



Building and leveraging sports brands: evidence from 50 years of German professional soccer

Hauke A. Wetzel¹ · Stefan Hattula² · Maik Hammerschmidt³ · Harald J. van Heerde¹

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Abstract

Although professional sports are a major interest for consumers and a soaring contributor to economic growth, very little is known about how sports brands are built over time and what makes some sports clubs' market performance so much stronger than others. Based on a unique dataset of 40 German professional soccer brands tracked from 1963 through 2014, this research studies how the value drivers recruitment, winning, and publicity feed sales-based brand equity (SBBE) and attendance. One of the novel findings is that not only do strong brands benefit from higher levels of SBBE, but they are also able to leverage SBBE more effectively the longer they are on the market, which widens the gap between strong and weak brands across time. We also find that the effect of the value drivers on attendance evolves from direct to indirect via SBBE. Overall, the increasing brand leverage effect yields important implications for marketing theory and for sports brand management.

Keywords Brand leverage · Sales-based brand equity · Brand age · Brand building · Recruitment · Winning · Publicity · Sports marketing

Hauke A. Wetzel, Stefan Hattula, Maik Hammerschmidt and Harald J. van Heerde contributed equally to this work.

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✉ Hauke A. Wetzel
h.wetzel@massey.ac.nz

Stefan Hattula
stefan.hattula@bwi.uni-stuttgart.de

Maik Hammerschmidt
maik.hammerschmidt@wiwi.uni-goettingen.de

Harald J. van Heerde
heerde@massey.ac.nz

¹ Massey Business School, Massey University, Private Bag 102 904, Auckland 0745, New Zealand

² Marketing Department, University of Stuttgart, Keplerstrasse 17, 70174 Stuttgart, Germany

³ Faculty of Business and Economics, University of Goettingen, Platz der Goettinger Sieben 3, 37073 Goettingen, Germany

Introduction

Professional sports are a major interest for many consumers. Seventy percent of U.S. adults regularly attend, watch, or follow professional sports events (Harper et al. 2014). Professional sports are also a soaring contributor to economic growth. The global industry for sports events amounted to approximately \$91 billion by the end of 2017 (Statista 2018). Along with increasing global attendance rates of professional sports, its growth consistently beats GDP growth by 10 to 290%, with no slowdown in sight (Collignon and Sultan 2014; Jones 2015).

Yet it is remarkable that a few sports clubs grow even faster than the broader market, accumulating an immense fan base and wealth. Sports clubs such as Bayern Munich or Real Madrid in European soccer, the Dallas Cowboys and the New York Giants in the NFL, and the Chicago Bulls in the NBA benefit from a fan base that treats the club brand as a sanctuary and sets in motion an upward spiral of attendance rates. For instance, in the first five years of German professional soccer, the best-attended clubs topped the worst by 67% in terms of the number of tickets sold. Today, attendance for the best-selling club surmounts that of the worst-selling club by 1711%. Similarly, in the English Premier League, only six clubs now dominate the business; it is expected that these “rich clubs will get richer” (Dunn 2017).

This research aims to explain this observation. The goal is to understand how sports brands are built over time and what makes some clubs' market performance so much stronger than others. We do this by addressing the following research questions: (1) How important are sports brands for driving attendance rates? (2) What determines sports clubs' brand equity? (3) What explains the large difference between the extraordinary attendance rates of some club brands as opposed to the much lower rates of others?

To study these questions, we use as a starting point a framework inspired by the brand value chain (Katsikeas et al. 2016; Keller and Lehmann 2006). The framework posits that value drivers have a direct impact on the outcome variable (attendance rate) and an indirect effect via brand equity. Such a framework, however, does not account for the fact that value creation through the brand is a dynamic process (Borkovsky et al. 2017) and therefore does not explain the increasing gap in attendance between clubs over time. In line with the calls for more research into the time-varying drivers of brand strength and brand performance (Ataman et al. 2008; Slotegraaf and Pauwels 2008; Srinivasan et al. 2010), we offer a new argument to the literature that the effects of brand equity and of value drivers are not static, but evolve over time. In a nutshell, we argue that strong brands yield their owners an increased brand leverage effect at a higher brand age. That is, not only do strong brands benefit from higher levels of brand equity, but over time they are also able to leverage this more effectively in driving attendance. This also means that over time brand equity plays a much stronger role in explaining the effects of value drivers on attendance. Overall, this sets in motion an upward spiral of enhancing attendance rates that widens the gap between strong and weak brands.

