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IS FOOTBALL A MATTER OF LIFE AND DEATH – OR IS IT MORE IMPORTANT THAN THAT?

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Is Football a Matter of Life and Death – Or is it more Important than that?

Peter Dolton and George MacKerron

PRELIMINARY - PLEASE DO NOT CITE WITHOUT THE AUTHORS PERMISSION

Abstract

Football is the national sport of most of the planet. This paper examines how happy the outcomes of football matches make us. We calibrate these results relative to other activities and estimate the dynamic effects these exogenous events have on our utility over time. We find that football – on average – makes us unhappier – so why would we go through the pain of following a football team. This behavioural choice paradox occupies much of the paper so we investigate why we go on following our teams, even though matches make us more unhappy on average. We examine how much our story changes if we examine the dynamic effects of football matches over time in different hours before and after the game and the extent to which our happiness is influenced by what we would rationally expect the result to be beforehand – as based on the betting odds.

JEL Classifications: D23, D03, Z20

Keywords: happiness, football, behavioural economics, irrationality, dynamic effects of outcomes, framed subjective utility.

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1. Introduction.

Behavioural Economics in recent years have focussed on the characterisation of human behaviour and decisions which appear irrational but may be explained rigorously with economic analysis. We examine why people go to football matches, when on average we find that the outcome is likely to make them unhappier. We use data from 3 million observational responses of 32,000 individuals to a 'Mappiness app' on which they calibrate their happiness as well as what they were doing and where they were. We model this happiness relative to other activities and in a variety of circumstances.

At the outset, it should be recognised that we do not have a contribution to make regarding the vast literature on: what is utility, is utility a cardinal or ordinal concept; and whether it is possible to make interpersonal comparisons between different people's utility. In this paper we take utility, wellbeing and happiness as one and the same concept and use the terms interchangeably throughout the paper. We assume that when we ask people to rate how happy they are they are giving us a snapshot of their wellbeing or utility. For the purposes of this paper it does not matter what exactly the concept is called that we are measuring and nor does it matter in our econometric estimations whether utility is comparable across individuals or not. This is because all the estimates are from individual fixed effects models that calibrate the outcome happiness relative only to that person on average.

The contribution of this research is fivefold. Firstly, we are able to calibrate exactly how happy the outcome of a football match makes a person conditional on a set of circumstances, namely: who they were with and what was the likelihood of their team winning was. Secondly, because the event which triggers the emotional expression of utility is exogenous, and not in any way under the control of the person observed, then we will be able to retrieve a 'causal estimate' of the effect of the outcome of a football match on a person's utility. Thirdly, because our data comes from a data source which relies of people answering a 'ping' on their phone at random different times then we can derive estimates of exactly how a person's utility changes dynamically over time as the event is: anticipated, experienced and then reflected on after the event. In this sense, we can begin to build a picture of how happiness is affected over time before, during and after an event. Fourthly we investigate how much actually being at the match has . Finally, since we are able to retrieve all the betting odds relating to each match covered by our data, then we can measure the effects of these outcomes relative to what the betting odds market believes are the objective odds on any match. This means we can assess how important are objectively determined reference points in calibrating happiness.

The data used in this research has been used to study the effect of work on labour market happiness (Bryson and MacKerron, 2014), and the relationship between happiness and alcohol, Geiger and MacKerron (2016). Arguably the problem with these studies is that it is difficult to disentangle the effect that work has on happiness from the effect that happiness has on work. The advantage of studying the effect that football scores have on happiness is that the outcomes of any football match, before the match is played are exogenous. There is no way – as much as any fan may mistakenly think otherwise – that anything they can personally do will affect the outcome of a match.

An important logical question to answer is - why should economists care about the effect that football matches have on happiness? The first answer is that football is the biggest sport on the planet and the way it makes us feel must be correspondingly important. Football is followed by more people than any other country and its outcomes matter hugely for economies. A second reason that we should care about the insights of this study are that it helps us to understand situations in which the outcome of an exogenous event takes place and has a dynamic effect on our happiness. Understanding the process by which an event is anticipated, experienced and then reflected on is important for many aspects of daily life and yet it is rarely understood as an unfolding process. A third attraction of working with this data is that we find that the aggregate effect of a football match is cumulatively negative on people's happiness. So why would anyone pay to follow a football team even though it leaves us more unhappy than before? This means that we can study a situation in which we can characterise the objective odds of any team winning or losing and see how this affects the happiness over and above the actual effect of the result. So, this means we can assess how much worse we feel when we lost to a team that (the odds suggested) we should not have lost to - and vice versa – namely how much happier are we when we won but were not predicted to. This calibration of utilities relative to some reference point has been used by Card and Dahl (2011) to calibrate the extra potential for a supporter to perpetrate domestic violence.

The rest of this paper is organised as follows. In the next section, we provide the context to this study by an examination of the relevant literature to our question and method. In section 3 we look at a basic model which provides the link to our empirical work. We examine some basic propositions from this simplified model to guide what results we might expect of the econometric estimation. Section 4 introduces the unique data in our research. In sections 5 we discuss the identification of our econometric model and examine the baseline econometric results of the extent to which football match outcomes influence happiness of football supporters. We also explore the extent to which these effects last over time after the match. We also explore the extent to which they may be anticipation effects before the game. In section 6 we further explore the effect of these results on those who are not only football followers but also attend the match. In Section 7 we explore the extent to which these effects that we find are changed if we consider them as framing effects relative to the betting odds prior to the football match. Finally, we spend some time reflecting on the behavioural conundrum that the aggregate effects of being a football fan are negative. So why would individuals choose to inflict this pain on themselves? We discuss the alternative theories as some of these are at the heart of the most recent contribution sot behavioural economics.

2. The Relevant Literature

There is a large literature on the economics of football (see Dobson and Goddard 2000) and field sports (see Della Vigna 2009). Much of this literature examines the performance of players, teams and managers over time. A limited literature examines contracts of players and transfer fees. To our knowledge, very little has been written about the choices and behaviour of football fans. Our unique data facilitate us in our investigation of the behavioural economics of football fan allegiance and their attendance at football matches.

