Value determinants of advertisements on football clubs' and players' social media

by

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Abstract

Advertisers frequently use social media for interactive relationship marketing purposes. Moreover, sports clubs and players are using their social media to post content of advertising companies. Even though such posts have value for these advertising companies, previous research did not yet identify the factors that influence this value in a sports marketing context. This paper fills this gap through a discrete choice experiment and an empirical estimation of the utility sponsorship managers derive from a post advertising their company on football clubs' and players' social media. More followers, better performance and a lower price significantly increase the advertising company's utility. Moreover, Facebook and Instagram are preferred over Twitter, due to the latter's limited degrees of freedom for advertisers. This paper's results are useful for practitioners too, since they allow commercial managers of clubs and players to derive companies' willingness to pay for social media advertisements and make better pricing decisions.

Keywords: social media marketing, advertising, sports, willingness to pay, discrete choice

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1. Introduction

Social media such as Facebook, Instagram, Twitter, Snapchat and YouTube connect millions of people on a daily basis in society. Hence, social media offer businesses a convenient opportunity to get in touch with stakeholders such as (potential) customers (Hanna, Rohm, & Crittenden, 2011). Moreover, the attention of enterprises towards professional sports as a means of economic and commercial activity grew during the latest decades (Lagae, 2005). Consequently, companies started to use social media of famous sports players and clubs to reach a wide range of (potential) customers. Enterprises are willing to pay a lot of money for social media posts of those players or clubs containing content linked to the advertising enterprise. For example, social media analysts Blinkfire calculated that football player Neymar Jr earns on average 459,000 euro per advertising post on his social media (El Economista, 2018). Also clubs, such as Spanish football club Real Madrid, post advertising content, like the example involving Fly Emirates in Appendix A.

The objective of this paper is to analyse the value of social media posts for advertising companies, since clubs' and players' insight into the value of their social media posts for these advertisers is limited. Nevertheless, this information is crucial for price setting when such posts are sold to companies or offered as part of a sponsor deal. Given the particular impact of on-field performance on fan behaviour and the creation of brand awareness in sports, a specific social media marketing study focusing on sports is needed (Ngan, Prendergast & Tsang, 2011; Gladden & Funk, 2002).

To this end, the following research question will be answered: "Which club, player and social media related factors affect the willingness to pay of companies for posts on social media of players or clubs, advertising this company or their products, and to what extent?"

As a result, an analysis of the effects of specific content on the target audience (such as brand awareness, positive feelings and return) is beyond the scope of this paper. Next to this, the scope of this paper is limited to football, since this sport generates the most attention and the largest business figures worldwide, also on social media (Statista, 2017). Regarding social media channels, this research focuses on Facebook, Twitter and Instagram. The reason for this is two-fold. First, based on Statista (2017) data about the number of worldwide users, it seems that Facebook is the most popular channel, followed by YouTube, Instagram, Twitter and Snapchat. Second, it was analysed to what extent football clubs and players are active on social media by focusing on the 32 teams that participated in the UEFA Champions League in 2017/18. The results showed that all clubs are present on Facebook, Twitter, Instagram and YouTube. However, the number of followers on YouTube is significantly below those on Facebook, Twitter and Instagram. Concerning players, the social media presence of the most popular player of each Champions League club was analysed too. It was concluded that nearly all players have a profile on Facebook, Twitter and Instagram, whereas almost no player has his own YouTube or Snapchat channel. Consequently in football, Facebook, Twitter and Instagram are the most popular social media and hence best suited for social media advertisements. The Chinese social media channels are left beyond the scope of this research.

In order to formulate an answer to the research question, a discrete choice modelling approach has been adopted. First, a number of club- and player-related factors with potential influence on the value of posts has been identified. Subsequently, a conjoint analysis discrete choice experiment has been designed. Using 40 questionnaires completed by sponsorship professionals, the size and significance of the influence of the identified factors on the users' utility were estimated empirically in two separate models, one for a company post on clubs' social media, and one for a post on players' social media.

This research makes several academic and industry contributions. First of all, this is the first study identifying which factors significantly affect the value for companies of advertising on football clubs' or players' social media. Having an insight into these value determinants will improve decision-making of clubs and players about prices for their social media advertisements. Second, the results will allow clubs and players to increase the quality of social media posts by better taking into account the factors valued most by companies. Third, the insights from this research will lead to better sponsorship deals in terms of prices and quality. Fourth, to the best of the authors' knowledge, this is the first study that applies discrete choice modelling to make the link between social media marketing and sports marketing.

The remainder of this paper is organised as follows. The next section explores the relevant literature on social media and sports marketing. Section 3 describes the discrete choice methodology and Section 4 the collected data. The results of the analysis and the discussion are presented in Section 5. Section 6 derives a number of managerial implications. Section 7 contains the conclusions and suggestions for future research.

2. Theoretical Insights into Sports Social Media Marketing

This research is positioned at the interface of two research domains: social media marketing and sports marketing. Social media are defined by Kaplan and Haenlein (2010, p. 61) as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and that allow the creation and exchange of User Generated Content (UGC)". The user as a content contributor is what distinguishes social media from other online platforms and what makes it increasingly useful for relationship marketing purposes. This is also suggested by Constantinides and Fountain (2008) who define Web 2.0 as a collection of open-source, interactive and user-controlled online applications. As such, Web

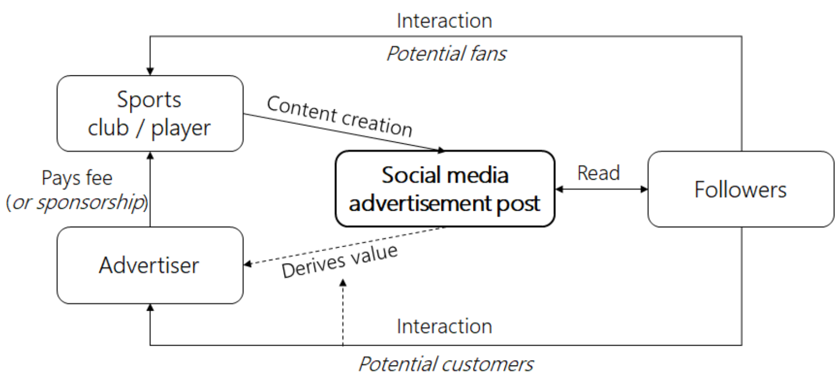
2.0 offers substantial opportunities for companies in terms of personalised and direct interactions with customers as well as for getting feedback on their needs and opinions.

