Why do fans go to football games? A discrete choice analysis of ticket buyers' preferences

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Abstract

Purpose: Ticket sales are an essential source of income for football clubs and federations. Analyzing the determinants of fans' willingness-to-pay for tickets is therefore an important exercise. By knowing the match- and fan-related characteristics that influence how much a fan wants to pay for a ticket, as well as to what extent, football clubs and federations can modify their ticket offering and targeting, in order to optimize this revenue stream.

Design/methodology/approach: Using a detailed discrete choice experiment, based on McFadden's random utility theory, this paper formulates a Bayesian hierarchical multinomial logit model. Such models are very common in the discrete choice modeling literature. The analysis identifies to what extent match and personal attributes influence fans' willingness-to-pay for games of the Belgian men's and women's football national teams.

Findings: The results show that the strength of the opponent, the type of competition, the location of the seats in the stadium, the day and kick-off time of the match and the ticket price exert an influence on the choice of the respondent. Fans are attracted most by competitive games against strong opponents. They prefer to sit along the sideline, and they have clear preferences for specific kick-off days and times. We also find substantial variation between socio-demographic groups, defined in terms of factors such as age, gender, and family composition.

Practical implications: We use the results to estimate the willingness-to-pay for match tickets for different socio-demographic groups. Our findings are useful for football clubs and federations interested in optimizing the prices of their match tickets.

Originality: To the best of the authors' knowledge, no stated preference methods, such as discrete choice analysis, have been used to analyze the willingness-to-pay of sports fans. The advantage of discrete choice analysis is that options and variations in tickets that are not yet available in practice can be studied, allowing football organizations to increase revenues from new ticketing instruments.

Keywords — football tickets; willingness-to-pay; sports economics; football management; discrete choice experiment; Bayesian hierarchical multinomial logit model

JEL classifications — C250, L830, Z2

1 Introduction

Football clubs and federations may have different objectives, such as maximizing profit and shareholder revenue, increasing budgets for their sporting and operational activities, trying to win as many matches and trophies as possible, or a combination of previous and other objectives (Kesenne, 2014). Although they have a variety of income sources, the revenue from ticket sales is an important one; it often accounts for 20 to 25% of total revenue (Tymes4, 2022). Analyzing the determinants of fans' willingness-to-pay for tickets is therefore an important exercise in order to optimize this stream of revenue, as it allows to set optimal ticket prices.

Consumers do not derive utility from goods as such, but rather from the combination of characteristics or attributes of a specific good (Lancaster, 1966). This utility idea has been incorporated in the random utility theory of McFadden (1974), a pioneering work describing how the discrete choice methodology models the choices made by economic agents, based on a number of good attributes and specific attribute levels.

In this paper, we study the determinants of the willingness-to-pay for tickets of the games of the Belgian national male and female football teams, using a discrete choice experiment, set up specifically for this purpose. More specifically, we study the factors that influence the willingness-to-pay for a general business-to-consumer (B2C) ticket of a single football match. Hence, VIP or business seats are excluded from the scope of this research. Several factors(potentially) influence this willingness-to-pay. Some are match-based, such as the opponent, the time and the location of the match; others are fan-specific, including their age, income, gender and family composition. We derive information on the willingness-to-pay by estimating a Bayesian hierarchical multinomial logit model, based on respondents' choices when confronted with various types of tickets at different prices. This methodology is very common in the discrete choice modeling literature, and is explained in more detail in the Methodology Section.

The data were obtained through a survey performed on football fans in Belgium, focusing on the home games of both the men's national A team, the Red Devils, and the women's national A team, the Red Flames. These matches are organized by the Royal Belgian Football Association, most often in Brussels (men) or Leuven (women). The geographical focus of this study is dictated by data accessibility. The Royal Belgian Football Association helped to guarantee a strong distribution of the survey among their entire fan base.

We are not the first to study the determinants of the willingness-to-pay for football tickets. Some earlier research on the topic has been based on theoretical micro-economic models (Courty, 2003), empirical revealed preference models using historic ticketing data (Rishe & Mondello, 2003), and dynamic pricing models based on revenue management (Drayer et al., 2012). However, to the best of the authors' knowledge, no stated preference methods, such as discrete choice analysis, have been used to analyze the willingness-to-pay of sports fans. The advantage of discrete choice analysis is that options and variations in tickets that are not yet available in practice can be studied, allowing football organizations to increase revenues from new ticketing instruments.

The structure of this paper is as follows. In the next section, we emphasize the importance of pricing of football games based on the scarce economic literature. Section 3 explains the methodology, including the design of the discrete choice experiment, the data collection, and the estimated model. In Section 4 we present the estimation results of the discrete choice experiment. The willingness-to-pay results are discussed in Section 5. Subsequently, the implications for practitioners are explained in Section 6. Finally, in Section 7, we present the main conclusions of this paper, point at the limitations of the research, and discuss some ideas for future research.

2 Economic background on the willingness-to-pay for football tickets

Whatever their objectives may be (maximizing profit, on-field performance, etc.), football clubs and federations, like other companies, are interested in ways to generate funds to finance their activities (Kesenne, 2014; Rascher, 1997). One important channel is to maximize the revenues from ticket sales. Setting optimal prices for these tickets requires insight into the determinants of the willingness-to-pay for tickets for particular football games, and the responsiveness or elasticity of ticket buyers to changing prices. The willingness-to-pay focuses on the specific level of an individual consumer or consumer segment. It represents the maximum price the (group of) consumer(s) is willing to pay for a given product (Chapman & Feit, 2015; Kalish & Nelson, 1991). The elasticity concept in general captures the percentage change of a dependent variable (for example, the number of spectators at a football game) in response to a percentage change in an independent variable (for example, the price for attending a football game). Price elasticity is more specifically the ratio of the percentage changes in the quantity demanded as a result of a relative price change of a good (Parkin et al., 2005).

If a football organization knows the willingness-to-pay of its customers (fans or supporters), the organization can match the ticket price to the willingness-to-pay of different customer groups and in that way optimize profits. The willingness-to-pay of supporters might depend on different variables such as behavioral, geographic, and demographic factors (Nufer & Fischer, 2013).

To estimate consumers' willingness-to-pay in this work, we designed and performed a discrete choice experiment. The results of such an experiment have the potential to provide insight into how much importance customers attribute to certain features of a product. Our applied methodology is described in detail in the next section.

3 Methodology

In order to get a picture of the factors that play a role in the purchasing process of Belgian football supporters, we carried out two discrete choice experiments: one for the Red Devils and one for the Red Flames. This section first describes what a discrete choice experiment is, then we explain how the attributes and levels used in the surveys were selected, and we discuss how the data were collected. Finally, we explain the statistical model that we used. When setting up the discrete choice experiments, we took into account the good practices checklist of Bridges et al. (2011).

3.1 Discrete choice experiments

Discrete choice experiments collect stated preference data and are carried out by presenting respondents with sets of alternatives, called choice sets, between which they have to chose. This task is repeated several times with different choice sets. Such discrete choice experiments are frequently used to quantify consumer preferences and have been successfully applied in areas such as marketing (Rossi et al., 2012; Train, 2009), transportation (Zijlstra et al., 2019), health care (Luyten et al., 2015), ecology (Fletcher Jr et al., 2015; Melero et al., 2018; Vardakis et al., 2015), environmental economics (Bennett & Blamey, 2001; Torres et al., 2013; Vojáček, Pecáková, et al., 2010), culture (Baldin & Bille, 2018), and sports (Balliauw et al., 2020). The latter paper also studied the economics of football clubs but, unlike the current paper, it focused on determining the value of social media posts. Although some of the other examples just mentioned studied price determination (e.g., for transport services or theater visits), to the best of the authors' knowledge the determination of optimal ticket prices through a discrete choice analysis including socio-demographic characteristics is new in the sports literature, a sector with peculiar economic characteristics (Kesenne, 2007).