There are very few papers in behavioural economics in the area of sport or which use sports data to provide insight into behavioural issues. One exception is Card and Dahl (2011). They use data on the results of 6 NFL football teams in the US over the seasons 1995 -2006 to investigate the link between adverse football results and domestic violence. They link their data with aggregate family violence incidence by local geography on the days in when matches were played. Since the match results are exogenous shocks to the supporters of the football teams then the link between these outcomes and domestic violence can be explored. The identification strategy relies on the framing of these results relative to the spread betting on the scores prior to the game. The argument is that football results which were worse than expected – as measured by these objective spread bets – are more likely to give rise to domestic violence. The 'framing effect' of exogenous outcomes relative to objective expectations enable the authors to argue that the link they find of football results to domestic violence is a causal relationship.

The Card and Dahl paper is limited in that it uses aggregate data to link football scores with aggregate family violence outcomes in the locality. In our investigation, we have detailed individual data on utility-happiness responses and we know what these people are doing and who they are with when they report this happiness. We examine the relative effect on their reported happiness of the results of exogenously determined football match outcomes. Like Card and Dahl we are also able to link these football matches with the betting odds on these matches prior to them being played.

We therefore have many advantages in our data over that of Card and Dahl. Our outcome measure in this paper is a direct measure of utility or happiness. Since the literature on what utility is and whether or how it can be measured we need a short digression to summarize this relevant literature.

Of central concern, here is whether interpersonal comparisons of utility are meaningful and whether it is possible to measure responses to happiness questions as indicative of utility. We will also be concerned about whether utility is summative over time after some initial shock. A further component of interest is the relationship between anticipated events and the extent to which, as an event approaches, people's utility reports before the event are comparable in ordinal or cardinal terms with reported utility after the event. We pick out the relevant components of this literature and refer back to them as we explore different aspects of our results.

3. A Model of Football Support Behaviour

3.1. The Basic Model

To begin with assume people have completely rational beliefs about the probability of their team winning, losing or drawing, respectively p_w, p_d, p_l . Then the total utility of being a football fan is given by the left-hand side of the expression below. Clearly it pays in utility terms to be a football supporter if this uncertain prospective gives a positive utility:

$$p_w U_w + p_d U_d + p_l U_l > 0$$

The next consideration is whether any football fan actually chooses to go to a specific match. Clearly the utility of actually being at the match is different from merely being a supporter who does not attend. So, the utility of going to a match is given by:

$$p_w U_w^a + p_d U_d^a + p_l U_l^a$$

If attendance at the match costs, C, then a fan will choose to go to the game if:

$$p_w U_w^a + p_d U_d^a + p_l U_l^a + C > p_w U_w + p_d U_d + p_l U_l$$

With no loss of generality if we assume that a draw is a completely neutral outcome we can simplify some of our expressions, i.e. that U_d^a and $U_d = 0$.

Assuming probabilities of match outcomes to be rational then a fan will attend a match if the marginal extra utility of attendance irrespective of the results, over simply supporting outweighs the cost:

$$p_w(U_w^a - U_w) + p_l(U_l^a - U_l) > C$$

But this expression is not trivial as typically the disutility of actually seeing your team lose is higher than the disutility of them losing if the supporter is not actually at the match. Hence the true expression should reflect the fact the second term on the left-hand side above is negative:

$$p_w(U_w^a - U_w) > C + p_l(U_l^a - U_l)$$

3.2 ***Subjective Probability Perceptions.***

In reality football fans are not usually rational about the probability of their own team winning. Let's now introduce this possibility by assuming that our representative fan holds the following subjective beliefs about their own team, where π_w, π_d, π_l are the probability beliefs of winning, drawing and losing held by the fan. Now the fan would decide to support a team if:

$$\pi_w U_w + \pi_d U_d + \pi_l U_l > 0$$

Correspondingly, then would decide to actually go to the match if the subjectively perceived benefits of any possible result minus the attendance cost outweigh the benefits of not going to the game:

$$\pi_w U_w^a + \pi_d U_d^a + \pi_l U_l^a + C > \pi_w U_w + \pi_d U_d + \pi_l U_l$$

It is worth reconsidering the

$$\pi_w (U_w^a - U_w) > C + \pi_l (U_l^a - U_l)$$

This means that there are two possible explanations for going to the game when it may appear non-rational to the outsider:

Firstly, because the subjectively held view of the probability that your team will win is much higher than the reality, i.e. that $\pi_w > p_w$ which implies that $\pi_l < p_l$.

Secondly that the extra utility of actually being at the match, when your team wins is much higher than the penalty of being at the match if they lose.

3.3 ***The Dynamic Model***

The next complication we should add is that the experience of utility as a result of the outcome of a football match is not a one-shot outcome. Football supporters feel the pain or joy of a result for hours afterwards and indeed may get a huge utility effect prior to the game, in anticipation of the match. Therefore the football supporter will wish to support their team in the combined effects of the match conditional on the result ends up being positive.

$$\pi_w \sum_{t=-3}^{T} \omega_t U_{wt} + \pi_d \sum_{t=-3}^{T} \delta_t U_{dt} + \pi_l \sum_{t=-3}^{T} \ell_t U_{lt} \quad > 0$$

Where t represents the hours before or after the game. Here we take the anticipation effects to be bounded three hours before the match kick-off – but this is just a convenience – it could be much sooner than that. In our empirical results, we will examine how long these effects are anticipated and how long they last.

The other new element in this dynamic model are the weights on the per period utilities: ω_t , δ_t , ℓ_t . We anticipate that these might build up towards the time of the match kick-off, but will decline away as time advances as the pain of a defeat or the euphoria of a win die away over time, but will again let our data tell us the story.

We can now reconsider the fans decision about whether to go to the game in a dynamic context. Assuming for convenience that the same dynamic process of the fading away of either negative or positive utilities occurs irrespective of whether you are at the match or now we can rewrite the attendance decision as:

$$\pi_w \sum_{t=-3}^{T} \{\omega_t (U_{wt}^a - U_{wt})\} > C + \pi_l \sum_{t=-3}^{T} \ell_t (U_{lt}^a - U_{lt})$$

Hence, we are now implying that the fan, in deciding whether to go to a match will weigh up the stream of future benefits or disappointments over the hours before and after a match in deciding whether to go or not.