Interaction is one of the key aspects of relationship marketing (RM), which aims at building, maintaining and enhancing relationships with customers. Additionally, it contributes to strengthening brand awareness, better understanding of customer needs and improving customer loyalty (Grönroos, 2004; Stavros, Pope, & Winzar, 2008). As argued by Grönroos (1994) and Gummesson (2011), RM should be considered as a paradigm shift in marketing due to its emphasis on interactive, win-win relationships and networks in which the customer is a co-producer of value. This is in contrast to the traditional marketing mix paradigm based on the 4Ps in which the buyer has a passive role and no personalised relationship and interaction between buyer and seller exist (Constantinides, 2006).

Since interactivity, personalisation and customer empowerment are distinctive features of both relationship marketing and social media, social media marketing (SMM) has become a crucial part of many organisations' RM strategy. According to Kim and Ko (2012), social media allow organisations to perform integrated marketing activities less costly and with much less effort than before. Other specific organisational objectives to be pursued through SMM include increasing brand awareness, stimulating sales, improving brand image, generating traffic to online platforms, reducing marketing costs and creating user interactivity by stimulating users to post or share content in an online community (Ashley & Tuten, 2015; Bianchi & Andrews, 2015; Schultz & Peltier, 2013).

This study combines SMM with sports marketing. The latter is defined by Shank and Lyberger (2014, p. 5) as "the specific application of marketing principles and processes to sport products and to the marketing of non-sports products through association with sports". This paper focuses on the second part of this definition, as it deals with sports entities promoting a company's product or brand through their social media. In addition, this research pays particular attention to advertising, which is defined by Richards and Curran (2002) as "a paid, mediated form of communication from an identifiable source, designed to persuade the receiver to take some action, now or in the future". In this paper, the source is a club or a player posting on its social media an advertisement of a company, while the receiver is a follower of this club or player. These relationships are illustrated in Figure 1.

Figure 1. Relationships and interactions between the stakeholders in social media advertising.



Sports marketing is important for both sports entities and advertising companies for several reasons. For sports entities, sponsoring and advertising are growing sources of revenues due to the ever-increasing commercialisation of sports. Ross et al. (2019) show that the highest earning football clubs generated about 40% of their total revenues from commercial activities including sponsoring and advertising in 2017/2018, so optimising advertising agreements is key to their success. Next to the financial importance of sports marketing, sports entities use RM to strengthen relationships with their customers, the fans, and to improve customer loyalty (Harris & Ogbonna, 2009; Lapio & Morris, 2000; Stavros, Pope, & Winzar, 2008). Fans are highly involved customers, seeking for long-term association with a sports team (Shani, 1997). In addition, sports consumers are more loyal than the average consumer (Waters et al., 2011). Consequently, they have a strong desire of constantly staying up-to-date about their favourite sports team's or player's news (Abeza, O’Reilly, & Reid, 2013). From the perspective of companies advertising through sports, the main reasons behind this advertising strategy are in line with the objectives of RM: enhancing customer relationships and creating brand loyalty (Donlan & Crowther, 2014). As social media can reach a wide group of consumers in a fast, interactive and relatively inexpensive way, they are valuable tools for companies to help them meet their RM objectives (Williams & Chinn, 2010). In addition, social media advertising is a new source of revenues for sports organisations and players (Williams, Chinn, & Suleiman, 2014). Therefore, this paper on the value of advertisements on clubs’ and players’ social media is highly relevant.

Existing academic research about SMM in sports is mainly theoretical and lacks a quantitative approach. Focusing on sponsorship decision-making, Johnston and Paulsen (2014) mention important limitations of previous research, such as the lack of addressing cost considerations and trade-offs, as well as the inability to assess whether decision-making is driven by comparing a set of attributes or by certain heuristics. Moreover, existing studies are unable to deal with the wide variety of attributes impacting decision-making. The same limitations are valid for past research in the domain of SMM in sports. This paper fills this research gap by applying discrete choice modelling to sports social media advertising in football. In this way, all potentially relevant attributes determining the value of football social media advertisements for advertising companies are taken into account simultaneously as a set of decision alternatives from which managers can choose.

3. Methodology

Discrete choice is a statistical research domain that analyses choices made by economic agents such as consumers, families and enterprises. This research domain emerged from the theory of consumer behaviour. Lancaster (1966) argued that consumers do not derive utility from goods as such, but from the combination of components or *attributes* of a specific good. This idea of utility has been incorporated in the random utility theory of McFadden (1974). This pioneering work describes how the discrete choice methodology models economic agents making choices, based on a number of good attributes, and the specific attribute states or *levels*.[1] To this end, respondents in experiments are faced with a number of trade-offs between products with different attribute levels (Boxall, Adamowicz, & Moon, 2009).