We adopt sales-based brand equity (SBBE) as the focal measure because it is economically highly relevant and relatively easy to observe over a long time period (Datta et al. 2017). As value drivers in the sports market, we focus on a club's recruitment spend to acquire new players (Sirianni et al. 2013), a club's performance on the field in terms of winning percentage (Yang et al. 2009), and its publicity in the media (Hewett et al. 2016). These drivers represent key metrics for professional sports: players (recruitment spend), success (winning percentage), and buzz (publicity). We link these drivers to attendance, both directly and indirectly, through SBBE.

We test the framework in the context of professional soccer. Among professional sports, soccer ranks number one globally, accounting for \$35.3 billion in revenues or 46.4% of the global market for sports events in 2013 and exhibiting a growth rate of 8.5% (Collignon and Sultan 2014). We use an econometric analysis of annual data from a panel of 40 German soccer brands tracked since the founding of the professional soccer league in 1963, covering 87% of all tickets ever sold for German professional soccer up to 2014. The analysis accounts for club and year fixed effects and uses multiple approaches to consider possible endogeneity of recruitment

spend. We also provide several validation procedures and robustness checks.

We find that value drivers have both a direct effect and an indirect effect on total annual attendance that operates through SBBE. Importantly, we find evidence for an increasing brand leverage effect. That is, not only does a strong brand yield higher attendance than a weak brand (i.e., brand leverage effect), but, as brand age increases, the same amount of SBBE yields even higher returns in terms of attendance (i.e., increasing brand leverage effect). The increasing brand leverage effect is mirrored in a decreasing direct effect of value drivers on attendance—in absolute and relative terms. Taken together, the evolution of the brand leverage effect and the devolution of value drivers' direct effects on annual attendance means that the path of the value drivers to attendance changes significantly across brand life. Early on, the indirect effects of the three value drivers (recruitment spend, winning percentage, and publicity) via brand equity account for 5 to 29% of the drivers' total effects on attendance. Later in brand life, indirect effects account for 44 to 85%, pointing to a growing role of the indirect path to attendance via brand equity.

The findings are not only new to the brand literature, they also entail valuable conclusions for sports managers. Specifically, we make the following contributions. We are the first to provide longitudinal insight into the unique factors that build sports brands. This aligns well with recent brand research that calls for more industry-specific examinations, including gaming (Nair et al. 2017), hospitality (Yi-Lin et al. 2015), movies (Carrillat et al. 2018), music (Saboo et al. 2016), and sports (Hartmann and Klapper 2017; Yang et al. 2009). Second, we show that sports brands benefit from a growing brand leverage effect as brand age increases. This finding explains why rich clubs are getting richer, leading to an ever-increasing gap between strong brands and weak brands. The evolution of the brand leverage effect is also a substantial finding for brand research as it calls for a deviation from the static perspective that dominates prior literature on the brand value creation process. Third, we assess the hypothesized links across brand life observations of up to 51 years as opposed to time spans of up to 11 years in prior brand research (Krasnikov et al. 2009). The resulting evidence provides robust guidance for the long-term strategies of sports managers. Further, while the sports context is nontraditional for the marketing literature, the conclusions to be drawn answer the ongoing question regarding the relative importance of the indirect, brand-centered path to firm performance versus the direct, transactional path (Hanssens et al. 2014). The research indicates at what stage of a brand's life the transactional path is more important (early on) and in what stage the brand-centered path is (later on), which has implications for researchers and managers.

This manuscript proceeds as follows. We first synthesize complementary streams in the brand literature to develop a theoretical foundation for the framework. Next, we discuss

the role of brand age for the evolution of the brand leverage effect and for the devolution of the transactional effects. We then introduce the sample and detail the method before we present and validate the results. Finally, we discuss the implications for researchers and managers and conclude with opportunities for future research.