3.4 *The Framing Reference Model.*

In this section, we consider the possibility that football fans derive extra utility or disutility from results that were unexpected. It is possible that there is extra utility from the win which was unanticipated and correspondingly much lower utility from the games the fans expected to win but were thwarted when their team lost against the odds. Such a model is consistent with many papers which model how individual's behaviour and decisions may be framed relative to some logical decision threshold (see Kozegi and Raban 2008).

If we specify the rational objective probability of the team winning, drawing and losing by: $\bar{p}_w$, $\bar{p}_d$, $\bar{p}_l$, respectively then we can write the total utility of the football fan after the game result is known as:

$$\pi_w U_w + (\bar{p}_w - \pi'_w)U_w + \pi_d U_d + (\bar{p}_d - \pi'_d)U_d + \pi_l U_l + (\bar{p}_l - \pi'_l)U_l$$

where π'_w, π'_d, π'_l, are the ex-poste after-match realisations of what the fan thinks their expected probabilities of a win, draw or loss were. This expression will form the basis of our third estimation model which seeks to identify the effects on utility of unanticipated shocks in the results of the matches as well as the underlying effects of the basic utilities caused the win, draw or loss of the fans team.

4 The Data

4.3 *Subjective wellbeing data*

Our data on subjective wellbeing derive from the *Mappiness* study, which enables individuals to record subjective wellbeing levels via smartphone. The study was originally designed to investigate links between environmental goods and subjective wellbeing (MacKerron and Mourato, 2013), but a large, timestamped, geo-located data set on subjective wellbeing and its context proves to have a variety of further applications (e.g. Bryson and MacKerron, 2016; Baumberg Geiger and MacKerron, 2016; Bryson and MacKerron, 2017).

App users receive randomly timed signals ('push notifications') – or 'pings' on their mobile device, requesting that they complete a very brief survey. The survey asks users to rate themselves on three dimensions of momentary wellbeing, stating how happy, how relaxed, and how awake they feel. Each score is elicited by means of a continuous slider, labelled from 'Not at all' to 'Extremely'. The user is then asked whom they are with; whether they are indoors, outdoors, or in a vehicle; and whether they are at home, at work, or elsewhere. Finally, they are asked what they were doing 'just now', choosing all that apply out of around 40 options (including attendance at a 'Match, sporting event'). The complete survey is reproduced in Appendix A. While the user responds, the app obtains the device's location via satellite positioning (GPS). It also records the precise date and time at which the survey was completed, and the time elapsed since the signal was received.

On signing up, users complete a short survey on personal, work and household characteristics. They can choose to be signalled between one and five times a day. Most stick to the default option, which is twice. They may also specify hours of the day during which they are likely to be asleep and do not wish to be disturbed.

The full data set contains several million observations on tens of thousands of individuals, primarily in the UK, collected from August 2010 onwards. *Mappiness* users cannot be considered representative of the UK population — on average, they are somewhat younger, wealthier, and more likely to be employed or engaged in full-time study. On average, a user provides around 60 responses over the course of around 6 weeks. This enables us to account for unobservable fixed differences across individuals via a fixed effects regression specification.

Users would ideally provide an immediate response whenever prompted by a random signal, since this would provide a true probability sample of moments in their lives. In fact, individuals sometimes respond after a delay or fail to respond at all. To ensure a degree of randomness in responses, and according to standard practice in research of this type (known to psychologists as the Experience Sampling Method, and to medical scientists as Ecological Momentary Assessment), we restrict our analyses to responses given within a certain period after the prompting signal is received. We set this period to be one hour, under which criterion approximately half of all signals result in a valid response. In previous research with this data set, results are not sensitive to varying that period.

4.4 *Football data*

The football data we use comes from three sources. First, stadia: we retrieved a listing of UK football stadia complete with geographical coordinates and home teams[1]. This listing was validated and in some cases corrected and extended via further online research.

Second, matches: we obtained data on all English and Scottish league matches for the 2011, 2012 and 2013 football seasons[2]. These data include, for each match, the home team name, away team name, date, result, and odds on a home win, away win and draw as offered prior to the match by a variety of bookmakers[3]. The match locations were then added by matching stadium data on the home team name. Since name matches were inexact (e.g. *Wolverhampton Wanderers* vs *Wolves*) trigram matching was used, with manual verification.

Third, kick-off times: after joining football matches to *Mappiness* responses (as described below) we merged in precise kick-off times for all relevant matches, which we obtained by scraping a popular football website.

4.5 *Linking the data.*

All data manipulation was performed either in Stata or in the open-source PostGIS spatial database. First, we pinpoint a *Mappiness* user as being a potential spectator at a football match if they respond within 500m of the centre of a football stadium, on a match day, and report being 'outdoors', 'elsewhere' (that is, neither at home nor at work), and at a 'Match, sporting event'.

We then attempt to infer the team supported. For users seen at multiple matches, we assume that they support the most frequently seen team (in the most common case, we see the user at a match between team X and team Y, and later at a match between team Y and team Z, and conclude that they support team Y). For users seen at only a single match, we assume that they

[1] From https://www.doogal.co.uk/FootballStadiums.php
[2] From http://www.football-data.co.uk/data.php
[3] Odds are as offered on Friday afternoon for weekend matches, and on Tuesday afternoon for weekday matches.

support the team playing at home, on the basis that the overwhelming majority of tickets for football matches are reserved for home fans.

Finally, we join each *Mappiness* response from each identified supporter with data for the most recently preceding football match involving the team we have inferred. We are thus able to link responses with match results throughout the intersection of a user's response period and the football season, not only with results at matches they attend.