According to Lancsar and Louvière (2008) and Swait and Adamowicz (2001a), discrete choice is better able to disentangle human preferences and has a larger potential to gather information on the human decision-making process than traditional market research. This approach however requires more effort from the respondents in the experiment (Swait & Adamowicz, 2001b). Johnston and Paulsen (2014) discern three specific advantages of discrete choice modelling. First of all, it allows the researcher to test for the impact of a level change of one specific attribute, keeping all else equal. This corresponds to the common economic practice of ceteris paribus analyses. Second, such approach is able to identify consumers' relative importance of attributes. Third, interaction effects between parameters could be included in the analysis as well. Hence, a discrete choice experiment offers a viable approach to get an insight in the value of the different attributes that influence companies' decision-making when involved in sports social media advertising. However, the methodology's limitations need to be taken into account as well when analysing the results. An important assumption is that products are the sum of their independent constituting parts and that decision makers are rational.

Ultimately, the data gathered from the discrete choice experiment allows the researchers to estimate the utility of a specific product *i*:

$$U_i = \alpha + \beta' X_i + \varepsilon_i, \tag{1}$$

[1] As an illustration, one could think of the colour (attribute) of a car, which could be white or blue (level).

with α the intercept coefficient and β' the vector of coefficients for product i's specific levels of the considered attributes in vector X_i and ε_i the error term. The design of the experiment is described in the next section. The final model is described in Section 3.2.

3.1. Design of the experiment

The discrete choice experiment in this paper is based on the conjoint analysis technique and takes into account some best practices identified by Johnson et al. (2013). Choice sets are composed of the selected attributes and respective levels. In this research, each choice set consists of two alternative social media advertisement posts, from which the respondent needs to choose the preferred option. When designing such an experiment, some methodological decisions need to be made, such as the inclusion of a no-choice option, the included attributes and levels as well as the dimensions of the experiment. This information is subsequently transformed into questionnaires. Since clubs and players differ in terms of commercial and social media activities, two separate models are required for posts on clubs' or players' social media.

3.1.1. Selection of attributes and levels. The retained number of attributes and levels is the outcome of a trade-off between statistical and response efficiency. On the one hand, more attributes and levels lead to a more realistic model with more explanatory power. On the other hand however, more attributes and levels lead to a more complex model (e.g., more interaction variables) and a more complex questionnaire to be completed (Street & Burgess, 2007; Johnson et al., 2013). Taking into account this trade-off, the approach of Adams et al. (2015) has been used to determine the set of attributes and levels. This approach is common in literature and encompasses three steps. First, the researchers select an initial set of attributes and levels, based on literature and own judgement. Second, an expert panel formulates remarks to improve the set, which in the third step are incorporated in the final set of attributes and levels.

The expert panel for this research consisted of five members. Three of them represented international clubs' commercial departments: Stéphane De Coninck from Club Brugge KV (Belgium), Lisa De Croocq from RSC Anderlecht (Belgium) and Brandon Páramo from Villarreal CF (Spain). Tomas Van Den Spiegel from Sporthouse Group (Belgium) was incorporated as an experienced practitioner in sports social media marketing. Finally, Toon Zijlstra, discrete choice expert at the University of Antwerp (Belgium) and the Netherlands Institute for Transport Policy Analysis (KiM), was the academic representative.

Table 1. List of attributes and levels of clubs' and players' social media posts.

Attribute	**Club levels**	**Player levels**
Social Media Channel	Facebook	Facebook
	Instagram	Instagram
	Twitter	Twitter
Number of Followers	100 000	100 000
	1 000 000	1 000 000
	10 000 000	10 000 000
	50 000 000	50 000 000
Price per post	10 000 euro	10 000 euro
	50 000 euro	50 000 euro
	100 000 euro	100 000 euro
	250 000 euro	250 000 euro
Performance	G5 UCL	90
	G5 EL + non-G5 UCL	80
	G5 rest + non-G5 EL	70
	non-G5 rest	60
Visibility	6 hours	6 hours
	12 hours	12 hours
	24 hours	24 hours

The list of attributes, which are the same for clubs and players, and the different levels for both are presented in Table 1. The first attribute is the social media channel on which the advertisement post appears. The three levels include the three most popular social media of clubs and players. Each channel involves a specific type of target audience and communication. According to the expert panel, it can reasonably be assumed that the experiment respondents aggregate these underlying properties into each channel when comparing the levels of this attribute. Additionally, the experts remarked that Chinese social media could be included as well, which is in line with the findings by Nielsen (2016) that China's role in world football is becoming increasingly important. However, the number of European clubs and players using these Chinese social media is limited. Hence, they have been left out of this paper.

Another important aspect of advertisements is the reach. Speed and Thompson (2000) and Roy and Cornwell (1999) identify increased company exposure and brand awareness as important objectives of advertising. To capture reach in terms of observable social media characteristics, two attributes are retained: the number of followers and the time a post is visible on top of the club's or player's homepage. The expert panel indicated that these two attributes make considering the frequency of posts by the club or player redundant. The levels for visibility have been suggested by Tomas Van Den Spiegel. The levels for number of followers have been based on the ranges observed in the number of followers of clubs and players active in the European club competitions in 2017-2018. Both sets of levels were subsequently validated by the expert panel.

Return on investment (ROI) plays a crucial role for companies deciding on advertising and sponsoring (Cornwell, 1995; Stotlar, 2004; Lund, 2006). Therefore, the price of an individual social media post is included in the experiment. This is moreover required to estimate the willingness to pay for the advertisement (Greene, 2012). The highest prices per post found in practice are nearing half a million euro. This is however an exceptionally high price. Hence the highest level included has been set to 250 000 euro. Dividing this level by two and rounding yields 100 000 euro for the following level. Similarly, 50 000 euro has been chosen as the following level. The final level has been set to 10 000, since the expert panel indicated that a sufficiently low price is required for advertisement on smaller clubs' or less popular players' media.