Theoretical background

While this study features a sports context, it is theoretically rooted in the brand literature. We integrate the arguments from two complementary streams in brand research. First, brand equity research links SBBE to antecedents and consequences. Studies in the brand equity stream point to the role of strong consumer-brand relationships for firms' market performance. Brand equity is broadly defined as the value a brand adds to a firm's offering (Farquhar 1989; Keller 2013). There are many different approaches to reflect brand equity that broadly align with two perspectives (Datta et al. 2017). The consumer-based perspective focuses on consumer brand perceptions as a source of brand equity (e.g., Aaker 2010; Keller 1993; Yoo and Donthu 2001). The sales-based perspective focuses on actual brand choice or share in the market, drawing on actual behavior to reflect a brand's worth (e.g., Ailawadi et al. 2003; Simon and Sullivan 1993).

The literature views the brand neither as an ultimate outcome nor an initial determinant of firm performance. Rather, brand equity is conceptualized as the key conduit in the link between a firm's idiosyncratic market positioning and a firm's market performance (Aaker 2010; Keller and Lehmann 2006). The key links include brand building, which considers brand antecedents' impact on brand equity (Ataman et al. 2008; Paul 2015), and brand leveraging, which focuses the consequences of having a high-equity brand (Bruce et al. 2012), including the effect on sales (or attendance in a sports setting).

The extant literature assumes the impact of brand equity on sales is stable over time, based on a snapshot of brand-consumer relationships (Srinivasan et al. 2010). A dynamic perspective on the consequences of brand equity is still missing in the literature. We address this gap.

To explain the role that time plays in the framework, we augment the insights from brand equity research with arguments from brand community research (e.g., Muñiz and O'Guinn 2001; Thompson et al. 2016). The literature on brand communities (Goulding et al. 2013; McAlexander et al. 2002; Schau et al. 2009) and brand tribes (Cova and Cova 2002; Morris 1981) suggests that when strong brands increase in age, they gain benefits from their consumer base that go beyond those typically theorized in brand equity research. Specifically, over time, consumers build social relationships with other admirers of a brand in addition to their own relationship with the

brand (Algesheimer et al. 2005; Muñiz and O'Guinn 2001). This triggers a collective value creation process that aids the admired brand (Schau et al. 2009). We build on these arguments below.

Conceptual framework

Figure 1 shows the framework adopted in this study. It contains the effects of the value drivers on sports clubs' SBBE (the brand building effect), SBBE's effect on attendance (the brand leverage effect), and value drivers' direct effect on attendance (the transactional effect). While the resulting framework arises from a sports context, it is inspired by the value chains used in more traditional marketing settings in that it links the brand to antecedents and consequences (Hanssens et al. 2014; Katsikeas et al. 2016).

SBBE takes a central role in the framework. *Sales-based brand equity* is the part of a brand's sales or utility on top of the contribution of its objectively measured attributes (Datta et al. 2017). Hence, SBBE captures a brand's contribution to the economic performance of sports clubs.

Figure 1 includes value drivers that are particularly important in sports. First, *recruitment spend*, defined as the transfer fees paid for the acquisition of new players, is among the biggest costs of sports clubs, illustrated by the record-breaking \$263 million Paris Saint-Germain paid for the transfer of Neymar Jr. (Blumberg 2017). New player recruitment is a key value driver to consider. For instance, the attendance of the Chicago Bulls doubled the first year after the arrival of Michael Jordan (Hausman and Leonard 1997).

Second, the essential goal of sports is winning, and winning clubs attract supporters. Conversely, poor on-field performance leads to lower attendance rates. For instance, in the last season of a four-year losing streak with a club record of 372 losses, the Chicago Cubs lost more than 8100 visitors or 20% of attendance per game, causing an estimated \$362,000 loss of income per game (Greenberg 2013). Thus, we include as a value driver a club's *winning percentage*, reflecting its actual performance on the field (Yang et al. 2009).

Third, sports are a publicly consumed good where value is created through buzz. For instance, the Cleveland Indians opened the Social Suite at their Progressive Field stadium, a 12-seat area equipped with press kits, a media guide, and press releases to cater to media representatives. In turn, ticket sales increased by 174%, leading other clubs to imitate the concept (Sutton 2011). Thus, we consider *publicity* and define it as public attention by the media surrounding a club (Hewett et al. 2016; Lovett and Staelin 2016). Overall, the choice of drivers aligns with related frameworks in services (Berry 2000) and sports (Ross 2006).