Both discrete choice experiments, for the men's and the women's Belgian national A football teams, were conducted in the form of online surveys, where each respondent was repeatedly given the choice between two alternative hypothetical tickets of these teams' home games. We created an experimental design using a list of variables, called attributes, that were expected to have an influence on the respondents' decisions. We also selected the levels that each attribute could take. For example, after choosing the *attribute* price of the ticket, the price *levels* had to be selected. We list and discuss the selected attributes and levels in Section 3.2.

In addition to the two alternative ticket options, we also included a *no-choice* option in each choice set. If neither of the two options was sufficiently appealing to the respondent, he or she could select the option *neither of the two*. There are several reasons to include a no-choice option. First, in the context of the utility-maximization model, it is assumed that respondents choose the option that offers the maximum amount of utility. However, if respondents are confronted with two choices that do not offer sufficient utility, the benefits of searching for better alternatives are greater than the costs. Respondents choose the no-choice option and look for more attractive alternatives when this offers higher utility the alternatives that do not appeal to them (Vermeulen et al., 2008). Second, a psychological motive is respondents' fear to indicate a "wrong" alternative in the case where the utility of both options is almost equal. It has been shown that discrete choice experiments with a no-choice option provide a better representation of reality (Johnson & Orme, 1996; Lancsar & Louviere, 2008).

With the attributes and levels at hand, the experimental designs for the surveys were constructed using the D-optimality criterion, the most traditional metric used in the literature to optimize statistical efficiency of discrete choice experiment designs (Bliemer & Rose, 2010, 2011; Bliemer et al., 2009; Burgess & Street, 2005; Grasshoff et al., 2003; Kessels, Jones, Goos, & Vandebroek, 2011). This metric is as an estimation-oriented criterion because it focuses on a precise model estimation by maximizing the determinant of the information matrix of the model. The designs were created in the statistical software JMP Pro 14. More details about the experimental designs are included in the Appendix.

3.2 Attributes and levels used in the study

For this study, we used existing literature to compile the list of attributes. Some are believed to be determinants of the attractiveness of a game and the quality of the viewing experience, others relate to the characteristics of potential spectators.

A first attribute is the ticket type, which indicates where a spectator will be in the stadium. The prices of tickets will depend on this location within the stadium and can differ greatly (Kaiser et al., 2019). For example, seats on the side of the field are often preferred over seats in a corner or behind a goal. Spectators are generally willing to pay more for sideline tickets, as these are the positions with the best view where also the main TV cameras are positioned.

A second set of attributes are related to the attractiveness of a game. This strongly depends on the competitive balance (Michie & Oughton, 2004). Many spectators want there to be a sufficiently high uncertainty about the outcome of the match. For example, for a strong national team, a strong opponent is often preferred because there is uncertainty about which team will win. In addition to the uncertainty of the outcome, two strong opponents are more likely to deliver a high-quality match. Moreover, what is at stake in a particular game also plays a role in how attractive the game is from the viewpoint of the fans. One expects them to prefer competitive matches over friendly ones. Because of this, we also included an attribute that takes into account these stakes.

Finally, Armstrong (2008) showed that both the day and the time of a match play a role in the preference of fans to attend a match. Therefore, we took into account various possible kick-off times in the experiment.

It is useful to divide the respondents into different homogeneous groups, using their demographic characteristics. After all, choice behavior is influenced not only by the attributes of a product, but also by certain characteristics of the decision maker. By dividing consumers into smaller subgroups, the difference in purchasing behavior can be determined. In a sports marketing context, age, gender and income are the socio-demographic characteristics that are most frequently used (Mullin et al., 2014). The reason for including the income of the respondent is that a higher income generally leads to the ability to spend more money on non-vital activities and products, such as a football match ticket.

We further took into account two attributes to capture respondents' family composition: whether they have a partner and/or children. According to Armstrong (2008), this is an important criterion when purchasing tickets for sporting events.

Finally, the distance that supporters have to travel might play a role in their purchasing decision. It is likely that travel time has a negative influence on the decision to buy a ticket. Past research has shown that a long trip can be overcome by a strong emotional attachment and loyalty to a sport, team or club (Smith & Stewart, 2007). One expects the stadium's location to be more important to occasional or neutral spectators than to loyal supporters (Dragin-Jensen et al., 2018). In this paper, the time to get to geographical area of (Flemish) Brabant, where the stadiums of the national teams are located, was surveyed.

After selecting the attributes, we identified their levels, so that the respondent can compare the different options. Levels must be plausible, actionable, and must be set up in such a way that the respondent can make trade-offs between the different values (Kjær, 2005; Ryan, 1999). The final attributes and their respective levels are the following:

- *Opponent's strength.* We used FIFA's team ranking, based on teams' performance in international matches, qualifiers and friendly matches. Based on this, we divided the opponents into three categories: strong (positions 1-10), moderate (11-50) and weak (51 and higher).

- *Game type.* Both men's and women's Belgian teams participate in a number of competitions, such as the European Championship or the World Cup. However, qualification rounds are to be played before these competitions. In addition, there are also friendly matches, which are not played within the competitive context of an official FIFA or UEFA tournament. Finally, there is the Nations League, which is a biennial national competition organized by UEFA. Only the Belgian men's team participated in the Nations League at the time of the experiment, so this attribute level was not included in the women's team survey.

- *Seat location.* The place of a spectator in the stadium can influence their willingness-to-pay. To determine the levels of this attribute, the existing types of regular seating places were taken into account. Standing places, which are seldom allowed, as well as VIP and business seats were left out of scope. The stadium was divided into three zones, which represent the three levels of this attribute, which are

  - side: a seat along one of the two sidelines of the field,
  - corner: a seat in one of the four corners of the stadium, and
  - goal: a seat behind one of the two goals.

- *Day of the week and kick-off time.* The following six moments of the week were selected for the study, as they are the ones that occurred the most frequently at the time of the study: Thursday at 8:45 pm (representing a match in the middle of the week), Friday at 8:45 pm, Saturday at 6:00 pm, Saturday at 8:45 pm, Sunday at 6:00 pm, and Sunday at 8:45 pm.

- *Ticket price.* To obtain realistic values for the ticket price levels, we used ticket prices for matches that were observed at the time of the study. For the men's team, we used prices of €15, €25, €50, and €75; for the women's team prices of €5, €8, €12, and €15 were included.

The attributes and levels selected for our study were subsequently validated by the ticketing and marketing staff of the Royal Belgian Football Association.

3.3 Data collection

Once the attributes and their levels had been chosen, we created the D-optimal experimental designs for the surveys of the Red Devils and of the Red Flames. Each respondent had to answer 10 different questions. The surveys were created and distributed using the Qualtrics software. Since Dutch and French are the two predominantly spoken languages in Belgium, we provided a version in both languages in order to reach the largest possible target audience. An example of a translated question can be seen in Figure 1. In the introduction of the survey, a short explanation was given about the purpose of the research and the meaning of the attributes and levels, after which the choice sets were presented. Finally, a number of socio-demographic questions were asked.

Which ticket would you choose?

	Choice A	**Choice B**
Day and time	Sunday at 20:45	Saturday at 18:00
Type of seat	Goal	Goal
Type of match	Nations League	Qualification
Strength of the opponent	Strong	Strong
Ticket price	15 euros	25 euros

○ Choice A

○ Choice B

○ Neither of the two

Figure 1: Example of a question in the survey.
Source: Own composition.

A common problem when conducting surveys is the occurrence of measurement errors caused by overly complex or ill-defined choice sets, or also because respondents do not pay enough attention to the survey. We therefore included two control questions.