4.6 *Transforming the Odds Data.*

One important part of the innovation in this paper is that it uses the odds on the outcome of each match in our data. We scraped the web for all the betting odds of all the major bookmakers for each match. This data comes in the form of the odds of the home team winning, the home team losing and the odds of a draw. We then transformed this data into the probability of each event for each game. This then leaves us with the problem of netting out the bookmaker's mark-up for profit – i.e. that the probabilities of the three outcomes derived from the bookmaker odds will always sum to more than one. This difference between the combined probabilities quoted by the bookmakers is due to the added percentage that they include to provide them with the profit margin they operate with to accept the gambles. We accordingly scale back these probabilities in proportion to the initial odds so that the eventual 'objective' probabilities we work with sum to one. A simple numerical example will suffice to make the point and explain how we have transformed the bookmaker odds to proportionate probabilities that sum to one. Assume the odds given by the bookmaker for the home team are 4-6 on a win, 1-1 on a loss and 4-1 on a draw. Treated at face value this would suggest the bookmaker estimates the probabilities to be respectively: .6, .5 and .2. However, we know that this is impossible and merely reflects that this bookmaker is seeking a mark-up on bets totalling around 30%. So, what we propose is that we scale back these probabilities in proportion. If we divide each of the original probabilities by 1.3 then we will get 'scaled back probabilities' which are actuarially fair and sum to one but maintain the relative size and ranking of the original bookmaker's odds. In this case this would mean transformed probabilities of: 46, .38 and .15 (rounded to the second decimal place).

5 The Identification of the Econometric Model.

The general model which provides the estimating framework for our different models is written in general terms:

$$U_{ijt} = \theta_i + X_{it}\gamma + f(y_{ji}, \bar{p}_j, \sum_{t=-3}^{T} H_t)$$

Where U_{ijt} are the outcome happiness levels of individual I, and time t relating to match j, y_{ji} represents the outcome of the matches j, followed or attended by fan i, $\bar{p}_j$ represents the objective probabilities provided by the data from the bookmakers prior to each match j, X_{it} represents the factors relating to the circumstances of fan i at time t when pinged, and θ_i represent the fixed effects for each fan. The last term in H_t represents a set of hour dummies relating to when the ping was received before or after the match, we allow for up to 3 hours before the match but tired various specifications for the T time periods after the match. We estimate three versions of the model. The first includes the dynamic effects relating to the different hours for any football supporter irrespective of whether they are at the match or not. The second model relates to whether the fan was actually at the match and the third includes the objective probabilities of a win lose or draw on the match j in question.

The identification of this model is based on the fact that the outcomes of the games, y_{ji} are exogenous to the individual and their decisions. There is no possible way for the fan to have any influence over the outcome of the match. The fan merely responds and reports their level of utility, U_{ijt} at various points in time before during and after the match. Each fan reports these happiness measures many times.

One potential threat to identification could be that the measurement of these U_{ijt} outcomes are heterogeneous by person and not directly comparable. This problem is overcome in this data by the fact that we have multiple observations on each person at different points in time. This means that by including person specific fixed effects, θ_i we are essentially calibrating each person relative to their own mean. Hence, we do not need to concern ourselves with how people actually interpret the scale they are asked to report their happiness on.

The final element of our identification strategy uses the arguments of Card and Dahl (2011). In our third estimation model, we seek to identify the extra marginal effects of potential unanticipated surprise results. In order to do this, we take object bookmaker odds on the matches and transform them to probabilities with relative meaning. We now seek to describe the results of estimating these three models.

6 The Dynamic Model Estimation Results.

In this section, we report the basic results which relate to the basic dynamic model. Specifically, we estimate a model which relates to our whole sample of all those respondents to the pings no matter what they are doing, when they are pinged or respond, or who they are with, or where they are. So the first thing to emphasise is that our results are the respondents marginal extra utility or disutility of being a football supporter before a match is played and after the result is known in real time. We control for the situation that the person is in when they are pinged. We have dummies 42 activity dummies, 7 companionship dummies, i.e. who you are with when pinged and we also control for how many times a person responded to pings in the past.

The second important aspect of our modelling is to address the potential problem of the natural rhythms of happiness at different times of the day and different days of the week. We 'soak' up this natural variation in mood induced by light, season, day of the week and other related factors by having day of the week dummies and time of the day dummies. We also interacted these dummies to allow for the fact that times of the day are different by days of the week in the happiness they induce. We did experiment with having dummies for each hour of the day but essentially the results remain the same as the ones we report in Table 1.

The third aspect of our results which should be emphasized is that our results are Fixed Effects estimates at the level of the individual. So, we are absolved from the perennial debate about the validity of the problem of making inter-personal comparisons of utility. Our results and coefficients are to be interpreted as the aggregate effect over the whole sample population of changes in individual's utility as a result of football matches relative their own metric of how they judge and score their happiness. So, the benchmark for these results are the comparing individual to themselves doing other things, at other times relative to the population. In simple terms this means that we do not have to worry about the fact that one person's metric on happiness or utility is always in the 0-40 part of the scale as they are essentially miserable people – or that in contrast – another person always scores their happiness in the 60-100 range as they are inherently a happy person. By using fixed effects estimation at the person level, we are netting out for these inter-personal differences and the estimation results measure the effects of the football match outcomes in terms of their effects on happiness relative to their underlying average permanent steady state- i.e. relative to that person's own mean happiness response. So, the effects are the marginal differences in utility relative to their own baseline.

With this basic description in mind of the key components of our econometric model estimation we can now consider the results of the dynamic model reported in Table 1. These results measure the dynamic effects of the outcome of the football team that has been identified as being followed by our football fans. We see that one hour prior to the match the fans experience a 1.5 positive effect. This translates to a 3.9 positive effect one hour after the match if their team wins, and a 3.2 negative effect if their team draws. The position is dramatically worse if their team loses. The negative effect is 7.8 in the first hour, 3.1 in the second hour, 3.2 in the third hour. There is weaker evidence in the 4th, 7th and 8th hour. To contextualise the magnitude of these effects we provide the coefficients on other activities for the same sample in Table A2 I the appendix. We can see that the highest effects are from intimacy of +12, and the lowest effects is from being ill in bed – of

There is a possibility that these later effects could be experienced the next morning after the game the day before. This 'hang-over' effect could be more like in mid-week games with evening kick-offs where the misery of the defeat has not had time to sink in until after a period of sleep. (People do not respond to pings late at night.) In Figure 2 we graphically show these effects to aid a visual interpretation of their effects. Notice that we include the 95% confidence intervals around the point estimates of each hour effect. This indicates that the effects we report are significantly different from zero and merit serious consideration.

