	-.825	.239	-3.45	.001	-1.293	-.356	***

Mean dependent var	0.306	SD dependent var	1.849
R-squared	0.239	Number of obs	10855
F-test	1703.644	Prob > F	0.000

**** p<.01, ** p<.05, * p<.1*

Table 2: Calibration of Predicted Score Lines from Implied Win Probabilities

https://doi.org/10.14324/111.444.2755-0877.1691

To test the predictions, I formally run the regression below.

$$UnmandatedChanges_{i,g+1} = \beta_0 + \beta_1 Win_{i,g} + \beta_2 Loss_{i,g} + \beta_3 PD_{i,g} + \beta_4 PD_{i,g} * Loss_{i,g} + \beta_5 UnexpectedSD_{i,g} + \beta_6 UnexpectedSD_{i,g} * Loss_{i,g} + \beta_7 UnexpectedXG_{i,g} + \beta_8 UnexpectedXG_{i,g} * Loss_{i,g} + \varepsilon_{i,g+1}$$

Here i indexes the team and g indexes the game during the season, $UC_{i,g+1}$ are the number of changes a manager makes to their line-up in the subsequent game excluding suspensions and injuries picked up in and between games, $UnexpectedSD_{i,g}$ is the score differential between the reference team i and their opponent in game g minus the predicted scoreline, $Win_{i,g}$ is an indicator variable with a value of 1 if the reference team won the match and 0 otherwise, $Loss_{i,g}$ is an indicator variable with a value of 1 if the reference team lost the match and 0 otherwise, $PDI_{i,g}$ is the score differential implied by the market average betting odds, $UnexpectedXG_{i,g}$ is the xG differential minus the predicted scoreline, and $\varepsilon_{i,g+1}$ is the error term.

Score differential terms should have negative coefficients, as winning makes you less likely to make changes, and the predicted differential should have insignificant results. Table 3 shows the results.

	Unmandated Changes
Win	-.292***
	(.043)
Loss	.233***
	(.043)
Predicted Differential	.159***
	(.027)
PD * Loss	-.218***
	(.034)
Unexpected Score Differential	-.092***
	(.018)
Unexpected SD * Loss	-.079***
	(.026)
Unexpected xG Differential	-.104***
	(.016)
Unexpected xG * Loss	.014
	(.025)
Points in Last 5 Games	-.077
	(.068)
Team Controls	Yes
Game-specific Controls	Yes
Mean Changes	2.236
Observations	15910
R-squared	.265

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 3: Regression Results

https://doi.org/10.14324/111.444.2755-0877.1691

The outcome variables are both significant, with wins being associated with 0.292 fewer changes, and losses with 0.233 more changes. In losses, the predicted scoreline has a net-negative coefficient, suggesting that managers are biased. Finally, whilst xG has a constant coefficient in wins and losses (rational behaviour), as the score differential gains additional weight in losses, the relative weight of performances falls in losses, potentially suggesting that the less salient metric (performance) loses weight in losses.

Overall, having considered data from the most-skilled football managers, these results are highly generalisable, suggesting that principals become overconfident in positive outcomes, and should extend a greater level of scrutiny to all results. Increased data collection on efforts and performances alone is not a panacea, as this data is of little use if it is not considered accurately. The results indicate that avoiding the common wisdom to ‘not fix what isn’t broken’ is crucial to success, whilst encouraging a broader range of opinions and possible solutions in suboptimal outcomes is desirable. It truly is not the end result that matters, but how we get there that makes all the difference

https://doi.org/10.14324/111.444.2755-0877.1691

References

Baron, J. and Hershey, J. C. (1988). ‘Heuristics and biases in diagnostic reasoning: I. Priors, error costs, and test accuracy’. Organizational Behavior and Human Decision Processes, 41 (2). doi: 10.1016/0749-5978(88)90030-1.

Brechot, M. and Flepp, R. (2020). ‘Dealing With Randomness in Match Outcomes: How to Rethink Performance Evaluation in European Club Football Using Expected Goals’. Journal of Sports Economics, 21 (4). doi: 10.1177/1527002519897962.

Brownback, A. and Kuhn, M. A. (2019). ‘Understanding outcome bias’. Games and Economic Behavior, 117. doi: 10.1016/j.geb.2019.07.003.

Chetty, R., Looney, A. and Kroft, K. (2009). ‘Salience and taxation: Theory and evidence’. American Economic Review, 99 (4). doi: 10.1257/aer.99.4.1145.

Garcia-del-Barrio, P. and Szymanski, S. (2009). ‘Goal! profit maximization versus win maximization in soccer’. Review of Industrial Organization, 34 (1). doi: 10.1007/s11151-009-9203-6.

Holmstrom, B. (1979). ‘Moral Hazard and Observability’. The Bell Journal of Economics, 10 (1). doi: 10.2307/3003320.

Késenne, S. (2006). ‘The Win Maximization Model Reconsidered: Flexible Talent Supply and Efficiency Wages’. Journal of Sports Economics, 7 (4). doi: 10.1177/1527002505279347.

König-Kersting, C., Pollmann, M., Potters, J. and Trautmann, S. T. (2021). ‘Good decision vs. good results: Outcome bias in the evaluation of financial agents’. Theory and Decision, 90 (1). doi: 10.1007/s11238-020-09773-1.

Lefgren, L., Platt, B. and Price, J. (2015). ‘Sticking with what (Barely) worked: A test of outcome bias’. Management Science, 61 (5). doi: 10.1287/mnsc.2014.1966.

Sloane, P. J. (1969). ‘The economics of professional football: the football club as a utility maximiser’. Journal of political economy, 64 (3).

Tversky, A. and Kahneman, D. (1974a). ‘Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment.’ Psychological review, 90(4), p.293.

Tversky, A. and Kahneman, D. (1974b). ‘Judgment under Uncertainty - Heuristics and Biases’. Science, 185 (4157).

https://doi.org/10.14324/111.444.2755-0877.1691