Beyond purchase intention in sports sponsorship: an alternative approach to measuring brand equity using best-worst scaling

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Abstract

Purpose – The purpose of this paper is to study the effects of sports sponsorship on brand equity using two managerially related outcomes: price premium and market share.

Design/methodology/approach – This study uses a best–worst discrete choice experiment (BWDCE) and compares the outcome with that of the purchase intention scale, an established probabilistic measure of purchase intention. The total sample consists of 409 fans of three soccer teams sponsored by three different competing brands: Nike, Adidas and Puma.

Findings – With sports sponsorship, fans were willing to pay more for the sponsor’s product, with the sponsoring brand obtaining the highest market share. Prominent brands generally performed better than less prominent brands. The best–worst scaling method was also 35% more accurate in predicting brand choice than a purchase intention scale.

Research limitations/implications – Future research could use the same method to study other types of sponsors, such as title sponsors or other product categories.

Practical implications – Sponsorship managers can use this methodology to assess the return on investment in sponsorship engagement.

Originality/value – Prior sponsorship studies on brand equity tend to ignore market share or fans’ willingness to pay a price premium for a sponsor’s goods and services. However, these two measures are crucial in assessing the effectiveness of sponsorship. This study demonstrates how to conduct such an assessment using the BWDCE method. It provides a clearer picture of sponsorship in terms of its economic value, which is more managerially useful.

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1. Introduction
Until recently, sports sponsorship has been growing every year because it is almost unrivaled as a marketing platform to reach emotionally engaged fans (WARC, 2020). However, with the pandemic, global sponsorship has decreased dramatically amid cancellations or postponements of sports events globally, including the Tokyo Olympics and the Euro 2020 soccer tournament (Brown, 2020; Cutler, 2020). Their loss in sponsorship income has caused sponsors to question whether they were getting their money’s worth, given the declining attendance of fans at live sporting events (IEG, 2020). This situation is predicted to improve steadily as the industry adapts to a new postpandemic world, with brands becoming more careful regarding their choice of partnerships (Andrews, 2021; Malcom, 2021). However, assessing the effectiveness of sports sponsorships remains a challenge. Even at the best of times, only 50% of companies (at best) have some sort of return-on-investment (ROI) system to evaluate the effectiveness of their sponsorship (Jacobs and Surana, 2014). Our paper could help in better assessing the ROI in sports sponsorship, as its main aim is to study the effects of sports sponsorship on brand equity using two managerially relevant metrics: price premium and market share.

One approach to assessing the effectiveness of sponsorship is to measure changes in the equity of the sponsoring brand. For instance, if Adidas is the sponsoring brand of a sports team, then the success of its sponsorship can be gauged by the improvement in its brand equity, typically measured by changes in brand awareness and associations. This consumer-based version of brand equity (CBBE) has been evaluated, and a positive effect has been found on sponsorship (Henseler et al., 2007; Wang et al., 2011, 2016). However, the pandemic has raised expectations, and companies are now demanding more sponsorships (e.g. sales of branded merchandise) to improve their ROI. For instance, the world’s largest brewer, Anheuser-Busch InBev, is now actively monetizing its sponsorship assets to derive new revenue streams and improve its ROI:

Co-branded merchandise, NFTs, ticketed high-value-to-consumer fan fests that we own, packaged travel experiences to games, tournaments, and festivals. Driving topline revenue from sponsorship, which goes beyond sales rights, amplifies sponsorship return on investment (SROI) in a meaningful way for us. (Malcom, 2021)

These raised expectations have created the opportunity to develop a way of assessing brand equity that goes beyond brand awareness and image in sports sponsorship research. One direct method of this is to gauge whether the merchandise of a sponsoring brand (e.g. t-shirt) can attract a price premium, that is, whether fans are willing to pay more for such branded merchandise. Furthermore, by using choice experiments involving different attributes associated with the merchandise of competing brands, what factors drive changes in market share can be inferred. The important point is as follows: by connecting research to a specific piece of sponsored asset (i.e. branded merchandise), the assessment of the sponsorship becomes more concrete and direct. A manager will be in a better position to conclude if the focal sponsorship has indeed increased the equity of the sponsoring brand because it is now linked to its merchandise.

Research has traditionally relied on brand awareness and image to assess sponsorship effectiveness (Cornwell and Maigman, 1998; Gwinner and Eaton, 1999). However, this approach ignores potential changes in the price premium and market share as factors for assessing brand equity via sponsorship (Park and Srinivasan, 1994). Measures of brand awareness and image can be problematic because they are also affected by a brand’s advertising during the
sponsoring period. On the other hand, by concentrating on specific merchandise, a manager can better evaluate the ROI of the focal sponsorship, as the profit of the merchandise being sold can now factor into this evaluation. This is also far superior to the use of simple purchase intention measures, another common method of assessing sponsorship success. For instance, our approach gives managers a direct way of assessing the costs and benefits of sponsorship (and not advertising). It can also be used to pretest the potential damage of a sponsorship to competing brands by revealing corresponding declines in the equity of their sponsoring assets. It therefore comes closer to calls for more studies on the ROI of sponsorship activities (Meenaghan and O’Sullivan, 2013; Rumpf and Breuer, 2018).

This study answers the call by using a best–worst discrete choice experiment (BWDCE) to investigate the effects of sports sponsorship on brand equity using real fans of soccer teams. It is important to use real fans (e.g. Carrillat et al., 2015) because these are the people who actually buy the goods and services of the sponsor. Using students (or nonfans) as subjects does not provide an accurate assessment of a brand’s equity (e.g. Dean, 2004; Yousaf et al., 2018). However, we found that fans were willing to pay more for the sponsor’s t-shirt, with the sponsoring brand achieving the highest market share. Prominent brands generally fare better than less prominent brands. The best–worst scaling method was also 35% more accurate in predicting brand choice than when using purchase intention. Hence, our research makes three major contributions to the literature. First, we introduce a robust methodology that measures sports sponsorship’s effects on brand equity through better metrics (i.e. price premium and market share), improving accuracy in predicting brand choice compared to the purchase intention measure. Second, by observing the effects of the sponsorship on changes in brand choices and prices, rather than on attitude or perception, our study offers a more concrete approach of assessing the ROI in sports sponsorship. Third, our results underscore the vital role of the sponsoring brand’s market prominence in achieving better sponsorship outcomes.

2. Theoretical background

2.1 Brand equity

There are many perspectives on brand equity; broadly, four different perspectives are commonly discussed: financial, price elasticity, revenue premium and the consumer perspective. We focus on the consumer perspective, as we are interested in how fans perceive a brand. However, first, we must briefly discuss the first three perspectives.