Due to impact of on-field performance of clubs on their fans' buying behaviour and the creation of brand awareness, it has been decided to include club and player performance in the experiment (Ngan, Prendergast & Tsang, 2011; Gladden & Funk, 2002). Determining its levels has however been less straightforward. For clubs, the national league ranking in the past season has been used, making a distinction between UEFA Champions League (UCL), Europe League (EL) spots and the rest of the league table. Moreover, teams from the strongest football countries (G5: England, Spain, Italy, Germany and France) reach higher scores in UEFA (2018) rankings than teams from smaller countries, as their national league performances are valued higher. Therefore, it has been decided to equate G5 teams with non-G5 teams that qualified one level higher. Hence, G5 EL teams and non-G5 UCL teams have been combined in one level. For players, a score out of 100 has been given, which is in line with the scores given to players by the popular video game FIFA. Four categories have been constructed: 60, 70, 80 and 90 points. These categories are based on the example of Jamie Vardy of Leicester City FC, who recently went through all these different categories over a short time span. The same illustration has been used in the final questionnaire and is described in Appendix B.

The fit between the image of the club or player and the image of the advertising company has been identified as a final attribute. Previous research of Johnston and Paulsen (2014) and Peluso, Rizzo and Pino (2019) proved the importance of this fit for sponsors, since it has an impact on the image of the sponsor itself too (Gwinner & Eaton, 1999).

However, due to the inability to accurately observe and define its levels in real life and the methodology's assumption of rational decision makers, it had to be omitted.

3.1.2. No-choice option. In literature, a distinction is made between forced choice experiments and experiments including a no-choice option, which is relevant when none of the options is sufficiently attractive, or when the choice maker would require more information about the alternatives (Street & Burgess, 2007; Dhar, 1997; Karni & Schwarz, 1977). The no-choice option results in a more realistic interpretation of the results, since the model allows estimating the absolute utility of the choice, instead of its relative value (Lancsar & Louvière, 2008). The advantages of including a no-choice option are (i) a better representation of reality (Batsell & Louviere, 1991; Carson et al., 1994; Haaijer, Kakamura, & Wedel, 2001), (ii) increased statistical efficiency (Anderson & Wiley, 1992; Louviere, Hensher, & Swait, 2000) and (iii) a model that is more closely related to the theory of demand (Boxall & Adamowicz, 2002; Bateman et al., 2003; Louviere, Hensher, & Swait, 2000). A potential disadvantage is that so-called difficult choices are avoided (Haaijer, Kakamura, & Wedel, 2001; Tversky en Shafir, 1992). Such choices occur when it is difficult for the decision maker to trade off the alternatives, e.g. as a result of including too many attributes of each alternative in the experiment. Given the rather low number of five included attributes for two alternative choices, the disadvantages of the no-choice option have been considered less important than its advantages. Hence, the no-choice option has been included in the experiment.

3.1.3. Dimensions of the experiment. The five selected attributes with a total of 18 levels give rise to 576 possible social media advertisement specifications. Moreover, each choice set consists of two alternatives and a no-choice option. Hence, 165 600 choice sets could be composed, which is by far too many for the final questionnaire. In order to trade-off statistical efficiency and response efficiency, the formula "levels *minus* attributes *plus* one" is a standard to determine the minimum number of choice sets to be evaluated by each respondent. Since 14 choice sets for clubs and 14 for players may still be too many for one respondent, two questionnaires with 10 choice sets for clubs and 10 for players have been composed. This avoids respondents ending the questionnaire before completion, while still presenting sufficient different choice sets to each respondent. The advantage of such a heterogeneous design is that it is statistically more efficient than a homogeneous design, since more variation between the attribute levels is present in the choice sets. (Chapman, 1984; Sándor & Wedel, 2005)

Another decision variable is the number of attributes that can have a different level within one choice set. Since it is difficult for respondents to evaluate choice sets with more than four differing attributes (Green, 1974; Grasshoff, Großmann, Holling, & Schwabe, 2003), a maximum of four varying attributes has been chosen in the design of the experiment. According to Kessels, Jones, Goos, & Vandebroek (2009) and Kessels, Jones and Goos (2011), such partial profiles also increase response efficiency, although statistical efficiency is lower. However, in case of one or more dominant attributes, also choice sets wherein this dominant attribute is held constant are generated, allowing for better evaluation of the other attributes' relative utility.

The design of the experiment is done in the software JMP Pro 13, which generates the choice sets. A Bayesian D-optimal design is applied, which assigns 'prior preferences' to the attributes. By taking foreknowledge on the relative preference of attribute levels over other levels into account in the design phase, better statistical results can be obtained. This is a consequence of a more efficient design, since choice sets contain the most relevant trade-offs, while obvious choices are avoided (e.g., all levels optimal vs. all levels with expected low utility) (see Kessels, Jones, Goos, & Vandebroek (2011)). The prior information used for this research design is based on the literature and economic theory. More followers, higher visibility, better performance and a lower price are expected to be preferred by sponsoring companies.

Figure 2. Example of a choice set for clubs in Qualtrics.

9/10. Which choice would you make?

	Choice A	Choice B
Medium	Instagram	Facebook
Amount of followers	1 million	1 million
Price per post	250 000 euros	100 000 euros
Performance	G5 UCL	G5 EL/Non-G5 UCL
Hours visible	6	12

- ○ Choice A
- ○ Choice B
- ○ No Choice

3.1.4. Presentation of the questionnaires. After designing the experiment in JMP Pro 13, the choice sets have been included in a questionnaire that has been presented to the participants by means of the software Qualtrics. This software has also collected the responses. The assignment of one of the questionnaires to the respondents is random, and has been done by Qualtrics as well. A screenshot of an example question is included in Figure 2. Moreover, Appendix A contains additional screenshots with information that was given to the before the start of each experiment.