A first one was a choice set with one alternative containing all attribute levels with the highest expected utility, and another alternative with the lowest expected utility. The time of the match was held constant for both alternatives in this choice set. More specifically, the first alternative was a Nations League match with side seating against a strong opponent at €15 for the men's team and €5 for the women's team (this alternative was expected to yield the highest utility). The other alternative was a friendly match with corner seating against a weak opponent at €75 for the men's team and €15 for the women's team (this alternative was expected to yield the lowest utility). The time of the match was Friday at 8:45 pm for both alternatives. Respondents who chose the alternative with the lowest utility were assumed to be bad respondents and were therefore removed from the data set.

A second control question involved the replication of a given choice set from the survey, with the alternatives presented in reversed order. A respondent choosing inconsistently also led to exclusion from the sample.

After the surveys were created, we addressed possible respondents via communication channels of the Royal Belgian Football Association and fan clubs from the Red Devils and Red Flames, Royal Antwerp FC (from the Dutch speaking North of Belgium) and Standard Liège (from the French speaking South of Belgium).

We were able to reach 1094 respondents via the described channels. Out of these 1094 respondents, 915 indicated to be supporters of the Red Devils and 324 supporters of the Red Flames. Note that this implies that some people filled out both surveys. Filtering based on the control questions resulted in a total of 308 responses of inattentive, distracted supporters being removed from the data: 238 for the Red Devils and 70 for the Red Flames. As a result, we had data from 677 supporters of the Red Devils and 109 of the Red Flames; but out of these, we only had demographic data for 589 supporters of the Red Devils and 98 of the Red Flames. Tables 1 and 2 show the distributions of the demographic variables of the respondents.

Table 1: Distribution of the demographics of the 589 respondents that support the Red Devils.

Attribute	Level	# of respondents
Age group	<25	277
	25 - 45	150
	>45	162
Distance to Flemish Brabant	<20 mins	87
	>= 20 mins	502
Gender	Male	424
	Female	165
Has children?	No	267
	Yes	322
Has partner?	No	283
	Yes	306
Income	<€1000	158
	€1001 - €1800	38
	€1801 - €2500	104
	€2501 - €3000	62
	>€3000	108
	Would rather not say	119

Source: Own composition.

Table 2: Distribution of the demographics of the 98 respondents that support the Red Flames.

Attribute	Level	# of respondents
Age group	<25	30
	25 - 45	45
	>45	23
Distance to Flemish Brabant	<20 mins	7
	>= 20 mins	91
Gender	Male	58
	Female	40
Has children?	No	41
	Yes	57
Has partner?	No	37
	Yes	61
Income	<€1000	20
	€1001 - €1800	23
	€1801 - €2500	3
	€2501 - €3000	21
	>€3000	13
	Would rather not say	18

Source: Own composition.

3.4 Discrete choice modeling

In order to estimate the impact of the attribute levels on the fans' utility, we used a Bayesian hierarchical multinomial logit model, which is also called multi-level, random-coefficient, or mixed model. Logit type models are well grounded in economic theory (Anderson et al., 1993), and they are arguably the most commonly used in the choice modeling literature (Akinc, 2019; Chapman & Feit, 2015; Goos & Hamidouche, 2019; Hein et al., 2022; Revelt & Train, 1998; Rossi, 2019; Train, 2009). Additionally, the ubiquity of tools for fitting logit type models makes its use an attractive option for modelers.

The model we used assumes that each respondent faces S choice sets involving J alternatives each, and that, within each choice set $s \in \{1, ..., S\}$, each respondent chooses the alternative that has the highest perceived utility. The probability that respondent n chooses alternative $j \in \{1, ..., J\}$ in choice set s, denoted by p_{njs}, is the probability that the perceived utility of alternative j in choice set s, denoted by U_{njs}, is larger than that of the other alternatives in the choice set. Since each alternative in a choice set has a set of observable attributes that characterize it, the perceived utility U_{njs} can be expressed as

$$U_{njs} = \boldsymbol{x}_{njs}^T \boldsymbol{\beta}_n + \varepsilon_{js}, \tag{1}$$

where $\boldsymbol{x}_{njs}$ is the column vector that contains the attribute levels corresponding to alternative j in choice set s for respondent n, and $\boldsymbol{\beta}_n$ is the vector containing the model parameters for respondent n. The error terms ε_{js} are assumed to be independent and identically Gumbel distributed. As a result of this distributional assumption, the probability that respondent n chooses alternative j in choice set s is

$$p_{njs} = \frac{\exp\left(\boldsymbol{x}_{js}^T \boldsymbol{\beta}_n\right)}{\sum_{t=1}^{J} \exp\left(\boldsymbol{x}_{ts}^T \boldsymbol{\beta}_n\right)}. \tag{2}$$

In this model, each respondent n has their own set of individual parameters $\boldsymbol{\beta}_n$.

This is because we assume that there is heterogeneity in our data set, i.e., different people have different preferences. This makes the hierarchical model more powerful than a model with single-level parameters because it can fit the data better and make more accurate predictions. Additionally, the use of the Bayesian paradigm allows for each of the individual-level parameters to borrow strength from each other, since the model does not estimate each individual's parameters in a vacuum, but rather it uses all of the data (Gelman et al., 2013). We assume that each $\boldsymbol{\beta}_n$ is drawn from a normal distribution with mean values depending on demographic data:

$$\boldsymbol{\beta}_n \sim \mathrm{MVN}(\Delta^T \boldsymbol{z}_n + \boldsymbol{\mu}, \Sigma), \tag{3}$$

where MVN denotes a multivariate normal distribution, $\boldsymbol{z}_n$ is a vector containing the centered demographic variables of respondent n, $\boldsymbol{\mu}$ is a vector of parameters describing the average population part-worths of the attributes, Δ is a matrix of parameters (each column corresponds to an element of $\boldsymbol{\beta}_n$), and Σ is the covariance matrix of the heterogeneity distribution.

The part-worths of the attributes are interpreted as latent utilities that respondents place on the attributes. They measure how much utility respondents derive from each attribute and indicate whether overall utility is impacted positively or negatively by each attribute level. The part-worths serve as the input to determine willingness-to-pay and probabilities of attribute choice later on.

An important design question is how the no-choice option should be represented in the utility equation. In this work, we use the so-called extended no-choice multinomial logit model. The model contains an additional indicator variable that represents the no-choice option in the utility equation, called the alternative specific constant. The alternative specific constant takes a value of 1 if the no-choice option is selected and a value of 0 otherwise. If the no-choice option was chosen, the respondent's utility is determined solely by the coefficient of the alternative specific constant. When this coefficient is positive, this is interpreted as a preference of the respondents for the no-choice option, e.g., to stay at home, rather than buy a match ticket (Haaijer et al., 2001; Vermeulen et al., 2008).

4 Model results

In this section we present the results of the data analyses we performed. We fitted the model described in Section 3.4 to the Red Devils as well as to the Red Flames data. The fitting was done with the R programming language (R Core Team, 2017) and the `bayesm` package (Rossi, 2019), which uses Markov Chain Monte Carlo algorithm, particularly a hybrid Gibbs sampler with a random walk Metropolis step. Details about the implementation, such as the number of Markov Chain Monte Carlo chains, number of iterations, and convergence of chains, can be found in the Appendix.

4.1 Red Devils

Figure 2 shows the point estimates and 95% posterior probability intervals of the elements of the parameter vector $\boldsymbol{\mu}$ for the Red Devils data, as described in Equation (3). Since we centered the demographic variables when fitting the model, the parameter vector $\boldsymbol{\mu}$ represents the average population part-worths of the attributes of the tickets for matches of the Red Devils.

For the categorical variables, we used effects-type coding, as opposed to the more traditional dummy variable approach in which one of the attribute levels acts as a reference. The effects-type coding offers the advantage that a separate part-worth can be constructed for each level of each attribute.