The framework uses annual *attendance* as the dependent variable, which is the number of tickets sold in a season. In

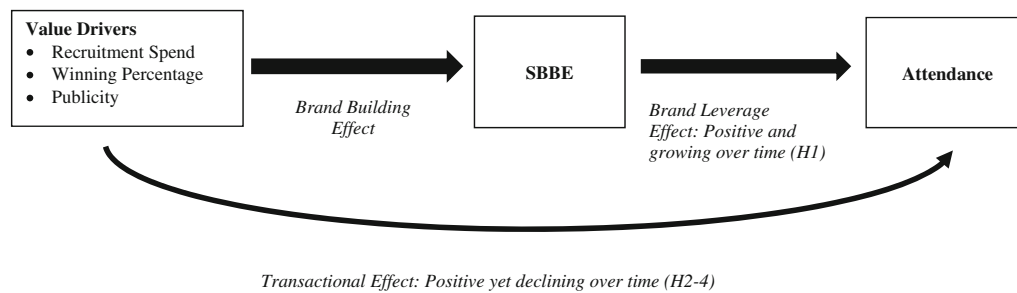


Fig. 1 The role of SBBE for the effects of recruitment spend, winning percentage and publicity on attendance

sports consumption, the unique atmosphere created by a crowded stadium makes attendance a key aspect of sports clubs' market performance (e.g., Lewis 2008).

This paper's key scholarly innovation is to develop and test new theory on the moderating role of brand age on the framework shown in Fig. 1. Brand age reflects a brand's heritage grown over time by the accumulated consumer experiences with a brand. We define *brand age* as the time that a sports club has been an actor in the professional sports market. Given that we are interested in the role that SBBE plays as the heart of the framework, we focus on how brand age moderates the brand leverage effect and the transactional effects. This allows us to compare brand value drivers' indirect effects on attendance (via SBBE) with their direct effects over time.

We next discuss the theoretical argumentation in line with the framework. First, we discuss the *brand building* effects of recruitment spend, winning percentage, and publicity on SBBE. We then expand on the *brand leverage* effect of SBBE on attendance and on the *transactional* (i.e., direct) effects of recruitment spend, winning percentage, and publicity on attendance. Finally, we discuss the *moderating* effects of brand age, for which we develop formal hypotheses.

Building and leveraging sports brands

Brand building effects

The conceptual framework links recruitment spend, winning percentage, and publicity to SBBE. Recruitment spend is necessary to acquire players at the market. Players provide the core service of a sports club (i.e., playing games), and they are essential to the club's brand presentation in the market (Morhart et al. 2009; Sirianni et al. 2013; Yang et al. 2009). Indeed, player skills support creating and sustaining SBBE by presenting and promoting a sports brand. For instance,

acquiring the right skills enables a club to form a team with a better fit between players and club. The alignment between a brand and its personnel facilitates the conceptual fluency of a brand (Paul and Bhakar 2018; Sirianni et al. 2013). Also, a star player's image may spill over to a club's SBBE (Yang et al. 2009). Given that recruitment spend is aimed at hiring such skills (Ployhart et al. 2011), we expect to find a brand building (i.e., positive) effect of recruitment spend on SBBE.

In a match between two sports clubs, winning is the ultimate goal. For consumers of a sports brand, winning is the most convincing argument for the superiority of the admired brand, particularly if winning happens regularly (Gladden et al. 1998). Consumers favorably evaluate desirable outcomes such as a win by the supported club (Yang et al. 2012) and identify with brands that provide them with such favorable experiences (Decrop and Derbaix 2010). This should result in a brand building effect of winning percentage.

Publicity is known to enhance the mere awareness of a brand and triggers shifts in consumer opinions (Chandrasekaran et al. 2017), both of which help to develop stronger brand associations (Stephen and Galak 2012). For publicly consumed goods such as sports, publicity also reinforces the perception of a shared interest or even passion for a club (Gladden et al. 1998). We thus expect a brand building effect of publicity.

Brand leverage effect

SBBE embodies an asset that firms can leverage to drive market performance (Keller 2013). Brands serve as symbols with which consumers identify and use to project their self-image (Fischer et al. 2010). In sports, a brand's function as a symbol is highly relevant because in the absence of tangibles, consumer decisions largely center on the brand (Berry 2000). Hence, we expect to find a positive effect of SBBE on attendance and refer to it as the brand leverage effect.