3.2. The Model

The design of the experiment gives rise to the following specific models for the utility of a social media post *i* with its own attribute levels, respectively for clubs (*C*) and players (*P*):

$$\begin{aligned} U_i^C = {} & \beta_0^C ASC + \beta_{1,1}^C Facebook_i + \beta_{1,2}^C Instagram_i + \beta_{1,3}^C Twitter_i + \beta_2^C Followers_i \\ & + \beta_3^C Price_i + \beta_{4,1}^C NonG5rest_i + \beta_{4,2}^C G5rest\_NonG5EL_i \\ & + \beta_{4,3}^C G5EL\_NonG5UCL_i + \beta_{4,4}^C G5UCL_i + \beta_5^C Visibility_i + \varepsilon_i, \end{aligned} \tag{2}$$

$$\begin{aligned} U_i^P = {} & \beta_0^P ASC + \beta_{1,1}^P Facebook_i + \beta_{1,2}^P Instagram_i + \beta_{1,3}^P Twitter_i + \beta_2^P Followers_i \\ & + \beta_3^P Price_i + \beta_{4,1}^P Cat60_i + \beta_{4,2}^P Cat70_i + \beta_{4,3}^P Cat80_i + \beta_{4,4}^P Cat90_i \\ & + \beta_5^P Visibility_i + \varepsilon_i, \end{aligned} \tag{3}$$

with the attribute levels given in Table 1 and the coefficients as described for Eq. (1). The estimated coefficients are given in Table 2 and Table 3 respectively and discussed in Section 5.

In Eqs. (2) and (3), the intercept has been left out, while the *ASC*, the alternative specific constant dummy, has been included. *ASC* takes the value 1 if no choice is made, else it equals 0. This is a consequence of including a no-choice option. The coefficient of the *ASC* can be interpreted as the average utility of the omitted attributes, or the utility of the no-choice option. In this way, it expresses the preference to retain the current, status-quo situation (Train, 2002; Boxall et al., 2009; Campbell, Hutchinson & Scarpa, 2008). Such a status-quo would imply that no investment in sports social media advertisements would be made. An estimated negative *ASC*-coefficient that is significantly negative (positive) implies such a ‘disproportional’ status-quo aversion (preference) (Kontoleon and Yabe, 2003).

Moreover, Eqs. (2) and (3) contain (linear) variables which are made continuous for the discrete attributes *followers, visibility* and *price*. This results in a more realistic analysis, as these variables are continuous in reality too. Another advantage is that these attributes now only require one coefficient to be estimated, which is a prerequisite for an unambiguous determination of the willingness to pay for specific attribute levels. For the same reason, interaction terms were not included in the model either, next to the reason that too many additional coefficients would have to be estimated.

Subsequently, the coefficients are to be estimated separately for club and player social media advertisements. This estimations are also carried out in JMP Pro 13, based on the responses gathered from Qualtrics. To this end, a maximum likelihood estimation is carried out based on a logit specification while taking into account the following condition for the coefficients of each discrete attribute k (with L_k levels) (JMP, 2018; Kessels, 2016):

$$\forall k\colon \sum_{l=1}^{L_k} \beta_{k,l} = 0. \tag{4}$$

4. Data description

In order to empirically estimate the coefficients, data are to be gathered from questionnaires filled out by the respondents. However, in line with the conceptual model of sponsorship package selection of Johnston and Paulsen (2014, p. 640), the experiment assumes that the decision makers have sufficient interest in investing in sports social media advertisements. To this end, sponsorship managers of active football sponsors and their advisors make up the target group of this experiment. Consequently, the sponsorship managers of sponsors of European clubs, national federations, FIFA, UEFA and tournament-specific sponsors have been approached through LinkedIn and William Fenton, Board Director at the European Sponsorship Association.

Out of 431 surveys that were sent out electronically, 40 anonymous respondents completely filled out the survey, resulting in a total of 400 evaluated choice sets for clubs and 400 for players. Such a sufficiently large sample size is needed to guarantee statistical efficiency.

5. Results and discussion

Tables 2 and 3 respectively contain the estimates of the model coefficients from Eqs. (2) and (3) for posts on clubs’ and players’ social media. Except for visibility, the identified attributes of advertisement posts on both clubs' and players' social media have a significant impact on the utility of advertising companies. Moreover, the signs of the coefficients are in line with the insights from the literature review in Section 2. More followers and longer visibility generate more exposure, which in turn increases utility. Also a better performance of the club or the player leads to higher utility. The negative sign of the price coefficient is a confirmation of the negative slope of the demand function. Finally, the no-choice *ASC* is significantly negative for both models, confirming that the retained respondents are sufficiently willing to invest in sports social media advertisements.

Table 2. Estimated utility model for posts on clubs' social media.

Factor	**Estimate**	**p-value***
Social Media Channel		<0.0001
> [Facebook]	0.2348	
> [Instagram]	0.2968	
> [Twitter]	-0.5315	
Number of Followers	1.66×10^{-8}	<0.0001
Price per post	-4.31×10^{-6}	<0.0001
Performance		<0.0001
> [non-G5 rest]	-0.5429	
> [G5 rest + non-G5 EL]	-0.2158	
> [G5 EL + non-G5 UCL]	0.3349	
> [G5 UCL]	0.4239	
Visibility	0.0159	0.1736
No-choice ASC	-1.3830	<0.0001
AIC	679.9463	
BIC	715.1679	
-2*LogLikelihood	560.6446	

Note: *p-values for the likelihood-ratio test, distributed chi-squared.

Table 3. Estimated utility model for posts on players' social media.