The financial perspective is driven by the need to assign a value (that is, a dollar figure) to a brand to account for the goodwill its firm enjoys. In accounting terms, goodwill comprises essentially all the intangible assets (including the brand name) that allow a firm to earn cashflow beyond its return from tangible assets (such as plants, property and inventory). For instance, in 1998, Nestlé bought confectionery producer Rowntree-Mackintosh (which owned Kit Kat, Aero, Polo, Fruit Pastilles, Smarties and Quality Street) for US$4.5bn, or six times its net tangible assets and twenty-six times its annual profit (Lohr, 1988). This approach is clearly useful for mergers and acquisitions where it is important to assign a financial value to a brand (or brands). However, accounting figures lack timeliness because their reporting substantially lags actual operating results on the ground level. This makes it difficult to evaluate how marketing is currently affecting a brand’s equity.

The price elasticity perspective is another way of considering brand equity and is more in line with marketing (Simon, 1979). In a traditional pricing model, when a brand cuts its prices, customers are likely to buy more of its offerings, and sales increase. The rate at which sales rise is called the price elasticity. Conversely, if the brand increases its prices, there will be fewer sales. It follows that if a brand has high brand equity, it should be able to maintain its sales even when its prices increase (up to a point); that is, it can expect an inelastic response to any
price increase (Boulding et al., 1994; Moran, 1994). It will also be less vulnerable to price reductions by its competitors, which are equivalent to price increases (because customers are less likely to switch to these competitors). Therefore, examining the extent to which sales change with price provides insights into the value of a brand. It also allows understanding which brands customers are switching to and hence provides clues about their competitive set.

The revenue premium perspective is related to the price elasticity perspective but takes the sales volume of a brand into consideration (Ailawadi et al., 2003). It states that if a brand has high equity, it should be able to better maintain its sales volume at any desired price than an inferior brand, such as a private label brand. The result of multiplying the volume and price of a high-equity brand is a higher revenue figure than that of a private label brand. The difference between these two revenue figures represents the premium a high-equity brand can command. This approach allows a manager to quantify what “excess” income can be obtained from a brand with high equity compared to a private label brand. However, this approach is not widely accepted because it does not clarify which private label brand should be used in the baseline calculation (Davcik et al., 2015). This is especially true in the current era, as the quality and marketing of private labels have improved substantially, providing better value and resulting in less perceived risk and better brand equity (Gielens et al., 2021; Girard et al., 2017). One major advantage of both the price elasticity and revenue premium approaches is the ready availability of sales volume and prices of retail goods.

However, this advantage is not found in sports sponsorship, where there are no readily available data to directly connect the effects of marketing (i.e. sponsorship) to purchases. As such, direct measures must be taken to assess how consumers may react to a sponsorship. A consumer perspective of brand equity therefore allows us to measure how consumers (i.e. fans) perceive a sporting brand during a sponsorship period. It also allows us to run conjoint experiments and test different scenarios on choice behavior. (We will return to this point later.) Therefore, in contrast to the other perspectives on brand equity, this approach rests squarely on how fans react – a consumer perspective.

One widely accepted consumer perspective approach in the brand equity literature has emerged from the work of Aaker (1991) and, later, Keller (1993). Aaker (1991, p. 15) was the first to recognize the importance of this concept and defined brand equity as:

\[ \ldots \text{a set of brand assets and liabilities linked to a brand, its name and symbol that add to or subtract from the value provided by a product or service to a firm and/or that firm's customer.} \]

To Aaker, brand equity consists of five components: brand loyalty, name awareness, perceived quality, brand associations and other proprietary brand assets (e.g. patents and trademarks). Keller (1993) takes a slightly different view and considers brand equity to have an effect on the brand’s customers because of what they know. He defines CBBE as the:

\[ \ldots \text{differential effect of brand knowledge on consumer response to the marketing of the brand} \]

\[ \ldots \text{customer-based brand equity occurs when the consumer is familiar with the brand and holds some favorable, strong, and unique brand associations in memory.} \ (Keller, 1993, p. 45)\]

Thus, according to Keller (1993), the two major dimensions of brand equity are brand awareness and brand associations.

Because Aaker (1991) and Keller (1993) were the originators of the brand equity concept, careful reading of their conceptualizations shows that they share something in common. Both agree that brand equity occurs when the elements of the brand (e.g. brand name, logo or symbol) can add value to a generic product and that this knowledge creates a differential effect in the consumer’s mind such that the brand is then perceived to be more valuable. This simply means whether knowing the brand – usually the brand’s identity – makes any difference in how people feel and/or influences what they do about the product (or service).
For instance, members of a target segment may change the amount of money they are willing to pay once the brand is identified.

A consumer perspective is thus appealing for marketing managers because it centers squarely on how target consumers (i.e. fans) react to a brand in response to its marketing activities (e.g. sponsorship). For instance, if it can be shown that fans are now willing to pay 40% more for the goods of a sponsoring brand (e.g. its t-shirt), then, clearly, the focal sponsorship has been effective; the equity of the brand has increased in the eyes of the fans. In this study, we have adopted a direct assessment of brand equity as an outcome of sponsorship (see also Wakefield et al., 2020).

2.2 Brand equity: approaches of measurement
Several methods have been proposed to measure brand equity, and these methods can generally be categorized into the following two groups:

1. Direct; and
2. Indirect (Christodoulides and de Chernatony, 2010).

Direct measurements (e.g. Park and Srinivasan, 1994) aim to measure the “added value of the brand” (Agarwal and Rao, 1996, p. 238). In contrast, indirect measurements (e.g. Pappu et al., 2005; Yoo and Donthu, 2001) seek to measure brand equity through its demonstrable constructs (e.g. awareness and perceived quality) (Christodoulides and de Chernatony, 2010). While indirect approaches are useful for revealing the potential sources contributing to brand equity (Agarwal and Rao, 1996; Christodoulides and de Chernatony, 2010), direct approaches measure the additional value that the brand contributes to the product (Jourdan, 2002).

Multiattribute methods are robust direct approaches for measuring brand equity. When using such methods, researchers use a choice modeling method (e.g. a discrete choice experiment) to measure brand equity, mainly as a form of customer preference (e.g. Park and Srinivasan, 1994; Winzar et al., 2018). Using a multiattribute method to measure brand equity has some advantages. First, it allows brand equity to be measured across multiple brands simultaneously, thus allowing comparisons to be made with competing brands. Second, when estimating consumers’ preferences, the marginal willingness to pay (mWTP) for the brand and its market share can be directly calculated. As a result, managers can gain clear insights into the competitive position of the brand in the market.