Let us first focus on the part-worths corresponding to the three levels of the attribute opponent. According to Figure 2, $\mu_{\text{weak}} = -6.72$, $\mu_{\text{medium}} = -0.12$, and $\mu_{\text{strong}} = 6.84$. Hence, for the average population, the difference in utility of seeing the Red Devils against a weak opponent rather than against a hypothetical average opponent is 6.72, with the weak opponent being less desirable because the sign of the μ_{weak} parameter is negative. Similarly, the difference in utility of seeing the Red Devils against a strong opponent rather than against a hypothetical average opponent is 6.84, with the strong opponent being more desirable because the sign of the μ_{strong} parameter is positive. Finally, the difference in utility of seeing the Red Devils against an opponent of medium strength rather than against the hypothetical average level opponent is 0.12.

The attribute type of game also has three levels: *Nations League*, *Qualification*, and *Friendly*. The results show that the average respondent prefers qualifiers slightly over Nations League games and that these two game types are strongly preferred over friendly games.

The interpretation is similar for the attributes seating and timing. More generally speaking, the side seat is more desirable than a goal seat, and a goal seat is preferred over a corner seat. As for timing, the least desirable time and day for a match is Thursday at 20:45, whereas the most desirable one is Saturday at 18:00, followed by Friday at 20:45. In general, all moments that are not too close to the start of a working day are preferred.

We can also analyze the size of the effect of each attribute level. The largest positive parameter is μ_{strong}, followed by $\mu_{\text{qualification}}$. So, these two attributes have the highest positive effect on the utility of a match ticket. This explains why teams seek to host as much as possible strong opponents in important games. On the other hand, the largest negative value is μ_{friendly}, followed by μ_{weak}, meaning that these two attributes have the highest negative effect on the utility of the respondents. These two facts are reflected in the fact that tickets for friendlies against weak opponents are usually the most difficult to sell.

An additional interesting insight is how the ticket price affects the respondents' utility, and how this differs according to the respondents' income. We have information about the income of 470 respondents that filled out the Red Devils survey.

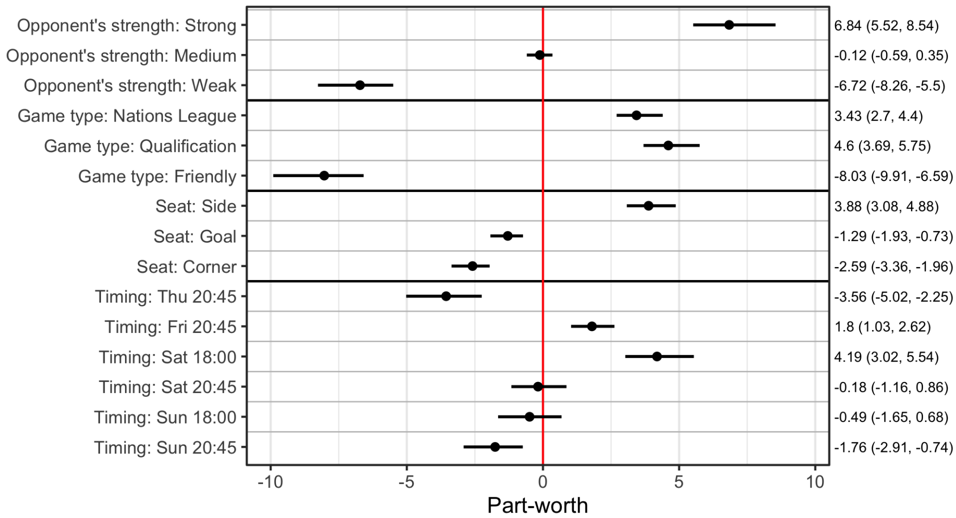

Figure 2: Point estimates with 95% posterior probability intervals of the part-worths contained in the parameter vector $\boldsymbol{\mu}$ for the Red Devils data set.
Source: Own composition.

One way to see how income and buying attitude are related is by quantifying how many respondents would buy tickets of different prices, and see how this changes between different income groups. To this end, we used the Red Devils model to compute each individual respondent's probability of buying any type of ticket at different prices, namely €50, €75, €100 and €125. We then pooled the individuals according to their reported income and computed the percentage of respondents in each income group that would buy a ticket at each price. The results can be seen in Figure 3. Not only does the percentage of respondents decrease with price, but the rate at which it declines also differs from group to group. The decline is larger for low income groups than for high income groups, so the graph confirms that lower income respondents are more price-elastic. However, note that the lowest income group is an exception in the sense that it mainly contains young students who probably do not rely on their own income to buy tickets. They might rather rely on the allowance they receive, for instance from their parents, or they directly ask their relatives for money to buy the tickets (for them).

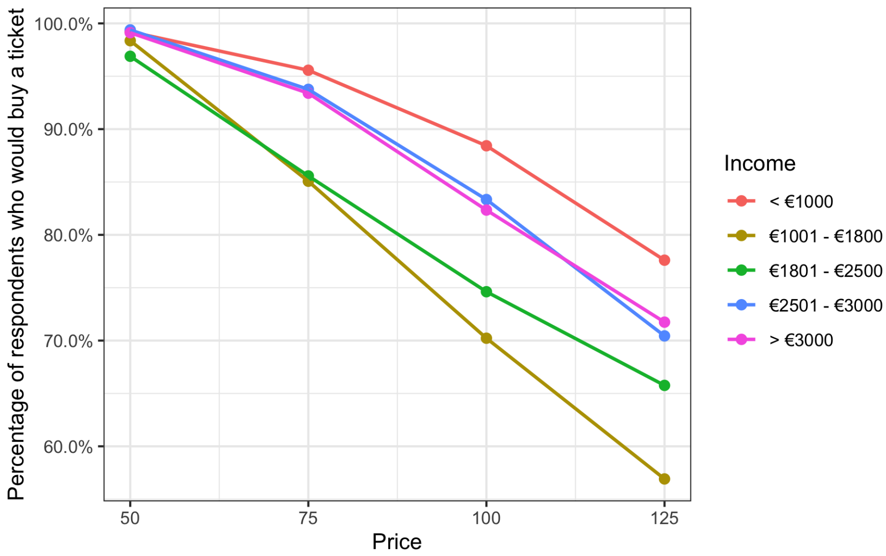

Figure 3: Percentage of respondents in each income group who would buy a ticket at a specific price, according to the Red Devils model.
Source: Own composition.

4.2 Red Flames

Figure 4 shows the point estimates and 95% posterior probability intervals of the elements of the parameter vector $\boldsymbol{\mu}$ for the Red Flames data, as described in Equation (3). The interpretation is analogous to that of the Red Devils. Figure 4 shows that $\mu_{\text{weak}} = -35.9$, $\mu_{\text{medium}} = 1.9$, and $\mu_{\text{strong}} = 33.8$. Just like with the Red Devils, the order of the preferences for the opponent's strength is as expected: a strong opponent is preferred over a medium strength opponent, which in turn is more desirable than a weak opponent.

Also for the other variables, we find that the results for the Red Flames data are roughly the same as the ones for the Red Devils. The Red Flames respondents also prefer a qualification match over a friendly one and the order of preferred seats is the same, that is, the side seat is more desirable than a goal seat, and a goal seat is more desirable than a corner seat. For timing: Thursday and Sunday are less preferred, but in the Red Flames the difference between these two is not so big. The order for different times on Friday, Saturday and Sunday is similar, but not exactly the same. We can also notice that there is more overlap in the probability intervals of the $\boldsymbol{\mu}$ parameter values, due to a much smaller sample of respondents.

Like for the Red Devils, the attributes that have the highest positive impact are strong opponent and qualification match, whereas the ones that have the highest negative effect are a weak opponent and a friendly game type.