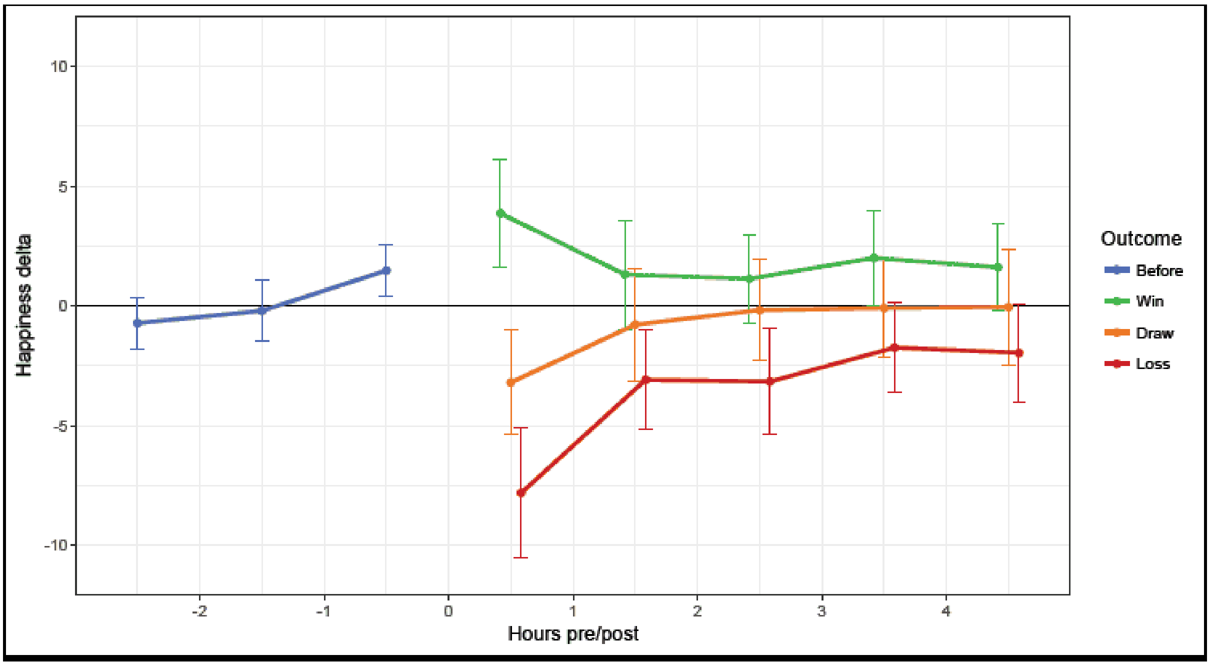
The scale and endurance of these effects are quite dramatic and clearly very asymmetric. People are much more negatively affected by the adverse results of match defeats than they are positively affected when their team wins. This effect last much longer and may add up to around 4 times the negative impact on happiness for a defeat as compared to the positive effect of a win.

Table 1: Dynamic Utility Model

Variables	coefficient	robust std. err.
Reported happiness (0 – 100)		
Before match		
3 – 2 hours	1.473**	(0.535)
2 – 1 hours	-0.214	(0.654)
1 – 0 hours	-0.725	(0.539)
After win		
0 – 1 hours	3.857***	(1.147)
1 – 2 hours	1.307	(1.163)
2 – 3 hours	1.126	(0.945)
3 – 4 hours	1.996*	(1.015)
4 – 5 hours	1.603+	(0.931)
After draw		
0 – 1 hours	-3.203**	(1.119)
1 – 2 hours	-0.788	(1.193)
2 – 3 hours	-0.183	(1.079)
3 – 4 hours	-0.0964	(1.054)
4 – 5 hours	-0.0552	(1.244)
After loss		
0 – 1 hours	-7.819***	(1.383)
1 – 2 hours	-3.094**	(1.072)
2 – 3 hours	-3.167**	(1.127)
3 – 4 hours	-1.748+	(0.966)
4 – 5 hours	-1.966+	(1.040)
Day of week dummies (6)	Yes	
Time of day in 3 hour blocks × weekday vs weekend/holiday dummies (15)	Yes	
Activity dummies (42)	Yes	
Companionship dummies (7)	Yes	
Prior response count dummies (3: to power 1, 2, 3)	Yes	
Respondent fixed effects	Yes	
Constant	57.81***	(1.031)
R-squared (within)	0.122	
Observations	2,085,410	
Number of respondents	32,201	

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Figure 1: Dynamic Utility Model Timing Effects Before and After the Match with 95% Confidence Intervals.



7 Results Relating to Attendance at the Match.

So far, we have considered the effect of football match results on football fans irrespective of whether they attend the match or not. In our simple behavioural model, we considered the possibility that utilities of football results and potentially very different if you are actually at the match. Part of being a football fan involves the whole experience of the match attendance, enjoying it as a spectacle and soaking up the atmosphere. Hence, we should allow for this in our estimation.

In these results, for parsimony and precision reasons we supress the dynamic pattern we considered in the previous section and focus on the first hour marginal effects on utility of being at the game or not conditional on the result. The relevant estimation results are reported in Table 2. The reported results confirm the previous estimates vis-à-vis the size of the marginal effects of the hour after the game for a win, draw or loss of your team. The effects are respectively +2.4, -3.2 and -7.2.

Table 2: Utility Model With and Without Attendance at the Match.