2.3 Brand equity and sports sponsorship
The effect of sports sponsorship on brand equity has been studied for several years (Cornwell et al., 2005). There are two areas of research. One area examines the effects of sponsorship on the brand equity of the sponsored property. For instance, if Puma were to sponsor a football team, one may ask if the brand equity of the football team would increase. The key outcome measures relate to either image transformation (i.e. image spillovers) (e.g. Yousaf et al., 2018) or changes in consumers’ affective and behavioral responses (e.g. watching more games) to the property (e.g. Olson, 2010). The other area of research, which is more relevant to the current study, examines whether the brand equity of the sponsor’s goods and services would increase among its fan base. The answer to this research question is not always clear-cut, as discussed below. However, this research question is important because sponsorship is usually costly, and during the pandemic, sponsors have questioned their sponsorship agreements and sought a better return on their investment (Howarth, 2020; Pash, 2020).

Table 1 summarizes previous studies on the effects of sports sponsorship on the equity of sponsors’ brands. All these studies, except for that conducted by Wear et al. (2016),
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<td>Wang et al. (2011)</td>
<td>Direct: Yoo and Donthu’s (2001) overall brand equity scale</td>
<td>Fans of sporting teams (survey-SEM)</td>
<td>Sponsorships of a baseball team and a soccer team in two developing countries</td>
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<td>Pre-event OBE and brand experience, but not brand attitude, positively affect post-event OBE</td>
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<td>de Amorim and de Almeida (2015)</td>
<td>Fans of two soccer teams (Survey-SEM)</td>
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<td></td>
<td></td>
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<td>Youssaf et al. (2018)</td>
<td>University students and staff (experiment-GLM)</td>
<td>Sponsorship of an Indian cricket team</td>
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<td>Sponsorship, relatedness, market prominence</td>
<td></td>
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<td>Coelho et al. (2019)</td>
<td>2014 FIFA World Cup audience (survey-SEM)</td>
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<td></td>
<td>Fit and event image affect OBE; the organizer’s reputation indirectly affects OBE</td>
</tr>
<tr>
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<td>Hickman (2015)</td>
<td>Share of wallet</td>
<td>Fans of an NFL team (survey-mean differences)</td>
<td>Sponsorships of an NFL team in the USA</td>
<td>Team identification, sponsorship awareness, purchase intention</td>
<td>N/A</td>
<td>Mixed results were found regarding the effects of sponsorship on sponsors’ share of wallet</td>
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<tr>
<td>Levin et al. (2013)</td>
<td>Indirect: Yoo and Donthu’s (2001) multidimensional brand equity scale</td>
<td>Fans of NASCAR and NFL (survey-ANOVA and correlation)</td>
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<td>Wear et al. (2016)</td>
<td>Undergraduate students (survey-regression)</td>
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<td>No relationship was found between the predictors and brand equity</td>
<td></td>
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<tr>
<td>Wang et al. (2016)</td>
<td>Direct: each dimension was examined independently via Yoo and Donthu’s (2001) multidimensional brand equity scale</td>
<td>Students (survey-SEM)</td>
<td>Sponsorships of a Chick-fil-A Kickoff game and college football playoffs in the USA</td>
<td>Responsibility fit, activity fit, aggressiveness fit, simplicity fit, emotionality fit, event attitude</td>
<td>Responsibility fit and brand awareness/association affect perceived quality, which, in turn, along with emotionality fit, positively affects brand loyalty. However, event attitude and simplicity fit had no impact on any of the CBBE dimensions</td>
<td></td>
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<tr>
<td>Tsordia et al. (2018b)</td>
<td>Direct: each dimension was examined independently, in multiple studies</td>
<td>Fans of a basketball team (survey-SEM)</td>
<td>Sponsorship of a basketball team in Greece</td>
<td>Team identification, perceived fit</td>
<td>(continued)</td>
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Table 1. Purchase intention in sports sponsorship
<table>
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<tbody>
<tr>
<td>Tsordia et al. (2018a)</td>
<td>Direct: each dimension was examined independently via a modified version of Aaker’s (1996) measurement tool</td>
<td>Fans of a basketball team and fans of the team’s rival (survey-SEM)</td>
<td>Sponsorship of a basketball team in Greece</td>
<td>Perceived fit</td>
<td>Brand personality, perceived quality, brand engagement, brand loyalty</td>
<td>In the fan group, perceived fit positively affects all CBBE dimensions, except for brand loyalty. In the rival’s fan group, perceived fit has no impact on any dimension. However, in both groups, brand personality affects the other CBBE dimensions</td>
</tr>
<tr>
<td>Donlan (2013)</td>
<td>Direct: each dimension was examined independently via a modified version of Aaker’s (1996) measurement tool</td>
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<td>Brand awareness, brand associations, perceived quality, brand loyalty</td>
<td>For the newly established brand, sponsorship affects only awareness. For the established brand, sponsorship affects associations, perceived quality and loyalty, but not awareness. Sponsorship exposure affects all CBBE dimensions. However, the magnitude of the effect largely depends on contextual factors surrounding the sponsorship (e.g. sponsorship duration)</td>
</tr>
<tr>
<td>Donlan (2014)</td>
<td>Direct: each dimension was examined independently via an approach developed by the authors</td>
<td>Fans and non-fans of two sporting events (survey-mean differences)</td>
<td>Sponsorship managers (survey-SEM)</td>
<td>Sport sponsorship, fit</td>
<td>Both predictors positively and directly affect brand equity</td>
<td></td>
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<tr>
<td>Henseler et al. (2007)</td>
<td>Indirect: Yoo and Donthu’s (2001) multidimensional brand equity scale</td>
<td>Companies engaged in sponsoring football clubs in the Netherlands</td>
<td>Sponsorship in sponsoring football clubs in the Netherlands</td>
<td>Sponsorship managers (survey-SEM)</td>
<td>Sponsorship duration, active management, sponsorship leverage</td>
<td>Both predictors positively and directly affect brand equity</td>
</tr>
<tr>
<td>Cornwell et al. (2001)</td>
<td>Direct: each dimension was examined independently via an approach developed by the authors</td>
<td>Sponsorship managers (survey-mean differences and regression)</td>
<td>Sponsorship managers (survey-mean differences and regression)</td>
<td>Sponsorship in sponsoring (mostly sports) in the USA</td>
<td>Sponsorship managers (survey-mean differences and regression)</td>
<td>Sponsorship duration positively affects brand equity. Active management and sponsorship contribute to brand differentiation and add financial value to the brand</td>
</tr>
</tbody>
</table>

(continued)
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<td>Dean (2004)</td>
<td>Direct: via a rank-based conjoint analysis</td>
<td>Undergraduate students (survey-regressions)</td>
<td>Fictional sponsorships of NASCAR</td>
<td>N/A</td>
<td>N/A</td>
<td>Sponsorship is preferred over no sponsorship. Additionally, sponsorship could increase the underdog brand’s market share</td>
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<td>Olson (2010)</td>
<td>Indirect: via multiple studies</td>
<td>Norwegian and Danish citizens (survey-SEM)</td>
<td>Sponsorships of a Scandinavian professional soccer club and a Scandinavian professional team-handball league</td>
<td>Object equity, sponsorship attitude, sincerity</td>
<td>Attitude, intention</td>
<td>All predictors positively affect brand equity</td>
</tr>
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Notes: SEM = Structural equation modelling; GLM = General linear model. aOnly the sports sponsorship context was included. bThis study was included because it examined one of the CBBE outcomes.