Transactional effects

The framework also allows for direct effects of recruitment spend, winning percentage, and publicity on attendance separate from their indirect effects via SBBE. First, spending more on recruitment means that a club can invest in skills (Ployhart et al. 2011). Having more skillful players on the team eventually results in more thrilling matches and thus a better consumption experience. This entails higher attendance regardless of whether brand attitudes change. The argument is backed by research on human resource management, which implies that spending on skills has a direct effect on firm performance (Jiang et al. 2012). Therefore, we expect recruitment spend to have a transactional effect by directly enhancing attendance.

We also expect winning percentage to have a transactional effect because winning clubs attract casual fans who like to be part of the positive atmosphere in the stadium that comes with winning (Charleston 2008). These fans may not necessarily develop a sense of belonging to the club (which is the brand building part), and they may stop coming when the club starts losing. Thus, if a club performs well and wins many of its games, we expect that attendance rates will go up even without considering the indirect path via brand building.

Publicity will likely have a positive effect on attendance, i.e., a transactional effect. Sports events thrive on the excitement fueled through the media prior to consumption. This excitement has merit on its own as it helps to attract new consumers (Trusov et al. 2009) and stimulate consumer purchase behavior (Houston et al. 2018). Thus, apart from the role it plays for shaping a sports brand, publicity can enhance attendance directly through a bandwagon effect.

The moderating role of brand age

We now explain why the effect of SBBE on attendance (i.e., the brand leverage effect) increases as a club grows older. The argument is rooted in brand community research. Whereas the traditional, static argument for the brand leverage effect builds on consumers' identification with a brand only, in a public consumption setting such as sports, identification goes beyond the brand itself (Morris 1981). Over time, relationships between admirers of a brand flourish in addition to their relationships with the brand—a brand community is formed (Goulding et al. 2013; Thompson and Sinha 2008). Specifically, as a brand grows older, brand community research suggests that the accumulation of history initiates evolutionary processes (Muñiz and O'Guinn 2001). Over time, consumers gain a shared sense of belonging to the collective of brand admirers and how it differs from other collectives (Thompson et al. 2016). In a sports context, tales of legendary games, epic ups and downs, and historic trophies that are won

or lost are added to the collective heritage of the club revered by the brand community. Also, the longer a brand is on the market, the more its consumers develop unique rituals and traditions (Goulding et al. 2013), including chants and dressing in the team's colors. To keep the community alive, a moral responsibility develops to ward off threats toward the collective whenever they may arise (Muñiz and O'Guinn 2001). In sports, these threats evolve over decades in the form of rivalries with other clubs. In sum, the brand community becomes richer and stronger over time.

We argue that the brand community that grows with brand age facilitates the translation of SBBE into actual attendance. In particular, SBBE drives attendance because consumers identify with the sports brand, which is the main brand leverage effect. Over time, the evolution of a brand community increases consumer benefits of acting on their brand identification by actually attending games. That is, the feeling of being part of a brand's history together with tens of thousands of other fans at a game, the rituals and traditions that create an electrifying atmosphere in the stadium, and the urge to protect the brand and the community make attendance an imperative for consumers to fully experience the brand with which they identify (Algesheimer et al. 2005; Decrop and Derbaix 2010). Additionally, their responsibility as community members provides a strong reason for consumers to act on their relationship with the brand by drawing new members into the stadium (Schau et al. 2009). These arguments imply that brand age unleashes a sports brand's potential to drive attendance, widening the attendance gap between clubs with high SBBE and those with low SBBE. The argument also implies that brands that are of similar strength in terms of SBBE can actually differ widely in their actual impact on attendance depending on their age. Hence we argue:

H1: Brand age strengthens the brand leverage effect; that is, the positive effect of SBBE on attendance is enhanced as brands grow older.

The effect hypothesized in H1 corresponds to the increasing brand leverage effect. This effect has not been accounted for in prior research, neither in sports nor in any other context. As initially suggested by Keller (1993), strong brands add differential leverage to a firm's offerings, which simply implies that strong sports brands are likely to sell more tickets than weak brands. We capture this static component through the brand leverage effect discussed in the previous section. H1, however, proposes that the same high amount of SBBE will lead to more attendance when brand age is high than when it is low. In other words, strong brands are increasingly rewarded over time. This is the dynamic component introduced by H1.