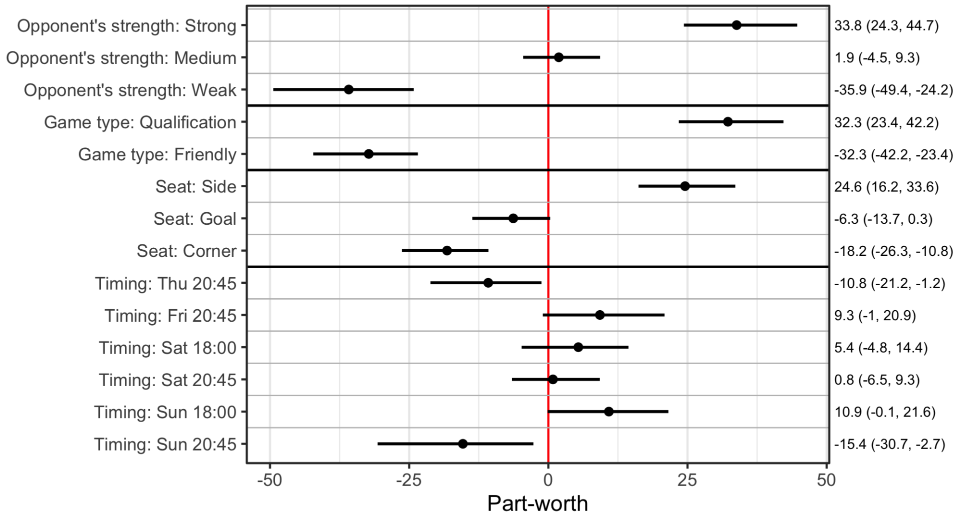

Figure 4: Point estimates with 95% posterior probability intervals of the part-worths contained in the parameter vector $\boldsymbol{\mu}$ for the Red Flames data set.
Source: Own composition.

5 Willingness-to-pay results and discussion

In this section, the previous results are translated into monetary terms through fans' willingness-to-pay for different tickets. The willingness-to-pay gives us a direct interpretation in monetary terms (i.c., euros), which ticketing managers might find more meaningful than utility. In this section we discuss the willingness-to-pay of different groups of respondents for each attribute. We only report the results of the Red Devils, because the limited sample size of the Red Devils' did not allow for a precise willingness-to-pay estimation.

Figures 5–8 show the willingness-to-pay graphically for various subsets of respondents. In each of the figures, we show the point estimates of each group's median willingness-to-pay and the corresponding 95% posterior intervals. The changes in the levels of the four attributes of the tickets are listed vertically, and the horizontal axis represents how much the respondents are willing to pay for that change. A negative willingness-to-pay means that the attribute level change is not appreciated, whereas a positive one means the opposite. Details on the computation of these values are given in the Appendix.

In Figure 5, we show the willingness-to-pay of three different age groups. There are three important differences between the groups. The group with the youngest respondents is the only one preferring a match on a Sunday night at 20:45 over a Saturday night at 20:45. The group of people older than 45 years are the only ones that would rather sit in the corner than behind the goal. Finally, young people seem much more sensitive to the quality of the opponent and the stakes of the match. For instance, for a strong opponent, respondents below 25 years old are willing to pay between €35.8 and €50.1 more than for a weak opponent. People over 25 are only willing to pay between €18.7 and €33.4 more.

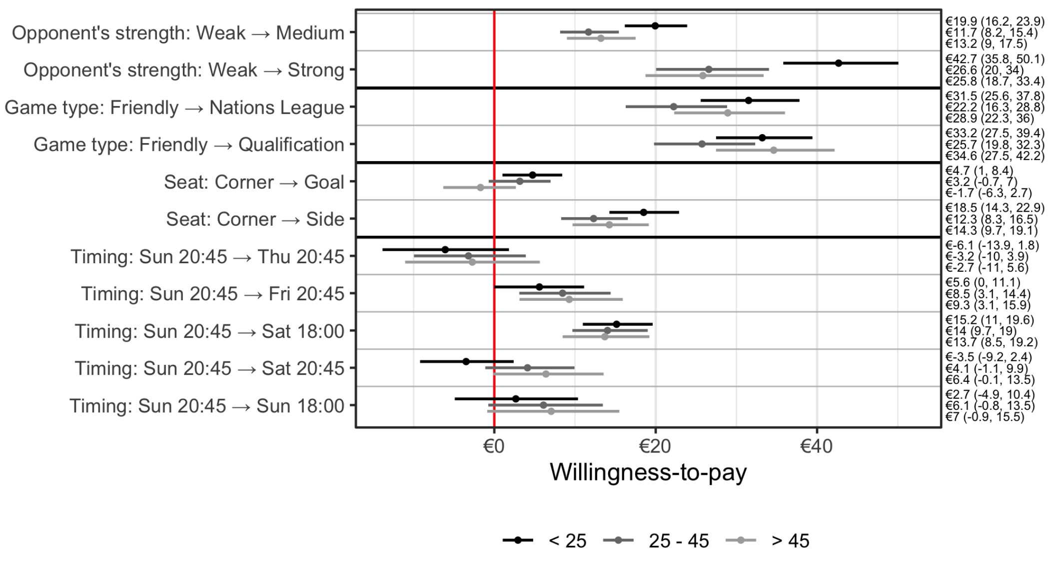

Figure 5: Willingness-to-pay of different age groups.
Source: Own composition.

Figure 6 depicts the willingness-to-pay of respondents, as a function of the distance they have to travel to Flemish Brabant. We can see that the people that live more than 20 minutes away are willing to pay much more for a change from a friendly to a Nations League match, and to see the Red Devils against a strong opponent. This could be due to the fact that because they have to travel further, they can only be convinced to attend important games against strong opponents. People who live nearby find it less of a problem when a game is played on Sunday night at 20:45, compared to some other kick off times, because they do not have a long trip to make the night before they have to go back to work.

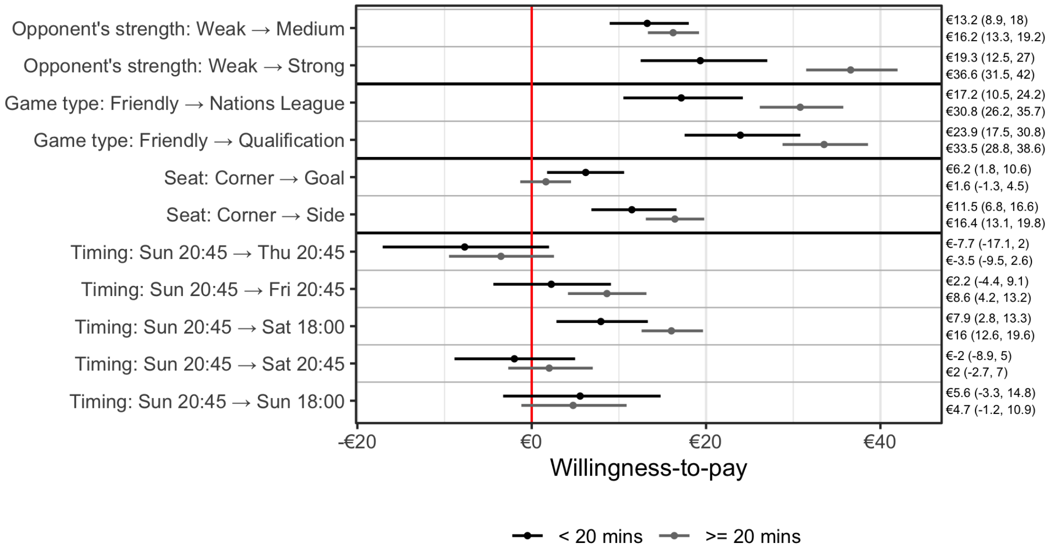

Figure 6: Willingness-to-pay of respondents divided by the time it takes to get to (Flemish) Brabant.