Source: Authors’ own work

Table 1.
confirmed that sports sponsorship contributes to enhancing brand equity (e.g. Cornwell et al., 2001). However, as shown in Table 1, these studies tended to examine what Olson (2010) called “high-level sponsorship” effects, such as sponsor credibility, team identification, self-congruity, congruence and “fit.” Although they provide valuable theoretical insights, marketing-related changes (e.g. willingness to pay a price premiums or changes in market share) as a way of assessing sponsorship effectiveness were notably absent.

2.4 Price premium and market share

From a managerial perspective, the price premium is a very important outcome of sponsorship. It represents the amount of money consumers are willing to pay for their “preferred brand over comparable/lesser brands of the same package size/quantity” (Netemeyer et al., 2004, p. 211). Aaker (1996), in his brand equity measurement tool (The Brand Equity Ten), suggested that the price premium is a basic measure of brand loyalty and further proposed that the price premium could be the single best measure of brand equity. Moreover, if sponsorship is effective, it should lead to an increase in market share, which is why Park and Srinivasan (1994) argued that both the price premium and market share should be the outcome measures of brand equity, as these tend to reflect true economic value. Furthermore, fans should be sampled because they are the ones most likely to pay a premium for sponsoring brands. Of the 18 previous studies reviewed (see Table 1), approximately one-third used students or nonfans as subjects, only two studies examined market share (i.e. Dean, 2004; Hickman, 2015), and no study examined price premiums. Similarly, in a recent meta-analysis covering 154 studies, none used price premium or changes in market share as dependent variables (Kim et al., 2015).

A few studies, however, have separately attempted to measure changes in market share or premium pricing. Hickman (2015), for instance, used the self-reported share of wallets as a surrogate measure for market share. This, however, relied totally on the participants’ ability to remember their past purchases. Dean (2004), on the other hand, conducted a small conjoint study. Using a fictitious scenario involving 63 students, the price attribute that was so important in conjoint studies (Meißner and Decker, 2010) was not used. Other researchers have attempted to measure price premiums using a single-item Likert scale measure (e.g. Donlan, 2013, 2014). The measurement item is usually worded in terms of the willingness of the participant “to pay a higher price for [Sponsor] product/services over other competing brands” (Donlan, 2013, p. 246). This measurement item does not, however, allow participants to specify how much more they are willing to pay or what competing brands they are supposed to compare against. It therefore lacks specificity, contradicting Aaker’s (1996, p. 106) exhortation, “The price premium measure is defined with respect to a competitor or set of competitors who must be clearly specified” (italics added).

Our literature review thus reveals that only a few studies have attempted to assess the effectiveness of sponsorship on brand equity using market-related outcomes (e.g. changes in market share or premium pricing), albeit in a less than ideal way. From the foregoing discussion, one could logically expect fans to be more willing to pay a price premium for a sponsor’s brand than for a nonsponsor’s brand. Furthermore, sponsors’ brands are expected to achieve the highest market share among fans compared to other brands. The following hypotheses are therefore proposed:

H1. Fans will prefer their sponsor’s brand over other brands.

H2. Fans are more willing to pay a price premium for their sponsor’s brand over other brands.

H3. Sponsors’ brands will acquire the highest market share among fans in comparison to other brands.
2.5 Best–worst discrete choice experiment versus purchase intention

Although market share and price premiums are advocated in this study, purchase intention has been the typical measure of the behavioral effect of sponsorship (Cornwell et al., 2005) and has been proposed as the best available approximation of the effects of sponsorship on the sales of sponsoring brands (Crompton, 2004). However, it has long been known that purchase intention is a poor predictor of actual buying behavior (Morrison, 1979). Typically, purchase intention is measured using rating scales that are subject to biases, including social desirability bias, acquiescence bias and hypothetical bias (Adamsen et al., 2013). In the sports sponsorship field, studies conducted by Zaharia et al. (2016) and Hickman (2015) failed to find any relationship between purchase intention and actual purchases. One of the main reasons for this intention–behavior gap is social desirability bias (Zaharia et al., 2016). Because fans want to be seen as supportive of their favorite team, they tend to overstate their intentions to buy the team sponsor’s brand (Zaharia et al., 2016). In addition, it is not obvious how a purchase intention score can be translated into financial outcomes. Purchase intention is thus not an ideal measurement tool for sponsors to use to assess their sponsorship investments.

Instead, we propose that individuals’ preferences obtained from a BWDCE are superior to purchase intentions in measuring the behavioral response to sponsorship. Similar to a discrete choice experiment (DCE), which is also known as choice-based conjoint (CBC) analysis, a BWDCE is based on random utility theory (RUT) (Thurstone, 1927), a well-established theory of human choice behavior (Louviere et al., 2010). The theoretical underpinning of BWDCEs more accurately reflects human choice behavior than purchase intention. Agarwal and Rao (1996) showed that individuals’ preferences obtained from choice experiments are not only among the top three measures that predict brands’ market shares but are also better than a 0-to-100-point purchase intention scale. Accordingly, we hypothesize the following:

\[ H4. \] Individuals’ preferences obtained from BWDCE are better at predicting fans’ brand choice than the rating scale of purchase intention.

3. Methodology

3.1 Best–worst scaling and purchase intention

Best–worst scaling (BWS), introduced in the academic literature by Finn and Louviere (1992), is a powerful choice modeling method for performing trade-off analyses among several attributes that are presented as objects, single profiles, or multiple profiles (Louviere et al., 2015). The basic idea of BWS is to provide respondents with numerous options in a systematic way and multiple times in small groups. Participants are asked to indicate which options are the best and worst (Louviere et al., 2015).

BWS has some advantages over other choice modeling methods. First, BWS allows the gathering of much more data with a smaller sample size than DCE or CBC (Flynn, 2010; Louviere et al., 2008). Second, while traditional conjoint analysis methods, such as rating or ranking, are based on conjoint measurement theory – an abstract mathematical construction – BWS is based on RUT (Thurstone, 1927), which, as stated earlier, is a well-established theory of human choice behavior (Louviere et al., 2010).

Three types of BWS exist:

1. the object case of BWS (Case 1);
2. the profile case of BWS (Case 2); and
3. the multiprofile case of BWS (Case 3) (Louviere et al., 2015).
In sports sponsorship, BWS Case 1 is the only case that has been implemented to study the topic of sponsorship servicing, although brand equity has not been investigated (O’Reilly and Huybers, 2015). In this study, BWS Case 3 (Louviere et al., 2008) was used because it is better at simulating real-world settings. In BWS Case 3, the attributes under examination are bundled into a product, making the buying situation less hypothetical. Note that BWS Case 3 is also called the BWDCE (Lancsar et al., 2017), which is the term adopted in this study.