The argument made for deriving H1 also has implications for the transactional effects of the value drivers. Specifically, the growth of a brand community over time influences

consumers' reliance on different pieces of information for decision making. When consumers participate in brand communities, they focus their attention on information about the brand and social information arising from the community (Thompson and Sinha 2008). Given consumers' limited cognitive resources, this means that there is less time and cognitive capacity left for decision making based on other information such as new players, actual performance on the court, or media interest (Muñiz and O'Guinn 2001; Purohit and Srivastava 2001). While such information continues to feed to the brand, they become less decisive to trigger consumer purchases directly. Overall, this means that objective information as it is provided through recruitment spend, winning percentage, and publicity becomes less important for directly driving attendance rates over time. Hence, we expect that the transactional effects of recruitment spend, winning percentage, and publicity diminish when brand age increases.

- H2: Brand age weakens the transactional effect of recruitment spend; that is, the positive direct effect of recruitment spend on attendance is reduced as brands grow older.
- H3: Brand age weakens the transactional effect of winning percentage; that is, the positive direct effect of winning percentage on attendance is reduced as brands grow older.
- H4: Brand age weakens the transactional effect of publicity; that is, the positive direct effect of publicity on attendance is reduced as brands grow older.

In sum, we expect that the direct versus indirect effects of value drivers evolve systematically over time. For a young sports brand, we expect strong direct transactional effects of the value drivers on attendance. The indirect paths via SBBE will not be that strong yet, because the brand leverage effect (of SBBE on attendance) has yet to grow. As a sports club is on the market longer, its brand becomes more relevant as an attendance driver while the value drivers become less and less important. Thus, for longer-established sports brands, the direct effects of the value drivers on attendance decrease whereas the indirect effects via SBBE increase.

Data and measures

Setting

We use annual data from the German professional soccer market as a setting to empirically test the theory. Its roots can be traced back to 1963, when the *Bundesliga* was founded. Today it accounts for attendance worth more than \$3.44 billion; it is ranked first in the world in attendance per game, with nearly 45,000 tickets sold on average (Collignon and Sultan 2014). A unique characteristic is that the availability of longitudinal data allows

us to track the clubs from their inception as professional sports clubs to now. German professional soccer is representative for many of the world's biggest leagues across different sports (e.g., English Premier League in soccer, Spanish Liga ACB in basketball, Japanese Nippon Professional Baseball). It features a wide variety of brands, some of which are only nationally well-known (e.g., FC St. Pauli), while others are among the best-known soccer brands in the world (e.g., Bayern Munich) and compete eye-to-eye with internationally renowned clubs such as Real Madrid or Manchester United.

Its competitive system includes a first, second, and third league as well as minor leagues, and operates a system of promotion and relegation between leagues. Seasons run from early August to late May, with a winter break of six weeks. Each league (18 clubs in the *Bundesliga*) has a home and away round-robin system with 34 games for each club in a league of 18 clubs. The club with the most points at the end of the season wins the league. Playoffs occur only for promotion and relegation positions. New clubs that would like to enter the highest league have to earn entry by moving up through the lower leagues.

The German soccer league is organized similar to other big European professional sports leagues such as the Premier League. League management is relatively hands-off compared to U.S. sports leagues where there are salary caps and/or rules about drafting rookies. The institutional system of German professional soccer favors a free labor market through a player transfer system that operates as a reserve system (Yang et al. 2009). The system enables club managers to make free choices of players and negotiate contract terms individually. Clubs negotiate transfer conditions before the end of a contract term. At the end of the contract term, players are free to choose another club. However, transfers underlie the regulations of the Union of European Football Association's (UEFA) Financial Fair Play, which is designed to reduce the risk of financial fraud. Furthermore, German soccer clubs are responsible for most of their media management, including public relations.