Source: Own composition.

In Figure 7, we can see the willingness-of-pay of respondents divided by gender. One first clear insight is that men prefer a football match on Saturday night at 20:45 over Sunday night at 20:45, whereas women prefer it the other way round. Additionally, women seem to have a higher preference than men for better seats on the side, stronger opponents and more important matches when they attend a national team's game.

Finally, Figure 8 shows the willingness-to-pay of two distinct groups: people with

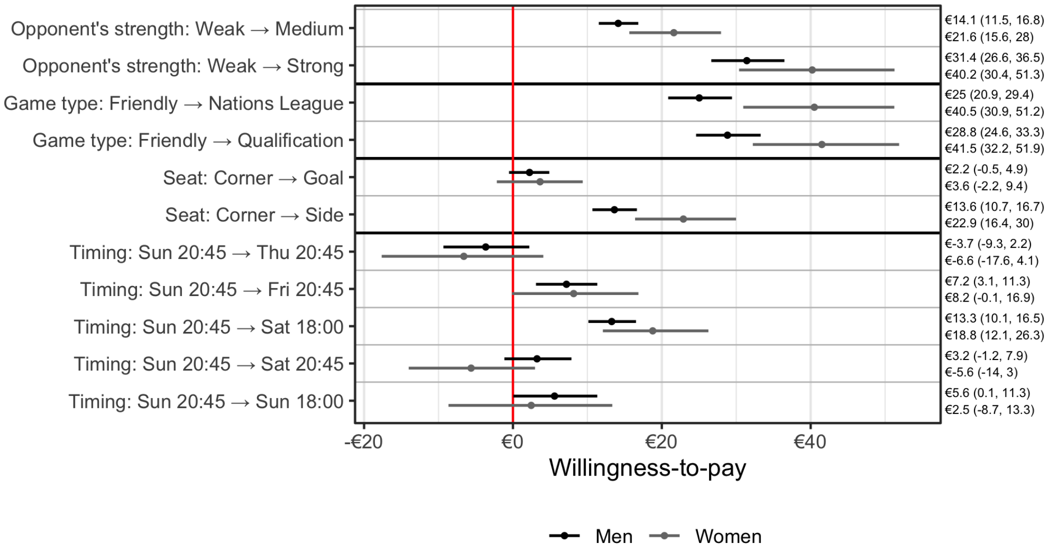

Figure 7: Willingness-to-pay divided by gender.
Source: Own composition.

a partner and children, and single people without children. Similarly to the difference between women and men, also here there is one main difference in preference, again for Saturday versus Sunday night games at 20:45: the respondents who are single and without children prefer a Sunday night game at 20:45, whereas the opposite happens with the respondents with a partner and with children. Single people might rather spend their Saturday evenings on other activities, whereas families might consider a football match as a nice family outing.

6 Implications for practitioners

The previous willingness-to-pay analysis has some managerial implications and leads to actionable insights for practitioners, including football associations.

First, the highest ticket prices can be charged for seats on the side of the field, for matches against top teams in competitive games, on Saturdays at 6 pm. Moreover, associations might want to charge lower prices for less preferred kick-off times, such as Thursday and Sunday at 20:45, to make up for the reduced utility caused by

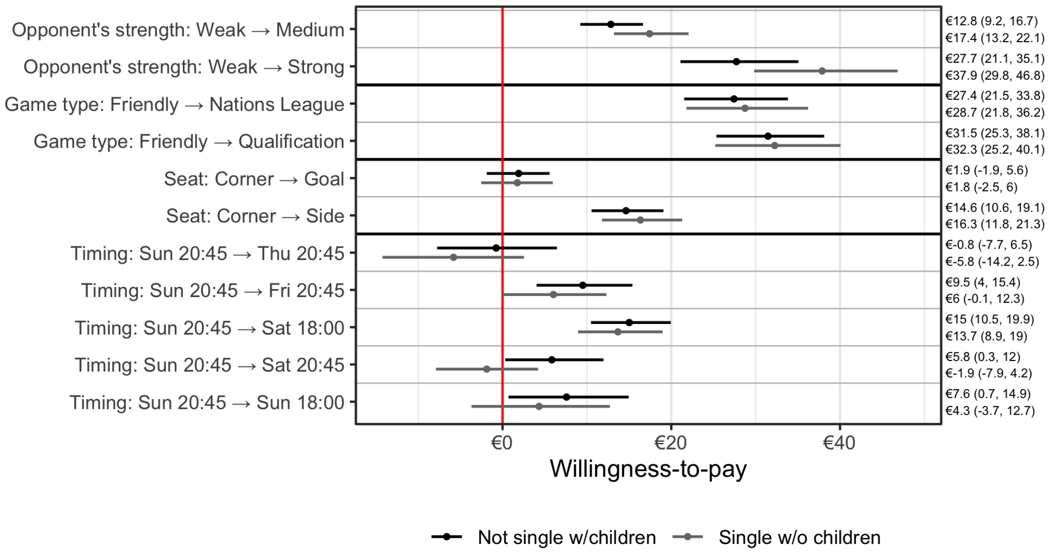

Figure 8: Willingness-to-pay of respondents with a partner and children, compared to single respondents without children.
Source: Own composition.

these time slots.

A second insight arises from the analysis based on the preferred sectors in the stadium. If marketing activations, such as dedicated seating blocks or sectors in the stadium, are to be set up for youth, senior or female attendees, it is best to organize them in the areas of the stadium that they prefer.

Third, for matches on a Saturday night, it might be good to link some kind of party experience to the match, especially if the opponent is less strong. In this way, people who prefer spending their Saturday night partying can benefit from both a game and a party experience. Similarly, on a Saturday night, specific actions for women, such as "bring a female friend for free", might be welcomed to increase female attendance.

Fourth, the analysis unveils a strong preference among women for competitive matches against strong opponents. Those games might offer an ideal opportunity to attract more female supporters to matches of the men's national team.

Finally, the analysis shows that people who have to travel longer to get to the stadium have a lower willingness-to-pay for non-competitive games against weak opponents. Organizing efficient group transportation to the stadium from the different regions of a country might help overcome this issue, especially for games during the working week and on a Sunday evening.

On top of the insights just described, the results can also be used by the Belgian Federation to optimize their ticket pricing strategy, leading to an increase in revenues from ticket sales. An illustration is provided using some back-of-the-envelope calculations.

Based on public attendance figures and ticketing prices from the RBFA website, the following simplified data are obtained for two matches of the Belgian Red Devils in their 2022 UEFA Nations League campaign. We hereby assume that 75% of the attendees pay for their tickets, namely the supporters in 3 out of the 4 stadium stands, as the main stand mainly implies invitees. For their game against a strong opponent (the Netherlands) on a Friday at 20:45, which was immediately sold out, the average ticket price was €60 and there were about $30,000$ paying attendees. For their game against an average opponent (Poland) a few days later on a Wednesday at 20:45, the average ticket price was €55, which is only €5 less, and there were about $20,000$ paying attendees.

How to attract more supporters for the game against Poland, played at a less attractive time? According to the WTP analysis, the price of €60 of the match against the Netherlands could be lowered by €20 for the match against Poland. The analysis showed that this would result in a preservation of the utility level: €15 for the reduced strength of the opponent and €5 for the different kick-off moment. At this lower price, the revenue would go from €1.1M ($20,000$ attendees at €55) to €1.2M ($30,000$ attendees at €40).

However, given the fact that the game against the Netherlands sold out immediately and the stadium capacity restriction of $40,000$ places, it can be assumed that even with a higher base price for the game against the Netherlands, the stadium would still have been sold out for that match. As a result, also a higher final price for the match against Poland would still have sold out the stadium and lead to higher revenues.