While BWS Case 2 is widely used in health-related research, BWDCE and BWS Case 1 are two forms of BWS that are frequently applied in the field of marketing (Adamsen et al., 2013), specifically in wine-related consumption research (e.g. Lockshin and Cohen, 2011). However, in the field of sponsorship, even in the broad domain of brand equity research, BWS has not been extensively used. Indeed, in sponsorship-related research, BWS has been used only by O’Reilly and Huybers (2015), who adopted BWS Case 1 to study the topic of sponsorship servicing. O’Reilly and Huybers (2015) have also encouraged future research to use BWS methods to study consumer-related topics in the sponsorship context.

Measuring intentions to purchase is more straightforward but can take many forms (e.g. five-point to seven-point rating scale, with or without verbal descriptions). It can also be measured more than once in different ways. However, the most established purchase intention scale asks respondents to indicate their probability of purchasing a brand on a 0–10 scale, where 0 indicates no chance and 10 indicates certainty (Juster, 1966). Each point on the scale is accompanied by a numerical and verbal description. One early review found this format to be superior in predicting future purchases compared to other formats (Day et al., 1991). Furthermore, there is no need to have multiple measures of purchase intention if the meaning of the question is concrete and clear and refers to a single object (Ang and Eisend, 2018; Rossiter, 2011).

3.2 Research context
This study targeted a selection of fans of three Australian A-League (soccer, also known as football) teams:

1. Melbourne Victory Football Club (MVC-FC);
2. Western Sydney Wanderers Football Club (WSW-FC); and

The three teams were selected because they are among the most popular four teams in the Australian A-League (Roy Morgan, 2018) and because of their association with different sports apparel sponsors. Adidas sponsors MVC-FC, Nike sponsors WSW-FC and Puma sponsors SYD-FC.

The three sponsors – Adidas, Nike and Puma – are different in terms of their brand valuation and market position. In the Australian sportswear market, Nike is Australia’s favorite sportswear brand, with an 8.5% market share, followed by Adidas, with a 6.5% market share, and Puma, with a 1.3% market share (Euromonitor International, 2018). Although Puma is a well-known brand in other countries, it is a small brand in Australia (it is ranked 13th in the Australian market in terms of its market share).

In this study, we decided to use these sportswear sponsors (i.e. Adidas, Nike and Puma) to accommodate multiple football teams (i.e. MVC-FC, WSW-FC, SYD-FC). All these football teams already have a sponsorship agreement with their respective sponsors. Using brands of other product categories (e.g. airlines or financial institutions) would limit the number of participating teams for this study. Sportswear (e.g. t-shirts) is a popular form of sponsorship for football teams.
3.3 Procedure and best–worst discrete choice experiment design

There are 10 teams in the A-League. Participants were first asked to indicate which of the ten A-League soccer teams they liked most. This question served as a filter question; those who were not fans of any of the three teams – MVC-FC, WSW-FC or SYD-FC – were thanked, ending the survey. Eligible participants were then directed to the first question:

Q1. If you were about to enter a draw to win a $50 voucher from Nike, Adidas, or Puma, could you please indicate which brand would you choose?

This question serves as a proxy for actual brand choice. We placed this question at the very beginning of the survey to minimize any effect of social desirability bias.

Next, the participants were presented with three images of the on-field home uniforms of the three football teams. In each image, we inserted the phrase “Official kit sponsor” and placed the sponsor’s trademark underneath the phrase. The participants were asked which on-field home kits they found most and least appealing. This question served as a priming technique to indirectly remind the participants of their team’s sponsor. Then, the six-item seven-point Likert scale (anchors: –3 = strongly disagree, +3 = strongly agree) developed by Mael and Ashforth (1992) was used to measure participants’ degree of identification with the team they indicated they liked most. After this, the participants were assigned a BWDCE buying task. Because the BWDCE task consisted of 12 choice sets (discussed below), a demographic question was presented after each three-choice set to make the data collection process more interesting and less burdensome.

For the BWDCE task, a plain white t-shirt was selected as the stimulus because it is most commonly available to all sponsors. This simple product also eliminated the effects of other attributes that are not of interest, such as design and color. Three product attributes – brand, price and fabric – with three levels each were investigated in this study. The price range was determined by calculating the average price of similar products on the sponsors’ websites (approximately $45) and then adding and subtracting $10 from the average (all prices are in Australian dollars). The three levels of fabric (100% polyester, 100% cotton, 50% cotton and 50% polyester) were based on the types of fabric in similar products found on the websites of the three brands. However, we must draw the reader’s attention to the fact that the inclusion of price and fabric was only intended to create a complete product that could be used for the BWDCE task. Hence, the results concerning price and fabric are not of interest in this study.

The orthogonal design was used to generate the possible combinations of the attribute levels, resulting in nine possible profiles. To divide the nine profiles into sets, the balanced incomplete block design (BIBD) method was used. The BIBD exhibits 12 choice sets, comprising three profiles in each set for comparison. We developed pictorial presentations of all profiles in the BWDCE task to approximate a real-world choice situation such that the choices are easy to process (see Figure 1). Choice options were randomized to remove any order effects.

At the end of the questionnaire, the participants were presented with a final demographic question as a distraction, after which they were asked to indicate on an 11-point single-item rating scale their intentions to purchase the sponsor’s t-shirt. The participants were asked:

If you were going to buy a sportswear product, how likely would you be to buy from [the apparel sponsor brand], which is the apparel sponsor of [selected favorite team]? (anchors: 0 = No chance I would buy [0%]; 10 = Absolutely certain to buy [100%]).

Each point of the scale has a numerical and verbal description.

3.4 Recruitment and sampling

A panel provider (i.e. Qualtrics) was used to recruit participants. To be eligible for participation, respondents had to be at least 18 years of age and fans of one of the three
For data assurance quality, the collected responses were screened by the duration of survey completion. The participants who submitted their answers in less than the median length of survey completion time were reviewed carefully. The judgment to remove the suspiciously low-quality responses was based on the standard deviation of the BWDCE task. That is, when the standard deviation was zero, it meant that the participants kept selecting the same options – option one as the most likely to buy and option two as the least likely to buy, for example – for all 12 sets presented.

Figure 1.
Pictorial presentation (example)

Source: Authors’ own work
The final aggregated sample included in this study represents 409 participants, consisting of 141 MVC-FC fans, 124 WSW-FC fans and 144 SYD-FC fans. As summarized in Table 2, some demographic differences existed among the fan groups. The Chi-square and Kruskal–Wallis tests indicated that there were some differences among the three groups in gender and education levels.