Data description

The annual soccer data accounts for all seasons played between the 1963/1964 season, when professional soccer started in Germany, and the 2013/2014 season, for a total of 51 years for 40 clubs (explained next). For each club in the sample, we begin the analysis with the season of the club's entrance into the professional market as this allows us to understand how these sports brands are built. Given the objective of this study to examine the role of brands over time, it is necessary to observe each club across a sufficient period. As suggested by

Table 1 Measures and sources

Variable	Operationalization	Data source	Literature
Attendance	Total number of tickets a club sold for national league matches in the respective season	www.dfb.de	Rishe and Mondello (2004); Schmidt and Berri (2002)
SBBE	Residual of a regression of attendance premium compared to lowest performer on host city's population, stadium capacity, number of goals scored, consumer price index, and calendar year in the respective season	www.dfb.de , Federal Statistical Office, club websites	Ailawadi et al. (2003); Datta et al. (2017)
Recruitment spend	Total euro amount a club spent for new players in the respective season (i.e., sum of transfer fees)	www.transfermarkt.co.uk	Burdekin and Franklin (2015)
Winning percentage	Number of wins divided by number of matches played in the respective season	www.dfb.de	Yang et al. (2009)
Publicity	Number of media mentions of the club in the print media in the respective season	<i>Frankfurter Allgemeine Zeitung</i> library portal	Stephen and Galak (2012); Trusov et al. (2009)
Brand age	Number of seasons elapsed since professional sports market entry	www.dfb.de	Brown and Lattin (1994)
Promotion	Dummy variables coded 1 for promotion in previous season, 0 else	www.dfb.de	Szymanski and Smith (1997)
Relegation	Dummy variables coded 1 for relegation in previous season, 0 else	www.dfb.de	Szymanski and Smith (1997)
Goals scored	Number of goals scored in a season	www.dfb.de	Dobson and Goddard (1995)
Youth players	Number of players from the own junior teams, which are not acquired from other clubs	www.transfermarkt.co.uk	–
Host city's population	Total number of host city's residents in the respective season	Official website of the respective city	Yang et al. (2009)
Club	Dummy variables coded 1 for the respective club, 0 else	–	–
Season	Dummy variables coded 1 for the respective season, 0 else	–	–

– indicates not applicable

Miller and Friesen (1984), we therefore only include those clubs that have been in the professional market for at least 20 seasons, which holds for 40 soccer clubs in total.¹ Some clubs started a few years after the inception of professional soccer, and some clubs left the professional market and continue to exist in minor leagues.² The 40 brands in the sample account for more than 87% of tickets ever sold in German professional soccer until 2014. Overall, the sample contains 1807 brand–season observations. Table 1 contains data sources and measurement approaches, as described next.

Measures

Sales-based brand equity SBBE is the contribution of a brand's identity to sales or utility beyond the contribution of its objectively measured attributes. Prior literature offers several metrics for measuring SBBE based on the marketplace performance of a brand (Datta

et al. 2017). These metrics are either at the individual consumer level, such as the brand intercept in a choice model (e.g., Kamakura and Russell 1993), or derived from the aggregate (market) level (Ailawadi et al. 2003). Recent aggregate approaches typically use the brand intercepts (e.g., Datta et al. 2017) or residuals (e.g., Slotegraaf and Pauwels 2008) of regressions of a brand's product category sales on their tangible drivers as an indicator of SBBE.

We adopt an aggregate estimate of SBBE because our research questions point to a brand-level examination, and aggregate estimates are often seen as more relevant for managers than the individual-level representations (Ailawadi et al. 2003). Specifically, we use a residual approach to measure SBBE as the part of the number of tickets sold due to carrying the brand name (Datta et al. 2017). In this approach, a sales premium is first calculated as the difference between the number of club i 's tickets sold in season t and the number of tickets sold by the weakest competitor, as indicated by the lowest number of tickets sold in t . This brand premium is then regressed on attendance determinants other than the brand, and the residual of this regression is used as a measure of SBBE (Slotegraaf and Pauwels 2008).

We build on prior literature to select the attendance determinants.³ First, we include host city's population size. While consumers often choose their favorite club nation-wide,

¹ Please note that this criterion only leads to an exclusion of 10% of observations, mostly from the early years of professional soccer where data availability is poorer than for more recent years. We further exclude the few club-season observations where stadium size was a constraint because every game was sold out (17 observations, or less than 1% of all observations). Note that excluding these observations does not substantially alter the correlations reported in Table 2 nor the results provided in Tables 3 and 4.