Variables	coefficient	robust std. err.
Reported happiness (0 – 100)		
1 – 0 hours before match, not at stadium	0.211	(0.531)
1 – 0 hours before match, at stadium	7.921***	(1.221)
0 – 1 hours after win, not at stadium	2.405*	(1.032)
0 – 1 hours after win, at stadium	9.809**	(2.981)
0 – 1 hours after draw, not at stadium	-3.174**	(1.014)
0 – 1 hours after draw, at stadium	-3.073	(4.717)
0 – 1 hours after loss, not at stadium	-7.203***	(1.410)
0 – 1 hours after loss, at stadium	-13.98**	(4.956)
Day of week dummies (6)	Yes	
Time of day in 3 hour blocks × weekday vs weekend/holiday dummies (15)	Yes	
Activity dummies (42)	Yes	
Companionship dummies (7)	Yes	
Prior response count dummies (3: to power 1, 2, 3)	Yes	
Respondent fixed effects	Yes	
Constant	57.81***	(1.031)
R-squared (within)	0.122	
Observations	2,085,410	
Number of respondents	32,201	

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

If we now examine the interaction terms relating to the effects of winning, drawing or losing interacted with actually being at the match we see dramatic effects. Firstly, we now see a large spike in the effect on happiness before the game. There is now a 7.9 marginal utility effect of anticipating the match if you are about to go. This is very understandable as it's a very exciting spectacle sport which would confer a lot of utility prior to the game in anticipation. Before the results is known all football, fans dream and most remain optimistic about the outcome.

After the result of the game is known then the effect of winning on utility is around twice its baseline effects. Specifically, losing and being at the stadium confers an extra -14 effect on utility over and above the baseline effect of the result. Reassuringly the positive effect of winning and being at the match is around 3-4 times higher than the effect of the baseline win result at around 9.8. This is clearly a very positive experience and one which many fans gamble optimistically on getting when they decide to go to the match.

The summative effect of these results is preserved if we also include hourly dummy interactions – but we begin to lose precision on the effects so we supress them in this exposition for clarity. These results are available from the authors on request.

8 **Results from the Framing Model Relative to Objective Odds.**

Card and Dahl argue that in their data the only possible identification strategy to retrieve the effect of NFL result son domestic violence is to use departures from the bookmakers predicted points spread before the game as a marker of what objectively might occur in the match. They seek to identify the effects of unanticipated shocks in terms of the result of the game on domestic violence. They suggest that the only identification possible in their data comes from the differences of actual football match outcomes from what was rationally predicted by the bookmakers. This is the only strategy that Card and Dahl can employ to retrieve their effects as they only have panel data on outcomes of matches merged with panel data on domestic violence. In our case we have individual data and can calibrate the effects of the exogenously determined random outcomes of matches on deviations in the timed utilities of these people relative to their normal state.

Nonetheless we are also anxious to calibrate the effects of a win when one was predicted and anticipated relative to when one was not anticipated. Likewise, for losing and drawing. If our team wins or draws when we expected them to win we might be correspondingly happier. Likewise, if our team loses when we expected it to win then we might be correspondingly unhappier. We find clear evidence of these effects.

In order to get the data on objective odds of winning, losing and drawing we scrapped the web for all the bookmaker's odds on our matches before the game. We transformed the odds to a sum probability of the three possible outcomes according the described above in our data section. We have performed the analysis using all the data from all the bookmakers rather than just one leading bookmaker – William Hill – but it makes little difference which way we aggregate the data.

In Table 3 we tabulate our results. We find that the effect of a loss when a win was expected is a further -10 point shock. Likewise, the effect of a draw when a win was expected is -4. Even the effect of a win, when a win was expected, causes an additional +3.1 effect. Interestingly we also find a pre-match effect of positive objective anticipation. Specifically, we enjoy the immediate build up to a game around 1.8 points more if the objective odds are in your team's favour.

Table 3: Utility Model with Expectations Based on Betting Odds.

Variables	coefficient	robust std. err.
Reported happiness (0 – 100)		
1 – 0 hours before match, win not expected	1.023	(0.822)
1 – 0 hours before match, win expected	1.776**	(0.674)
0 – 1 hours after win, win not expected	7.021**	(2.203)
0 – 1 hours after win, win expected	3.061*	(1.259)
0 – 1 hours after draw, win not expected	-1.897	(1.873)
0 – 1 hours after draw, win expected	-4.071**	(1.362)
0 – 1 hours after loss, win not expected	-6.252***	(1.579)
0 – 1 hours after loss, win expected	-10.03***	(2.121)
Day of week dummies (6)	Yes	
Time of day in 3 hour blocks × weekday vs weekend/holiday dummies (15)	Yes	
Activity dummies (42)	Yes	
Companionship dummies (7)	Yes	
Prior response count dummies (3: to power 1, 2, 3)	Yes	
Respondent fixed effects	Yes	
Constant	57.81***	(1.031)
R-squared (within)	0.122	
Observations	2,085,410	
Number of respondents	32,201	

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

'Win expected' implies Pr(win) ≥ Pr(loss). Outcome probabilities are calculated as the betting odds offered by William Hill on Friday afternoon (weekend games) or Tuesday afternoon (midweek games), rescaled such that Pr(win) + Pr(draw) + Pr(loss) = 1. For all matches observed, Pr(win) ≥ Pr(draw) ≤ Pr(loss).

Clearly then there are very large and clear effects of positive and negative surprises. This suggests that over and above the baseline effects of the results of football matches there are clear effects of surprises and results which are not as predicted from an objective standpoint.

These results, and those in the previous section suggest that there are possible margins for football fans to decide to support a team based on either a belief or optimism that they will win and confound the odds and that the true value of going to the game is much enhanced over and above what benefits occur to simply being a supporter. These results suggest that the simply behaviour model introduced in section 3 have some behavioural traction to explain why people follow football teams and why they might go to a football match – when it does not, on the face of it look like a rational thing to do. We now need to examine other possible explanations of why the irrationality of football fans might be explained.

9. Are Football Fans Irrational?: Some Caveats from Behavioural Economics.

It would appear from our results that football fans are irrational. If we aggregate the effects of football match outcomes over the hours after a match we see that the aggregate outcome is most likely to be overwhelmingly negative. This is because the negative consequences of losing on happiness are around 4 times higher than the positive consequences of winning.