3.5 Analytical approach

Stata software (version 16) (StataCorp, 2019) was used to conduct a multinomial logit (MNL) analysis to estimate the preferences of fans. Qualitative attributes, brand and fabric, were effect coded. Puma was the reference level for brand attributes, while 50% cotton and 50% polyester were the reference levels for fabric attributes. The effect-coding method was chosen over the dummy coding method because it can be used to calculate the effects of the reference level for each attribute (Bech and Gyrd-Hansen, 2005). The coefficient of the reference level for an attribute is calculated simply by summing the coefficients of the other levels of that attribute multiplied by a negative attribute (Bech and Gyrd-Hansen, 2005).

To examine this study’s first three hypotheses (H1, H2 and H3), three MNL models were performed to separately estimate each fan group’s preference, calculate the mWTP of each brand by each fan group, and obtain the needed information to compute the market shares.

To examine the fourth hypothesis, two logistic regression models were estimated. In both models, brand choice was the dependent variable. This variable was dummy coded (1 = the participants selected the sponsor of their favorite team, 0 = otherwise). In the first logistic regression model, purchase intention for the sponsoring brand was the independent variable. In the second model, we used individuals’ preferences for the sponsor’s brand obtained from BWDCE as an independent variable. We calculated BWDCE individual-level preferences using best-minus-worst regression (Winzar et al., 2018). However, for this part of the analysis, only 315 participants were included because 94 participants did not respond to the purchase intention question.

4. Results

4.1 Brand preference results

To test H1 (i.e. fans will prefer their team sponsor’s brand over other brands), three separate MNL models were performed for each fan group. The three models have McFadden’s pseudo-$R^2$ goodness-of-fit values between 0.16 and 0.20, indicating a good fit. (McFadden’s pseudo-$R^2$ should not be confused with the traditional (Pearson) $R^2$ used in OLS regression. While McFadden’s pseudo-$R^2$ theoretically ranges from 0 to 1, in practice, it rarely exceeds 0.30 (McFadden, 1979), so we can regard these MNL models as reasonably good model fits).

In general, H1 was supported in the cases of MVC-FC fans and WSW-FC fans, but not in the case of SYD-FC fans. Table 3 shows that among the MVC-FC fans (where Adidas was the sponsor), the results indicate that Adidas is the preferred brand ($B = 0.294, p < 0.001$), followed by Nike ($B = 0.167, p < 0.001$). Puma is the least desirable brand ($B = -0.461$). Notably, the coefficients of the three brands sum to zero; thus, the coefficient of Puma, which is the reference level, is simply the complement of the sum of the other two coefficients. A negative or zero coefficient does not mean that a brand is hated or unattractive; instead, such a coefficient shows each brand’s position relative to the other brands.

Among WSW-FC fans, Nike was the most preferred brand ($B = 0.460, p < 0.001$). Adidas was the second most preferred brand ($B = -0.022, p > 0.1$), and similar to the case of MVC-FC fans, Puma was the least preferred option ($B = -0.438$). Among the SYD-FC fans, none of the brands were statistically significant, implying that these brands did not differentially influence the participants’ preferences.
<table>
<thead>
<tr>
<th></th>
<th>MVC</th>
<th></th>
<th>WSW</th>
<th></th>
<th>SYD</th>
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<td>%</td>
<td>N</td>
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<td>%</td>
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<td>16</td>
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<td>19</td>
<td>26</td>
<td>18</td>
</tr>
<tr>
<td><strong>Team identification</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distribution on −3 to +3 scale</td>
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<td>M</td>
<td>0.37</td>
<td>M</td>
<td>0.60</td>
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<tr>
<td></td>
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<td>1.22</td>
<td>SD</td>
<td>1.20</td>
<td>SD</td>
<td>1.20</td>
</tr>
</tbody>
</table>

**Source:** Authors' own work
4.2 Price premium results

To test $H_2$ (i.e. fans are more willing to pay a price premium for their team sponsor’s brand over the other brands), the “wtp” Stata command was used (Hole, 2007) to calculate the mWTP of each brand. Although one can manually calculate the WTP values (e.g. Pracejus and Olsen, 2004; Winzar et al., 2018), Hole’s command has the advantage of computing the confidence intervals. Note that calculating the mWTP for a nonsignificant attribute produces estimates of mWTP that are also not different from zero (Hensher et al., 2005). Therefore, in the case of SYD-FC fans, we defined the mWTP for all three brands (i.e. Adidas, Nike and Puma) as zero, following Hensher et al. (2005).

Similar to $H_1$, $H_2$ was confirmed in the cases of MVC-FC fans and WSW-FC fans but not in the case of SYD-FC fans. Figure 2 shows that for MVC-FC fans, Adidas received the highest mWTP value, at $6.04. Compared to the other two brands, MVC-FC fans were willing to pay an extra A$2.61 for Adidas over Nike and an extra $15.5 for Adidas over Puma. For WSW-FC fans, on the other hand, Nike gained the largest mWTP amount, at $10.8. Furthermore, WSW-FC fans were willing to pay a price premium of $10.8 for Nike compared to Adidas and $21 for Nike compared to Puma.

There were no differential effects among the SYD-FC fans. For these fans, the mWTP for all brands, including Puma, which is a SYD-FC sponsor, was zero.

### Table 3. MNL models for each fan group

<table>
<thead>
<tr>
<th>Attribute</th>
<th>MVC-FC fans (sponsored by Adidas)</th>
<th>WSW-FC fans (sponsored by Nike)</th>
<th>SYD-FC fans (sponsored by Puma)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$B$</td>
<td>SE</td>
<td>$p$</td>
</tr>
<tr>
<td>Price</td>
<td>$-0.049$</td>
<td>0.003</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Brand levels</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adidas</td>
<td>$0.294$</td>
<td>0.031</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Nike</td>
<td>$0.167$</td>
<td>0.031</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Puma</td>
<td>$-0.461$</td>
<td>Reference level</td>
<td></td>
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<tr>
<td>Fabric levels</td>
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<td></td>
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</tr>
<tr>
<td>100% Polyester</td>
<td>$-0.835$</td>
<td>0.034</td>
<td>&lt;0.001</td>
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<td>50% Cotton and 50% Polyester</td>
<td>$0.079$</td>
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<td>McFadden’s pseudo-$R^2$</td>
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<td>McFadden’s pseudo-$R^2$</td>
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</table>

Source: Authors’ own work

4.3 Market share results

To test $H_3$ (i.e. sponsors’ brands will acquire the highest market share among their fans in comparison to the other brands), we estimated each sponsor’s market share among each fan group as a separate market when all product attributes are identical (i.e. price and fabric), except for the brand. The market share of each product was computed by dividing the natural log of the product’s utility by the total of the natural logs of all product utilities (Chakraborty et al., 2002).