Factor	Estimate	p-value*
Social Media Channel		<0.0001
> [Facebook]	0.4130	
> [Instagram]	0.5793	
> [Twitter]	-0.9923	
Number of Followers	4.33×10^{-8}	<0.0001
Price per post	-9.06×10^{-6}	<0.0001
Performance		<0.0001
> [60]	-0.6183	
> [70]	-0.5549	
> [80]	0.4738	
> [90]	0.6994	
Visibility	0.0053	0.7503
No-choice ASC	-1.8162	<0.0001
AIC	522.3028	
BIC	557.0243	
-2*LogLikelihood	503.8028	

Note: *p-values for the likelihood-ratio test, distributed chi-squared.

Another question to be asked is "which social media platform generates the highest utility for the respondents?" Independently of whether clubs or players are considered, companies slightly prefer Instagram over Facebook, although this difference is not significant (Wald test p-values are 0.74 and 0.53 for clubs and players respectively). Coelho, Oliveira and Almeida (2016) however highlight that more intense interactions between customers, companies and clubs or players are possible on Instagram. Twitter is less attractive for advertisements, due to its character limitation and the lower total number of users.

Another way of illustrating this information is by looking at the probability that a social media channel is used, all other attributes equal (ceteris paribus). This can be calculated using the logit specification. The probability that channel h is chosen from the H alternative channels with all other attributes equal, is given by:

$$\Pr(h) = \frac{e^{U_h}}{\sum_{s=1}^{H} e^{U_s}} = \frac{e^{\beta_{1,h}}}{\sum_{s=1}^{H} e^{\beta_{1,s}}}. \tag{5}$$

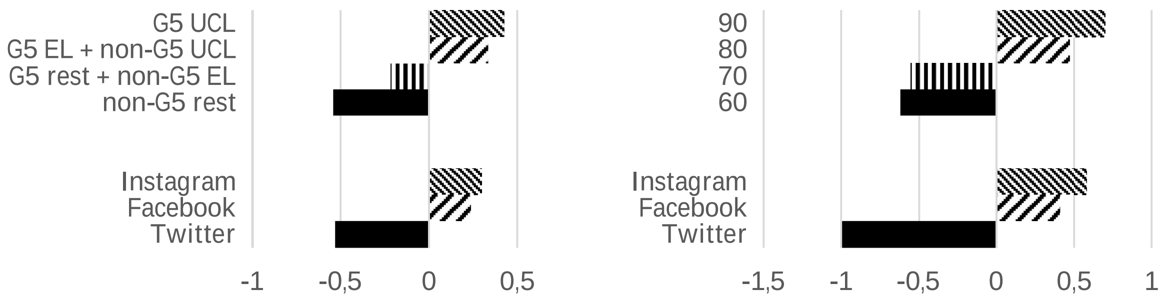
Applying this formula to social media of clubs and players yields the probabilities given in Table 4. Two results emerge. First, it is confirmed that Instagram is slightly more popular than Facebook. This relative preference is larger for player social media than for clubs. This could be explained by the fact that players publish more personal content like pictures and videos on the better suited channel of Instagram. Second, Twitter is significantly less popular for sports social media advertisements involving clubs and players, although the disfavour for Twitter is stronger for player posts.

Table 4. Social media channel preference, expressed as choice probabilities.

Social media channel	**Probability (clubs)**	**Probability (players)**
Facebook	39.5%	41.2%
Instagram	42.1%	48.7%
Twitter	18.4%	10.1%
Total	*100%*	*100%*

Figure 3 represents the utility of the levels of the discrete attributes channel and performance as zero-centred utility values for (a) clubs and (b) players. Again, the dominance of Facebook and Instagram over Twitter is confirmed for both clubs and players. Moreover, the figure shows the impact of performance on the advertiser's utility. For clubs, the highest change in utility is perceived between the categories 'G5 rest + non-G5 EL' and 'G5 EL + non-G5 UCL'. This means that as soon as teams from the major countries play European football, and the smaller countries' clubs take part in the UEFA Champions League, the utility of their social media advertisements increases sharply for companies due to the sharp increases in exposure for the advertisers. The same holds for players. The categories ‘80’ and ‘90’ generate much higher utility than the lower ones, implying that the best performing players, who get the most attention and create the most exposure, are best suited for social media advertisements.

Figure 3. Attribute level utility as zero-centred utility values.



(a) Clubs (b) Players

In order to check the sensitivity of the model to the received responses, the same model has been re-estimated once omitting the first five and once omitting the last five questionnaires received. This did not impact the results qualitatively. Moreover, in order to test the sensitivity to the specification, a model has been estimated with the logarithms of the continuous variables, to account for a potentially decreasing marginal impact of the attributes on utility. The models for clubs and players, which are again of a similar quality as the main models, are given in Appendix B. Also here, the conclusions are robust, except for two elements. For the advertisement on club’s social media, the ASC is only marginally significant, whereas the coefficient of post visibility becomes significantly positive. Visibility should hence not be neglected by the social media managers of clubs and players. Secondly, Facebook, which offers a large number of options for advertisers, is in this model slightly more popular for both clubs and players than Instagram. Hence, it can be concluded that both social media channels are well suited for sports social media advertisements.

6. Managerial implications

Clubs and players could wonder which attributes are the most important ones to focus on while managing social media advertisements. Taking the linear model as the base model has the important advantage of providing insights for clubs and players into the price setting of the advertisement and the active management of these social media. Based on the utility functions in Eqs. (2) and (3), it is possible to calculate the possible price increase, with a negative impact on utility, that goes with a utility increasing change in another attribute's level, in order to keep utility constant. These transformations of utility in monetary values for both club and player social media are presented in Table 5. The outcomes show a club for example that a post on a club's Facebook could be priced about 178 000 euro more than a post on its Twitter account. Instagram advertisements are even slightly more valuable. The table moreover shows the value of a thousand additional followers, which is between 3.85 and 4.78 euro. Moving into the two best categories of performance increases the value by more than 100 000 euro.