What might explain football fans continuing to go to matches or supporting if the pain of doing so exceeds the pleasure if they win? There are various possible explanations about why football fans may not be irrational – or specifically why we observe them continuing to follow football when it causes them more unhappiness than happiness.

1. ***Systematic bias in estimating the probability of winning***. One explanation is that - fans systematically over-estimate the probability of their team winning and never revise and learn from experience. Many football fans may continue to go to matches – always in hope and expectation that this particular match will go their way.

2. ***Mis-recording of Massive Highs***. It might be that there are massive highs of watching your team play – for example – when they score a goal during the game. It may be that our data does not record this information correctly as we don't observe the effects properly as they are too preoccupied enjoying themselves to respond to pings from their phone relating to the Mappiness App. In a follow-up study on this data we should be able to examine what the levels of happiness is for the limited set of observations which have near the timings of goals scored – as we have the timing of goals scored. There is some evidence that the scoring of a goal induces a massive high and this may be a partial explanation which is not adequately represented in our data.

3. ***Experiential Effect***. The simple pleasure of watching the match gives positive utility which we don't calibrate properly. We have already distinguished between the effects of following a team rather than attending the match in person. Over and above this attendance effect there may be a more general level of pleasure induced by simply enjoying the spectacle of a football match. This may be an effect of being a sports fan and – irrespective of the outcome in terms of the score – the attender may simply enjoy the football being played.

4. ***Network and Peer Effects.*** The camaraderie gives positive pleasure which we don't factor in - might get a handle on this by calibrating the pleasure of win (or pain of loss) by yourself compared to with friends. To some extent we have conditioned out for this effect as we allow for the general effect on a person's happiness of who they are with when they are 'pinged'. It is possible that the interaction effects of who you are with when you are doing certain activities are important. This possibility will be investigated in the future.

5. ***Being a Football Fan is Addictive*** – There is now a sizeable literature on the economics of addiction (Becker and Murphy 1988). Part of the logic of these models is that the addicted person is always trying to get back to the first high. In the football context, this could mean that a football fan selectively remembers the high of the great result in the past, and continues following the team, or attending the match, in the hope that this will be repeated. The problem of how to model the ability of fans to learn from past bad experiences or selectively only remember the good ones is unclear. Might youngsters be more enthusiastic and optimistic compared elderly fans who are more inured and cynical about failure.

6. ***The Value of Curiosity*** – Another possibility is that there is a large positive element to utility of finding out 'how the story ends'. It is possible that this is momentary – i.e. it applies only to the satisfaction and relief of finding out what the score is – irrespective of what that might be with its positive of negative effects. (See Loewenstein, 1994).

7. ***Being in a Tribe***. – Another effect that we do not measure is the positive pleasure of belonging to a wider group – 'a tribe'. Anthropologists (Morris, 1981) and novelists (Golding, 1954) write about the utility and benefits conferred of being in a human group. Part of the pleasure of a positive result is sharing it with a large group of other ecstatic fellow fans. The additional dimension of this effect is the identification of the individual with a group and the identity this confers. This belonging also means that benefits are derived from collectively hating those outside the tribe, or those in another tribe. We may well be able to investigate such effects if we separately distinguish those close rivals (Manchester City and Manchester United, Everton and Liverpool, Newcastle and Sunderland, Arsenal and Tottenham, Celtic and Rangers etc). Psychologists have also discussed these effects and the derived pleasures some fans get from the misfortunes of their close rivals. (Freud talks about 'going over to the dark side'.)

8. **Dynamic Effects of Happiness are not additive.** A final effect that is possible is that the effects we have estimated for each hour separately are not additive and separable. (see Clark et al 2008, When asked how happy a person is now, responds with a mixture of how happy they are at that moment, with some reflection of how happy they have been in the last hour or 2 or 3 then we may be getting a response which means that the effects we have estimated in our dynamic model are not additive and separable. But this possibility is countered by the fact that our estimation which does not separate out separate hours shows basically the same result – namely that the negative effects of losing far outweigh the positive effects of winning.

Each of the explanations offered above provides a possible logic of why the nominally irrational behaviour of following a football team and attending a match may appear to be irrational but could be rational and consistent with simple logic. Our simple behavioural models introduced at the beginning of this paper explain why the possibilities optimistic expectations of a victory combined with the extra pleasure of actually seeing your team win may induce a fan to attend a match – and this may be rational.

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APPENDIX TABLE A1

Variables	coefficient	robust std. err
Reported happiness (0 – 100)		
Before match		
3 – 2 hours	-0.724	(0.539)
2 – 1 hours	-0.213	(0.654)
1 – 0 hours	1.475**	(0.536)
After win		
0 – 1 hours	3.858***	(1.148)
1 – 2 hours	1.309	(1.164)
2 – 3 hours	1.128	(0.946)
3 – 4 hours	1.997*	(1.017)
4 – 5 hours	1.604+	(0.932)
5 – 6 hours	1.601	(1.338)
6 – 7 hours	-0.316	(2.062)
7 – 8 hours	1.364	(2.660)
After draw		
0 – 1 hours	-3.203**	(1.120)
1 – 2 hours	-0.785	(1.194)
2 – 3 hours	-0.182	(1.080)
3 – 4 hours	-0.0955	(1.055)
4 – 5 hours	-0.0523	(1.245)
5 – 6 hours	2.909	(2.211)
6 – 7 hours	-2.942	(3.390)
7 – 8 hours	5.749+	(3.169)
After loss		
0 – 1 hours	-7.820***	(1.383)
1 – 2 hours	-3.095**	(1.073)
2 – 3 hours	-3.166**	(1.127)
3 – 4 hours	-1.748+	(0.967)
4 – 5 hours	-1.966+	(1.040)
5 – 6 hours	-0.403	(1.483)
6 – 7 hours	-3.440+	(2.041)
7 – 8 hours	-8.664	(6.130)
Day of week dummies (6)	Yes	
Time of day in 3 hour blocks × weekday vs weekend/holiday dummies (15)	Yes	
Activity dummies (42)	Yes	
Companionship dummies (7)	Yes	
Prior response count dummies (3: to power 1, 2, 3)	Yes	
Respondent fixed effects	Yes	
Constant	57.81***	(1.031)
R-squared (within)	0.122	
Observations	2,085,410	
Number of respondents	32,201	

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

TABLE A2.