7 Conclusions, limitations and future research

Football clubs and federations try to maximize revenues from their ticket sales. In order to do this, insight into the factors that influence the willingness-to-pay of fans can be used to determine optimal prices for their tickets. To our knowledge, we were the first to apply a discrete choice experiment to this research area. Based on our experiment involving 589 supporters of the Belgian men's A national football team, we found that strength of the opponent and importance of the match matter the most. The stronger and the more important they are, the larger the willingness-to-pay. Additionally, seats along the sideline are worth the most. Moreover, some kick-off days and times are clearly preferred over others.

In order to identify differences in preferences between different segments in the population, socio-demographic factors were included in the analysis as well. For instance, younger people and women are more sensitive to the strength of the opponent and importance of the match. Moreover, gender, age and distance from the stadium impact the preference for certain kick-off days and times. These insights suggest specific actions that clubs and federations can take in order to maximize ticketing revenues from the different socio-demographic groups.Moreover, the findings can be used to improve the actual ticket pricing strategy of clubs and federations, in order to maximize revenues.

In addition to the analysis of the men's national team, we also surveyed 98 supporters of the women's national team. The analysis of these supporters showed a similar overall pattern as the one identified for the men's team. However, the number of responses was not sufficient to make a more detailed analysis of differences in willingness-to-pay among different socio-demographic groups.

Hence, the first suggestion for future research is to conduct a specific analysis of football tickets for women's teams. This would allow to also identify potential differences in willingness-to-pay among socio-demographic groups for tickets of these teams.

Additionally, a non-attendance analysis could be performed on the existing data to identify if members of certain demographic groups ignore specific attributes under the presence of some others. An example could be a respondent, although being part of a lower income group, who would buy a ticket for a match against a very strong opponent regardless of a (very high) ticket price.

Another potential future research area would be an analysis to find the optimal pricing that maximized both the club's revenue and the supporters' utilities at the same time. Moreover, a multi-level analysis with post-stratification could be applied to increase the generalizability of the results, by reducing the biases from the non-representative sample.

Finally, it would be worthwhile to verify if the same results hold for football federations in other countries than Belgium, as well as for football clubs in different countries. This would further enhance the generalizability of the findings. Part of the methodology elaborated in this paper could be applied for this purpose.

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Appendix A Optimal design of experiments

The D-optimality criterion is the most traditional metric used in the literature (Bliemer & Rose, 2010, 2011; Bliemer et al., 2009; Burgess & Street, 2005; Grasshoff et al., 2003; Kessels, Jones, Goos, & Vandebroek, 2011). It maximizes the determinant of the information matrix of the model. It can be seen as an estimation-oriented criterion because it focuses on a precise model estimation.

For the design creation, we assumed a multinomial logit model in which all respondents have the same preferences and prior parameter values. The multinomial logit model is a particular case of the hierarchical multinomial logit model described in Section 3.4, in which the individual parameters $\boldsymbol{\beta}_n$ are the same for all respondents, and there is no hyperparameter vector $\boldsymbol{\mu}$ nor socio-demographic variables $\boldsymbol{z}_n$.

The model assumes that a respondent in a choice experiment faces S choice sets involving J alternatives, and that, within each choice set $s \in \{1, ..., S\}$, each respondent chooses the alternative that has the highest perceived utility. Therefore, the probability that a respondent chooses alternative $j \in \{1, ..., J\}$ in choice set s, denoted by p_{js}, is the probability that the perceived utility of alternative j in choice set s, denoted by U_{js}, is larger than that of the other alternatives in the choice set, and their definition is the same as in Equations 1 and 2.

For the multinomial logit model, the information matrix depends on the unknown parameter vector $\boldsymbol{\beta}$, through the choice probabilities contained within $\boldsymbol{p}_s$ and $\boldsymbol{P}_s$. This is typical for models that are not linear in the parameters, such as discrete choice models, and it implies that prior information is needed to find optimal designs. This can be in the form of a point estimate, or in the form of a prior distribution (Atkinson & Haines, 1996; Kessels et al., 2006; Ruseckaite et al., 2017). The information matrix $\boldsymbol{I}(\boldsymbol{X}, \boldsymbol{\beta})$ for the multinomial logit model is the sum of the information matrices of each of the S choice sets (Kessels et al., 2006):

$$\boldsymbol{I}(\boldsymbol{X}, \boldsymbol{\beta}) = \sum_{s=1}^{S} \boldsymbol{X}_s^T (\boldsymbol{P}_s - \boldsymbol{p}_s \boldsymbol{p}_s^T) \boldsymbol{X}_s,$$

with $\boldsymbol{p}_s = (p_{1s}, ..., p_{Js})^T$, $\boldsymbol{P}_s = \text{diag}(\boldsymbol{p}_s)$, $\boldsymbol{X}_s^T = [\boldsymbol{x}_{js}]_{j \in \{1,...,J\}}$ denoting the model matrix corresponding to all alternatives in choice set s, and $\boldsymbol{X} = [\boldsymbol{X}_1, ..., \boldsymbol{X}_S]$ denoting the model matrix for all choice sets. The inverse of the information matrix is the asymptotic variance-covariance matrix of the parameter estimates.

For a model matrix $\boldsymbol{X}$ and parameter vector $\boldsymbol{\beta}$, the D-optimality criterion can be defined as

$$\mathcal{D} = \log \left(\det \left(\left[\boldsymbol{I}^{-1}(\boldsymbol{X}, \boldsymbol{\beta}) \right) \right]^{\frac{1}{p}} \right), \tag{4}$$

where $\boldsymbol{I}(\boldsymbol{X}, \boldsymbol{\beta})$ is the information matrix and p is the number of parameters in the model.

A design that minimizes Equation (4) using a point estimate of $\boldsymbol{\beta}$ is called a locally D-optimal design. The problem with locally D-optimal designs is that they may perform poorly for values of the parameter vector $\boldsymbol{\beta}$ for which they were not optimized. This weakness is highly relevant given that the true values of the model parameters are not known. An alternative is to compute Bayesian optimal designs, which take into account prior information and uncertainty about the parameter vector $\boldsymbol{\beta}$ in the form of a prior distribution $\pi(\boldsymbol{\beta})$.

In the choice experiments literature, most of the Bayesian optimal designs define the Bayesian D-optimality criterion as an average of the D-optimality criterion over the prior distribution (Bliemer & Rose, 2011; Bliemer et al., 2009; Kessels, Jones, Goos, & Vandebroek, 2011). Therefore, following Ruseckaite et al. (2017) and Becerra and Goos (2021), we define the Bayesian D-optimality criterion for the multinomial logit model as

$$\mathcal{D}_B = \log \left(\int_{\mathbb{R}^p} \left[\det \left(\boldsymbol{I}^{-1}(\boldsymbol{X}, \boldsymbol{\beta}) \right) \right]^{\frac{1}{p}} \pi(\boldsymbol{\beta}) d\boldsymbol{\beta} \right), \tag{5}$$

where $\pi(\boldsymbol{\beta})$ is the prior distribution of $\boldsymbol{\beta}$. A design that minimizes the Bayesian D-optimality criterion is called a Bayesian D-optimal design.

The assumptions for the prior parameter estimates in this work were that the ticket price would have a negative impact on the utility of the respondents, that an increasing strength of the opponent would lead to an increase in utility, that there was no difference in preference between the different days and times, that a side seat is more preferable to a goal and corner, that there is no difference between the latter, and that Nations League and Qualifiers are equally preferable, and more preferable than a friendly match.