Table 5. Willingness to pay for attribute level changes.

Attribute	**Level change**	**Price increase (clubs)**	**Price increase (players)**
Social Media Channel	*Twitter → Facebook*	€178 000	€155 000
Social Media Channel	*Facebook → Instagram*	€14 400	€18 400
Number of Followers	*1000 followers extra*	€3.85	€4.78
Performance	*Worst → Third best*	€75 900	€7 000
Performance	*Third best → Second best*	€128 000	€114 000
Performance	*Second best → Best*	€20 600	€24 900
Visibility	*1 hour more*	€3 690	€583

When the price of the advertisement has already been fixed, the number of followers is the best suited variable to be managed actively (De Vries, Gensler, & Leeflang, 2012). When the sports performance decreases, the club or player could try to attract additional followers to offset the utility decrease for the advertiser. Or else, a club or player could wonder how many additional followers are required on Facebook to equal the utility of a post on Instagram. Table 6 contains the required number of additional followers, for both clubs and players.

Table 6. Follower increases required to compensate for other attribute level deteriorations.

Attribute	**Level change**	**Extra followers (clubs)**	**Extra followers (players)**
Social Media Channel	*Instagram → Facebook*	3.73 M	3.84 M
Performance	*Best → Second best*	5.36 M	5.21 M
Performance	*Second best → Third best*	33.2 M	23.8 M
Performance	*Third best → Worst*	19.7 M	1.46 M

The results confirm that for clubs in small countries, playing in the UEFA Champions League is not only important for prize money income, but also for the value of their social media advertisements, given the visibility this competition generates. For teams from the G5 countries as well, playing European football is important. Also the best performing players realise benefits in terms of their social media advertisement values. Every assist, goal, safe or defensive action, especially when it leads to trophies, increases the exposure and hence the value of these players’ social media for advertisers.

In conclusion, when taking decisions on pricing, social media managers should take into account that companies value Facebook and Instagram much higher than Twitter advertisements, given its structural limits. Moreover, as long as sufficient visibility is guaranteed, it is advised to consider this element less in the pricing decision, since its impact is limited. The number of followers has a much larger influence on the value and it should be actively managed, especially to serve as a buffer against (temporary) disappointing sporting performances.

7. Conclusions and Future Research

Social media are well suited for two-sided, interactive and customer oriented relationship marketing purposes, since they offer convenient and direct links with customers and other stakeholders at a low cost. Sports clubs and players have been using their social media to post content of their sponsors and other advertising companies, as part of sponsorship agreements or as separate deals. Such posts have value for the advertising companies. However, up to now, it has been unclear which factors or attributes influence this value and to what extent.

This paper fills this research gap through a discrete choice experiment, leading to an empirical estimation of the utility sponsorship managers derive from a post advertising their company on football clubs' and players' social media. More followers, better sports performance and a lower price significantly increase the utility of the advertising company. Also the chosen social media channel has a significant influence, since Facebook and Instagram are preferred over Twitter, due to the latter's limited degrees of freedom for advertisers. In addition to its academic relevance, the results are also useful for practitioners. The empirical estimations allow social media managers of clubs and players to derive the companies' willingness to pay for an advertisement on their social media. This information can be used to optimise pricing decisions when social media posts are sold or included in sponsorship packages.

For academics, the results of this paper offer some avenues for future research. First, for this research to be as broadly applicable as possible, the selected attributes and levels, such as price, followers and even social media channels were chosen to apply as much as possible to both small and large European football clubs. Future research could further build on the findings of this paper and focus on small clubs, with lower numbers of followers and sponsors with smaller budgets. Moreover, given the increasing importance of being present on Chinese social media, this factor could be included in a follow-up study as well. Second, it can be argued that social media posts are part of a larger campaign of social media advertisements, e.g. Ronaldo who regularly posts content of Nike. Although it is possible to multiply the value of one individual post by the number of posts included in a campaign, it would be interesting to look into the value of entire campaigns in future research. Such value might differ from the sum of its elements, since the marginal value of additional posts is decreasing. This is a consequence of increased exposure to advertisements having a decreasing marginal influence on customer behaviour (Tellis, 2009). Third, literature deemed a fit of image between sponsor and sponsee crucial for successful sponsorships. The impact of this factor could not be measured objectively in this experiment. However, follow-up research could use case studies or in-depth interviews to analyse in detail its impact on sports social media advertisements. In such a research approach, no arbitrary measurement of fit in levels (e.g., from very high to very low) would be required. Finally, since the analysis in this paper focused on the content supply side, future research could analyse the impact of specific content in sports social media advertisements on the target audience’s behaviour and the return on investment for the investing company. Also here, the fit of image needs to be researched.