Variables	coefficient	robust std. err.
Reported happiness (0 – 100)		
Before match		
3 – 2 hours	1.473**	(0.535)
2 – 1 hours	-0.214	(0.654)
1 – 0 hours	-0.725	(0.539)
After win		
0 – 1 hours	3.857***	(1.147)
1 – 2 hours	1.307	(1.163)
2 – 3 hours	1.126	(0.945)
3 – 4 hours	1.996*	(1.015)
4 – 5 hours	1.603+	(0.931)
After draw		
0 – 1 hours	-3.203**	(1.119)
1 – 2 hours	-0.788	(1.193)
2 – 3 hours	-0.183	(1.079)
3 – 4 hours	-0.0964	(1.054)
4 – 5 hours	-0.0552	(1.244)
After loss		
0 – 1 hours	-7.819***	(1.383)
1 – 2 hours	-3.094**	(1.072)
2 – 3 hours	-3.167**	(1.127)
3 – 4 hours	-1.748+	(0.966)
4 – 5 hours	-1.966+	(1.040)
Selected activities		
Intimacy, making love	12.48***	12.48
Sports, running, exercise	7.846***	7.846
Theatre, dance, concert	6.947***	6.947
Listening to music	3.252***	(0.0953)
Watching TV, film	1.795***	(0.0580)
Travelling, commuting	-0.739***	(0.0755)
Working, studying	-2.922***	-2.922
Waiting, queueing	-3.171***	-3.171
Care or help for adults	-4.432***	-4.432
Sick in bed	-19.23***	-19.23
Additional activity dummies (32)	Yes	
Day of week dummies (6)	Yes	
Time of day in 3 hour blocks × weekday vs weekend/holiday dummies (15)	Yes	
Companionship dummies (7)	Yes	
Prior response count dummies (3: to power 1, 2, 3)	Yes	
Respondent fixed effects	Yes	
Constant	57.81***	(1.031)
R-squared (within)	0.122	
Observations	2,085,410	
Number of respondents	32,201	

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Appendix A: The survey instrument

If a signal has been received, the app launches directly into the questionnaire.

The questionnaire spans multiple screens, delineated below by horizontal rules. Tapping an option suffixed by '>' immediately advances to the next screen.

The first screen has a 'Cancel' button that discontinues the questionnaire, and each subsequent screen has a 'Back' button to return to the preceding screen.

THIS SCREEN IS ILLUSTRATED ABOVE

Feelings

Do you feel… ?

Happy (slider: Not at all … Extremely)

Relaxed (slider: Not at all … Extremely)

Awake (slider: Not at all … Extremely)

Next >

People

Please tick all that apply

Are you… ?

Alone, or with strangers only >

Or are you with your… ?

[ ] Spouse, partner, girl/boyfriend
[ ] Children
[ ] Other family members
[ ] Colleagues, classmates
[ ] Clients, customers
[ ] Friends
[ ] Other people you know

Next >

THIS SCREEN IS ILLUSTRATED ABOVE

Place

Are you… ?

Indoors >
Outdoors >
In a vehicle >

Place (2)

And are you… ?

At home >
At work >
Elsewhere >

If you're working from home, please choose 'At home'

THIS SCREEN IS ILLUSTRATED ABOVE

THE ACTIVITIES LIST IS ADAPTED FROM THE AMERICAN TIME USE SURVEY ACTIVITY LEXICON 2009 (US BUREAU OF LABOR STATISTICS) AND THE UNITED KINGDOM 2000 TIME USE SURVEY (UK OFFICE FOR NATIONAL STATISTICS).

Activities

Please tick all that apply

Just now, what were you doing?

[ ] Working, studying

[ ] In a meeting, seminar, class
[ ] Travelling, commuting
[ ] Cooking, preparing food
[ ] Housework, chores, DIY
[ ] Admin, finances, organising
[ ] Shopping, errands
[ ] Waiting, queueing
[ ] Childcare, playing with children
[ ] Pet care, playing with pets
[ ] Care or help for adults
[ ] Sleeping, resting, relaxing
[ ] Sick in bed
[ ] Meditating, religious activities
[ ] Washing, dressing, grooming
[ ] Intimacy, making love
[ ] Talking, chatting, socialising
[ ] Eating, snacking
[ ] Drinking tea/coffee
[ ] Drinking alcohol
[ ] Smoking
[ ] Texting, email, social media
[ ] Browsing the Internet
[ ] Watching TV, film
[ ] Listening to music
[ ] Listening to speech/podcast
[ ] Reading
[ ] Theatre, dance, concert
[ ] Exhibition, museum, library
[ ] Match, sporting event
[ ] Walking, hiking
[ ] Sports, running, exercise
[ ] Gardening, allotment
[ ] Birdwatching, nature watching
[ ] Hunting, fishing
[ ] Computer games, iPhone games
[ ] Other games, puzzles
[ ] Gambling, betting
[ ] Hobbies, arts, crafts
[ ] Singing, performing
[ ] Something else

Next >

BY DEFAULT, THIS DIGITAL CAMERA SCREEN IS SHOWN ONLY WHEN OUTDOORS

Please take a photo straight ahead

Or tap Cancel to skip this step

THIS SCREEN IS SHOWN ONLY IF A PHOTO WAS TAKEN

Map

Add this photo to the public map?
Yes >

No >

THIS SCREEN IS SHOWN ONLY WHEN OUTDOORS AND IN THE RARE EVENT THAT GPS LOCATION ACCURACY IS STILL WORSE THAN 100M. IT ADVANCES AUTOMATICALLY WHEN ACCURACY REACHES 100M OR A PERIOD OF 60 SECONDS HAS ELAPSED.

Location

Improving location accuracy
Skip >

THE SURVEY DISMISSES ITSELF IMMEDIATELY AFTER THIS SCREEN IS DISPLAYED
Finished
Thank you!