Using the previous assumptions, the prior values of the $\boldsymbol{\beta}$ parameter vector were set as follows $\beta_{\text{Corner}} = -0.25$, $\beta_{\text{Goal}} = -0.25$, $\beta_{\text{Side}} = 0.5$, $\beta_{\text{Friendly}} = -0.5$, $\beta_{\text{Qualification}} = 0.25$, $\beta_{\text{NationsLeague}} = 0.25$, $\beta_{\text{Weak}} = -0.5$, $\beta_{\text{Medium}} = 0$, $\beta_{\text{Strong}} = 0.5$, $\beta_{\text{75euros}} = -0.45$, $\beta_{\text{50euros}} = -0.15$, $\beta_{\text{25euros}} = 0.15$, $\beta_{\text{15euros}} = 0.45$, $\beta_{\text{TimeAndDay1}} = 0$, $\beta_{\text{TimeAndDay2}} = 0$, $\beta_{\text{TimeAndDay3}} = 0$, $\beta_{\text{TimeAndDay4}} = 0$, $\beta_{\text{TimeAndDay5}} = 0$, and $\beta_{\text{TimeAndDay6}} = 0$. The variance covariance matrix was chosen to be $\Sigma_0 = 0.035\boldsymbol{I}$, with $\boldsymbol{I}$ the identity matrix.

The first three values of $\boldsymbol{\beta}$ correspond to the seats; the next three correspond to the type of match; the next three to the strength of the opponent; the next four to the price; and finally, the last five values correspond to the time and day of the match (no preference, hence they are zero).

For our designs, both for the Red Devils and the Red Flames, we used the values of $J = 2$ and $S = 20$. However, we used some restrictions that can be set in JMP. First of all, we used a partial profile design, which means that we restricted the design optimization algorithm to only be able to change three out of the five attributes within each choice set. This was done because we wanted to keep at least two attribute levels fixed within the same choice set, thus giving the respondent fewer attributes to consider and simplifying the decision (Kessels, Jones, & Goos, 2011). Additionally, we divided the 20 choice sets into two different sets of 10 choice sets each, this way each respondent would only answer 10 questions instead of 20, also simplifying the decision process. These two sets of 10 questions each were allocated randomly among the respondents, with half of them responding each set of questions.

Appendix B Individual willingness-to-pay calculation

To compute the individual values of the willingness-to-pay used in Section 5, we used the samples from the posterior distribution of each individual. These samples were obtained via the MCMC algorithm implemented in the `bayesm` package. For example, to compute the willingness-to-pay for a change from a weak to a strong opponent of sample t of individual n, we take the coefficients of the strong and weak levels, as well as the price coefficient, denoted by $\beta^{(n,t)}_{\text{Strong}}$, $\beta^{(n,t)}_{\text{Weak}}$ and $\beta^{(n,t)}_{\text{Price}}$ respectively, and compute the willingness-to-pay as follows:

$$\text{WTP}^{(n,t)}_{\text{Weak}\to\text{Strong}} = -\frac{\beta^{(n,t)}_{\text{Strong}} - \beta^{(n,t)}_{\text{Weak}}}{\beta^{(n,t)}_{\text{price}}},$$

for $n \in \{1, \ldots, N\}$ and $t \in \{1, \ldots, T\}$, where N is the number of respondents and T is the number of (posterior) MCMC samples.

We did the same for all the level changes we were interested in. Once we have the individual willingness-to-pay for each sample, $\text{WTP}^{(n,t)}_{\text{level i}\to\text{level j}}$, we compute the median per respondent group of interest across all posterior samples. For example, we compute the T medians of the group of respondents that live less than 20 minutes away from Flemish Brabant, and the T medians of the group of respondents that live more than 20 minutes away from Flemish Brabant. Then, we compute the 2.5-th, 50-th and 97.5-th percentiles of each group to compare them, and that is what we show in Figure 6. The procedure is analogous for all the level changes and groups mentioned in Section 5.

Appendix C Prior distributions

The prior distributions we used for the parameters were the default priors from the `rhierMnlRwMixture` function in the `bayesm` package, which are the following:

$$\text{vec}(\Delta) = \delta \sim \text{MVN}(\mathbf{0}, A_{\delta}^{-1})$$

$$\boldsymbol{\mu} \sim \text{MVN}(\mathbf{0}, 100\Sigma)$$

and

$$\Sigma \sim \text{IW}(\nu, \nu\boldsymbol{I})$$

with $\boldsymbol{I}$ denoting the identity matrix, $\mathbf{0}$ a vector of zeros, A_{δ} a precision matrix set to be $0.01\boldsymbol{I}$, and ν a "tightness" parameter of the IW distribution with a default value of $p + 3$, where p is the number of variables. For more information, consult the documentation of the `bayesm` package (Rossi, 2019).

Appendix D Model convergence analysis

We used the `rhierMnlRwMixture` function from the `bayesm` package to fit the models used here. For each model, we ran 12 chains of the MCMC sampler using the same prior distributions but different starting values. Each chain was run for $400,000$ iterations, keeping every 100-th draw and filtering out the first half of the samples as burn-in, leading to $24,000$ samples in the end. The convergence of the MCMC chains was confirmed both visually and with the Gelman-Rubin convergence statistic (Gelman & Rubin, 1992).

The values of the Gelman-Rubin statistic for each of the respondent-level parameters of the Red Devils model can be seen in Figure 9. All values are very close to 1, indicating a good mixing of the chains. We did not create this plot for the Red Flames because we did not use individual level parameter estimates in the analysis.

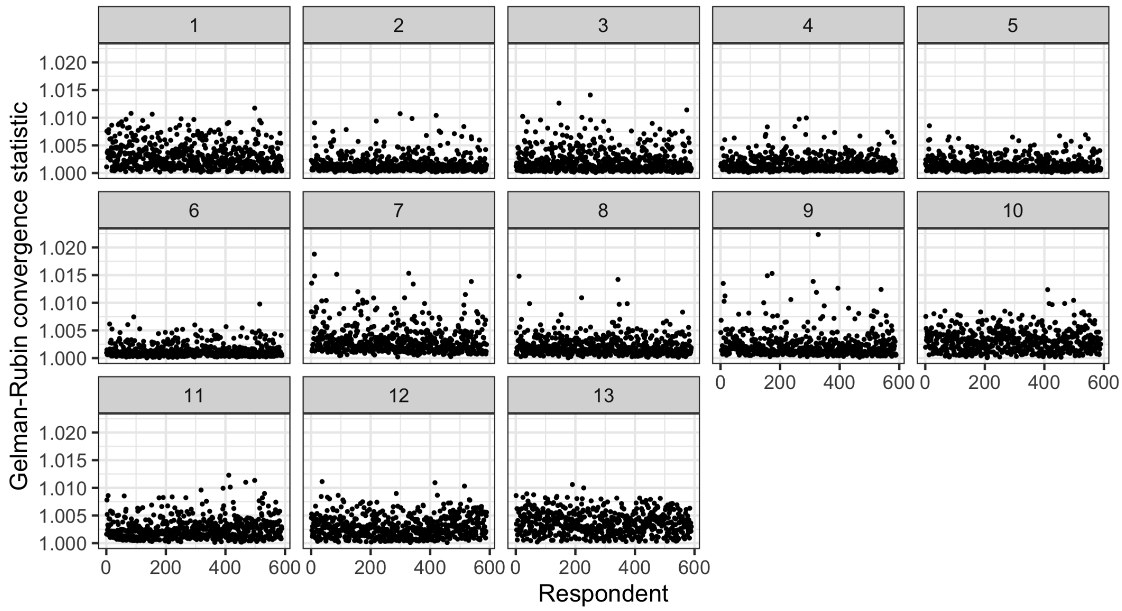

Figure 9: Gelman-Rubin convergence statistic of the individual $\boldsymbol{\beta}_n$ parameters from the model using the data from the Red Devils.
Source: Own composition.