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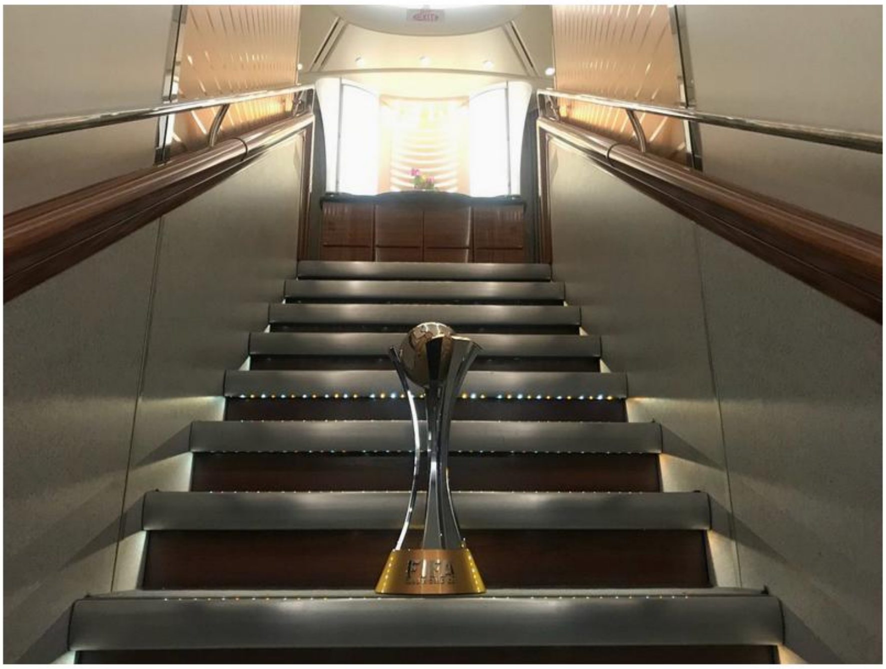
Appendix A. Qualtrics Screenshots.

Start of the questionnaire:

Dear respondent,

Thank you for your interest in this research about the economic value of social media advertisement in sports. In what follows, you will be asked to participate in a discrete choice experiment. The questionnaire exists of two parts, one for clubs and one for players. In each part, you will be asked to fill out 10 choice sets, always consisting of choice A and choice B. Please indicate which of these two hypothetical advertising packages you find most interesting to promote your brand or products on social media channels of football clubs and football players. If none of the two choices appeals to you, you may select the 'No choice' option.
Please note that all data will be collected anonymously.

The post below gives an example of the considered social media advertising posts.



Real Madrid C.F. 🇬🇧🇺🇸 @realmadriden · 17 dec. 2017

🏆🌍✈️ #RMCWC

We're on our way back to Madrid with the Club World Cup and @emirates!

#HalaMadrid

Instructions for club related choice sets:

Please read the instructions below carefully before starting the questionnaire.
We start with football clubs. An advertising package is defined by a number of characteristics. The two choices that will be shown, differ based on the options that are assigned to these characteristics. An overview of the characteristics and their options is presented below:

1. **Medium:** the social media channel on which your company can advertise.
   Options: Facebook, Instagram, Twitter
2. **Amount of followers:** the amount of followers the club has on the considered medium.
   Options: 100 000, 1 million, 10 million, 50 million
3. **Price per post:** the price your company pays per advertisement post on the social media channel of the club.
   Options: 10 000 euros, 50 000 euros, 100 000 euros, 250 000 euros
4. **Hours visible:** the amount of hours that the post is visible on top of a follower's newsfeed or the homepage of the club's medium.
   Options: 6, 12, 24
5. **Performance:** a brief explanation about the options for performance is presented below:

- <u>G5 UCL</u>: these are clubs from the so-called G5, the five biggest European leagues (England, Spain, Italy, France, Germany), that play in the Champions League.
  Examples for the 2017/2018 season: Real Madrid, Chelsea
- <u>G5 EL/Non-G5 UCL:</u> these are clubs from the G5 that are active in the Europa League OR clubs from smaller European leagues that are active in the Champions League.
  Examples: Villareal, SL Benfica, Anderlecht
- <u>G5 rest/Non-G5 EL:</u> these are clubs from the G5 that do not play European football OR clubs from smaller European leagues that are active in the Europa League.
  Examples: Bordeaux, Hamburg, Vitesse
- <u>Non-G5 rest:</u> these are clubs from smaller European leagues that do not play European football.
  Examples: Antwerp, FC Utrecht, V. Setubal

Instructions for player related choice sets:

Please read the instructions below carefully before continuing.
The following choices consider football players. The same characteristics are used, only performance is measured differently. Below you find the overview again:

1. **Medium:** Facebook, Instagram, Twitter
2. **Amount of followers:** 100 000, 1 million, 10 million, 50 million
3. **Price per post:** 10 000 euros, 50 000 euros, 100 000 euros, 250 000 euros
4. **Hours visible:** 6, 12, 24
5. **Performance:** this characteristic is related to the recent form of the player and is expressed as a score with a maximum of 100.
   Options: 60, 70, 80, 90

An example will illustrate this performance indicator. When Jamie Vardy played in the lower divisions of English football with Leicester City, he was assigned a score of about 60. After promotion to the Premier League and scoring his first goals, this increased to 70. When Vardy was Leicester City's top scorer during their Premier League winning season, his outstanding form resulted in a score of about 90. In his current form however, as a decent striker in an average Premier League team, his score would fluctuate around 80.

Appendix B. Estimated logarithmic utility models for posts on clubs' and players' social media.

	Clubs		Players	
Factor	**Estimate**	**p-value***	**Estimate**	**p-value***
Social Media Channel		<0.0001		<0.0001
> [Facebook]	0.3298		0.5315	
> [Instagram]	0.2388		0.4786	
> [Twitter]	-0.5686		-1.0926	
Log(Number of Followers)	0.1995	<0.0001	0.4029	<0.0001
Log(Price per post)	-0.4132	<0.0001	-0.7478	<0.0001
Performance		<0.0001		0.0004
> [Worst]	-0.6910		-0.5381	
> [Third best]	-0.1348		-0.3984	
> [Second best]	0.3243		0.3232	
> [Best]	0.5015		0.6133	
Log(Visibility)	0.3740	0.0229	-0.0001	1.0000
No-choice ASC	-2.0591	0.0599	-3.8979	0.0026
AIC	664.1505		503.0969	
BIC	699.3721		537.8185	
-2*LogLikelihood	645.6768		484.5969	

Note: *p-values for the likelihood-ratio test, distributed chi-squared.