Similar to $H_1$ and $H_2$, $H_3$ was supported for the MVC-FC and WSW-FC fans but not for the SYD-FC fans. Figure 3 shows that among SYD-FC fans, the market share among the three brands was virtually identical. However, $H_3$ was supported by Adidas and Nike.
Adidas’ market share in the MVC-FC fan market was the highest, at 43%, nearly 5% higher than Nike’s and 23% higher than Puma’s. Similarly, Nike acquired 49% of the WSW-FC fan market, with results that were 19% and 29% higher than the results for Adidas and Puma, respectively.

4.4 Best–worst discrete choice experiment versus purchase intention results

To test $H4$ (i.e., individuals’ preferences obtained from BWDCE are much better at predicting fans’ brand choice than the rating scale of purchase intention), two logistic regression models were estimated; the results are presented in Figure 4. Although both purchase intention and BWDCE predicted brand choice better than chance, BWDCE performed much better (see model 2 in Figure 1). Chi-square and McFadden’s pseudo-$R^2$ goodness of fit measures were much higher in the BWDCE model (greater is better), and parsimonious goodness of fit measures, Akaike information criterion (AIC) and Bayesian information criterion (BIC) were both a great deal lower for BWDCE than for purchase intention (lower is better). The odds ratio for BWDCE was 3.662 ($e^{1.298}$), with 79% accuracy in predicting “0” (not sponsored brand) or “1” (sponsored brand), whereas the odds ratio for purchase intention was 1.390 ($e^{0.330}$), with 58% predictive accuracy. This translates to a relative probability ratio of $0.79/0.58 = 1.35$, or a 35% improvement in the accuracy of prediction for the best–worst measure over the purchase intention measure. Based on these results, $H4$ was supported.
5. Discussion

The results of this study revealed clear evidence that sports sponsorship positively affects sponsors’ brand equity, even when we apply a more stringent method of assessing brand equity. These positive effects were evident in the results for fans’ brand preferences, price premiums and market share. Our study therefore demonstrates that sport sponsorship can change a fan’s buying behavior. This represents a more definitive proof that sports sponsorship is effective beyond attitude change.

Additionally, this study has demonstrated the superiority of BWDCEs over more traditional rating-based purchase intention measures. We showed that best–worst coefficients are better predictors of actual purchase choice than a traditional purchase intention measure. A side-by-side comparison of logistic regression models with the choice of the favorite team’s sponsor (0 = No, 1 = Yes) against either the B-W coefficient for the sponsored brand or purchase intention rating for the sponsored brand shows the clear superiority of the BWS approach. There is a 35% improvement in predictive accuracy using this approach compared to the well-established purchase probability method. It thus represents a more advanced way of assessing brand equity in sports sponsorship. Finally, our study also found that not all brands benefit equally from their sports sponsorships. Prominent brands tend to benefit more than smaller brands. This was particularly apparent when comparing the results of Nike sponsorship, the market leader, with those of the other two brands (i.e. Adidas and Puma). Fans exposed to the Nike sponsorship were willing to pay fourfold the price premium for Nike over Adidas – the highest premium achieved compared to the sponsorship of other brands. This is consistent with Roy and Cornwell’s

Note: Market shares assume that all product attributes are identical except for the brand
Source: Authors’ own work

Figure 3. Market share results
earlier study using attitudinal measures where they suggested, "While lesser-known brands can use sponsorship as a brand-building vehicle, they may not attain the same level of results as their high equity counterparts." Our study confirms their observation with premium pricing.

5.1 Theoretical contributions
This study sought to examine the effects of sports sponsorship on brand equity. Consistent with previous findings (e.g. Cornwell et al., 2001; Donlan, 2014; Wear et al., 2016), this study confirms that sports sponsorship can positively influence brand equity by showing that it can increase market share and price premium. This study provides three contributions to the literature. Our first main theoretical contribution is the above demonstration of the superiority of this methodology over more traditional ways of assessing sponsorship (e.g. increase in brand awareness and image) and linking it directly to a unique sponsoring asset. We have not only demonstrated the efficacy of sports sponsorship but have also shown more concretely that fans are willing to pay more for their team’s branded merchandise – i.e. the sponsor’s t-shirt. This represents a new method of sponsorship assessment because the
outcome of such sponsorship is now closely tied to a specific asset (i.e. branded merchandise). The value here is that causality is more firmly established. This is superior to merely measuring changes in brand awareness or image and is thus less vulnerable to the confounding effects of advertising, which can occur during a sponsorship period.

Although we have demonstrated this principle with only one piece of merchandise (i.e. a t-shirt), there is no reason that this methodology cannot be applied across other sponsored assets. For instance, the value of goods and services such as NFTs (or nonfungible tokens), fan festivals, or packaged tours can all be carefully assessed for their revenue-generating potential. In the aftermath of the COVID-19 pandemic, companies are now demanding more returns on sponsorships, whereby our method represents a path forward. However, this does not mean that one should totally abandon brand awareness and image as measurements of sponsorship success, as these are still desired outcomes. Our method, however, represents a more sophisticated yet focused assessment that is more in line with evaluating the financial returns of sports sponsorship.

Our second contribution lies in suggesting a more concrete approach of assessing return on investment (or ROI) in sports sponsorship. Measuring the ROI of sponsorship engagement has always been a substantial challenge (Cornwell, 2014; Meenaghan and O’Sullivan, 2013; Rumpf and Breuer, 2018). Meenaghan and O’Sullivan (2013) criticized reliance on awareness and media exposure as the main methods for measuring the ROI of sponsorship engagement and reported that these two measures lacked credibility. The BWDCE approach adopted here may offer a way forward because it is closer to monetary value through the measure of premium pricing or market share changes (see managerial implications). The methodology is also consistent with Rumpf and Breuer’s (2018) suggestion that measuring ROI using measures of brand choice might be a promising method for providing a financial calculation of the ROI of sponsorships. Such an approach is also cost-effective and easy to implement through panel data or online surveys compared to experimental studies carried out in laboratories (e.g. Olson and Thjømøe, 2009, 2012).

Finally, this study revealed that a sponsor’s market prominence plays a critical role in the effectiveness of sports sponsorship in enhancing brand equity. Previous research has found that leading brands are more likely to obtain more positive responses at the cognitive (Herrmann et al., 2014; Pham and Johar, 2001), affective (Biscaia and Rocha, 2018; Roy and Cornwell, 2003; Lardinoit and Quester, 2001) and conative (Biscaia and Rocha, 2018; Herrmann et al., 2014; Kim et al., 2015) levels, which is evidenced by the substantially better results of Nike’s sponsorship of their team than those of Adidas or Puma. This study confirms the influence of market prominence on the effectiveness of sports sponsorship.

Additionally, there is evidence to suggest that a brand’s (i.e. Nike’s) market prominence can act as a “buffer” against the negativity of fans of competing football clubs. Bergkvist (2012; see also Bee et al., 2021) reported that fans generally have negative purchase intentions toward rival clubs’ sponsoring brands, but this study shows that this is not the case for Nike. As the market leader, Nike seems to be least affected by the sponsorships of rival clubs. This “buffering effect” hypothesis opens new avenues for future research (see also Korkofingas and Ang, 2011).

### 5.2 Managerial implications

The causal relationship between sponsorship and brand equity has never been fully established in the past, partly because there are many definitions of brand equity and partly because the methodologies used do not permit us to do so. Most sponsorship studies also tend to ignore managerially useful dependent measures (see review of Goodchild, 2020; Kim purchase intention in sports sponsorship...
et al., 2015). The current study attempts to overcome these deficiencies and, hence, provide some useful suggestions for managers. They are as follows.

First, because our study shows that sponsorship can increase brand equity, it implies that our methodology “works.” Even amid more stringent measures such as premium pricing and market share, our study demonstrates that sports sponsorship can be effective. However, more importantly, because we have centered our research on a specific sponsoring asset of branded merchandise (i.e. the sponsor’s t-shirt), this causality has been more firmly established. Potential sponsors can use this methodology as a pretesting strategy to quickly evaluate how much the equity of their brand will increase (or decrease) when sponsoring different teams. Because sponsorship deals can reach millions of dollars, this knowledge could be very advantageous. For instance, if the market share calculation shows that sponsoring team A (versus team B or C) is most likely to increase market share by the largest percentage point, and if one percentage point is estimated to be equivalent to a certain dollar value, then this information can be used as a direct estimate of how much more a particular team is worth sponsoring over others. This then forms the upper dollar limit that the sponsorship contract cannot exceed.

Potential sponsors can also use this methodology to investigate other product categories (e.g. football boots). This is important because fans may be more willing to pay a premium for some products (e.g. t-shirts) but not others (e.g. football boots). Because different product categories have different profit margins for sponsors, this methodology can help in deciding which product category to use. Using the same logic, we can also extend this assessment to other sponsored assets beyond products (e.g. sponsored social events), which may be even more profitable. All this information, whether it is changes in market share or premium pricing of the sponsored assets, will help potential sponsors develop their best alternative to a negotiated agreement (BATNA) during their negotiation with the sports team.

Sophisticated club managers of sports teams can also apply the same methodology to their own advantage when negotiating with potential sponsors. For instance, if a football team (e.g. SYD-FC) is performing well and is beginning to effect changes in the market share or premium pricing of a sponsor’s products (e.g. Puma), this information can be leveraged at the bargaining table in the next round of negotiation. Such a strategy should not be underestimated because this tool allows a sophisticated negotiator to estimate, with some confidence, just how much of these benefits will accrue. For example, conjoint analysis, such as that used in this paper, has been applied in the valuation of environmental resources (Alriksson and Öberg, 2008), in legal copyright cases to determine the range of royalty payments due (Sidak and Skog, 2016) and, more recently, in estimating the financial value of the convenience and efficacy of COVID treatments (Bughin et al., 2022; Hosogaya et al., 2021). Of course, all forecast estimates are subject to caveats, e.g. product availability, competitive promotion or social influence, and thus forecasts should be moderated by domain knowledge to provide realistic upper and lower bounds.

Finally, this study should provide managers with more confidence that sponsorship can indeed increase brand equity. Academically, one may debate how brand equity is defined, but managerially, does it truly matter? If sponsorship can be shown to cost-effectively increase market share and/or predispose fans to pay more for the sponsor’s products, then who cares how brand equity is defined? Rather, it is the outcome that matters. With such “bottom-line” results, managers can take comfort in this (mercenary) logic and champion the importance of sponsorship to upper management should they begin to waver.
5.3 Limitations and future research
This study has some limitations. First, the participants were not asked about their sponsorship awareness. Instead, the study adopted the priming technique to remind the participants about the sponsor of their team. Although the results suggest that the priming technique is effective, as each brand was highly preferred by its sponsored team’s fans, not asking the participants about the sponsor of their team can be considered a limitation. Second, only three sponsors were used. The results for mWTP and market share may not reflect the real market because there are many more brands in the market. The market shares of the three brands relative to each other, however, are sound. Future studies can include more brands. Third, the analytical approach, the MNL model, does not account for heterogeneity in preferences or provide results at the individual level. Thus, future studies may consider using other models, such as mixed logit models. Fourth, the attributes of the t-shirt used in this study may be different from those that all consumers would consider important. Other features could be thus added: colors, logo sizes, slogans, etc. These features could exponentially increase the size of an experimental design. However, they will not alter the fundamental finding that indicates we can take empirical measures of the changes in brand preference and value using sponsorship. Fifth, the gender and age distributions were not the same among the three sample groups. Although the results appeared to make sense, the analysis showed no differences in results among demographic groups. However, the utility values may differ when the compositions of the groups are equal, and future studies should investigate this issue more deeply. Sixth, the focus of this study is on apparel sponsorship, given that this has a natural fit with sports teams. In the literature, it is well documented that fit enhances sponsorship effectiveness (e.g. Mazodier and Merunka, 2012). Future studies can therefore use BWDCE to investigate the effects of sponsorship on low-fit sponsors’ brand equity. In addition, because all the focal sponsors were in the apparel sector, it would be instructive to use the same method to investigate other types of sponsors, such as title or beverage sponsors. Finally, the three focal Australian soccer teams are among the most popular teams in the Australian A-League (Roy Morgan, 2018). Because the stature of a sponsored entity positively affects sponsorship outcomes (e.g. Speed and Thompson, 2000), future research should investigate whether the same or similar outcomes occur amid lower profile sports entities.

Indeed, other sponsorship-related topics can also be investigated using BWDCE (or any other choice-modeling method). For instance, future research can use choice-modeling methods to investigate the effects of sponsorship on price elasticity among fans, the effects of demographic characteristics on fans’ mWTP for sponsors (e.g. females vs males), fans’ mWTP for different sponsor tiers or levels (e.g. major vs minor sponsors) and fans’ mWTP for the products made by the sponsors of their team’s arch-rival. The use of choice-modeling methods is promising because they offer a more concrete way of assessing these and other aspects of sponsorship effectiveness.

We conclude this study with a broader philosophical note. BWS, including BWDCE, has been successfully applied in various areas of marketing. These areas include, for instance, consumer preferences in the food and beverage industry (Chrysouchou et al., 2022; Lerro et al., 2020), pricing policies (Shoji et al., 2021), green marketing (Jakomin et al., 2022) and tourism marketing (Kim et al., 2019). The diversity of these studies thus clearly demonstrates the usefulness of BWS in the marketing discipline. It should therefore be more widely used in sports sponsorship as well, given the applied nature of the subject.

References


StataCorp (2019), *Stata Statistical Software*, StataCorp, College Station, TX.


Further reading


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