² As Web Appendix A shows, 15 (25) brands entered the market in 1963/1964 (later than 1963/1964), and 8 brands dropped out of professional soccer before the 2013/2014 season but continued to exist in a minor league. We leave these clubs in the sample until the last observation season to avoid left- or right-censoring issues and to prevent including only surviving brands (Bowman and Gatignon 1996).

³ We purposely choose to not regress the brand premium on winning percentage (e.g., Yang et al. 2009) because winning percentage is conceptualized as a driver of SBBE.

the city size might impact the actual ticket sales due to a local concentration of market potential (Benz et al. 2009). Next, we include stadium size as the size of the stadium is an important atmospheric element that may influence ticket purchase decisions (Charleston 2008). We also control for the number of goals scored during a season because celebrating goals adds to the thrill of the game and enhances the consumption experience (Benz et al. 2009). We further include the consumer price index to approximate the cost of living (Triplett 2001), which affects the financial resources that are available for buying tickets. Finally, by including calendar year, we ensure that the residual measure captures SBBE and not a time trend in the sales premium due to, e.g., rising incomes (Ailawadi et al. 2003). **Web Appendix B** lists the parameter estimates for the residual approach to measure SBBE.

Later in this paper we offer extensive validation of the SBBE measure by correlating it with alternative measures and by replicating the findings in a series of robustness checks. Overall, the checks suggest that the adopted SBBE measure is valid.

Recruitment spend Gaining skills through recruitment comes with high acquisition costs. The soccer context offers an opportunity to observe these costs. Specifically, to measure recruitment spend we use a club's transfer fees, that is, the total euro amount a club spent for new players in respective seasons (Burdekin and Franklin 2015). We adjust this monetary measure for inflation using the German Consumer Price Index.

Winning percentage In sports, the competitive performance of clubs can be captured objectively in the form of winning rates (Yang et al. 2009). Specifically, a club's winning percentage is the number of wins divided by number of matches played in the respective season (Lewis 2008; Yang et al. 2009).

Publicity We capture publicity by the number of print media mentions of a club in a season (Stephen and Galak 2012; Trusov et al. 2009). We collect these data from the web archive of the German newspaper *Frankfurter Allgemeine Zeitung* (FAZ, www.faz-archiv.de/biblio/). Distributed nationwide, FAZ is among the three leading daily newspapers in Germany and is the only one for which the web archive ranges back to the 1960s.⁴ By relying on this centrally located, national newspaper, we ensure that publicity is measured

⁴ We cross-validate the information gained from FAZ with information from the web archive of the weekly German newspaper *Die Zeit*. Overall, the correlation between the appearance in both newspapers is .43 ($p < .01$, $N = 1289$). The correlation is lowest for the club Eintracht Frankfurt ($r = .14$, $p > .10$), which reflects headquarter location bias in the *Frankfurter (F)AZ*. Indeed, the ratio of media appearances in FAZ and *Die Zeit* is significantly higher (3.6 times higher, $t = 13.31$, $p < .01$) for Eintracht Frankfurt than for all other clubs. We correct for this bias by dividing the media coverage of Eintracht Frankfurt by this factor.

for each club in exactly the same way and based on the same number of reporters.

Attendance We measure the dependent variable annual attendance as the total number of tickets a club sells for national league matches in the respective season, that is, paid attendance (Rishe and Mondello 2004; Schmidt and Berri 2002).⁵

Brand age We measure brand age by counting the seasons a brand has been in the market (Brown and Lattin 1994), starting with a brand's entry into the professional soccer market and including the current season.

Other variables We control for other factors that are important in sports. We include one dummy variable for *promotion* and one for *relegation* of a club. The German soccer market includes three professional leagues and minor leagues. Clubs that perform best or worst within their leagues will move between leagues. Moving leagues may result in a rise (due to promotion) or drop (due to relegation) in attendance due to potential differences in league interest. As explained, we also control for the *number of goals scored* by a club in each season. We further consider the possibility that clubs sign players at young ages and develop them to benefit in the mid-run. Therefore, we include the *number of signed youth players*—i.e., the number of players from a club's own junior teams who are not acquired from other clubs—as another control variable. Moreover, we control for the time-varying *host city's population size*.⁶ Measured as the total number of the host city's residents in the respective season, the variable thus captures changes in local market potential across seasons. Finally, we include both *club* and *season* dummies (fixed effects) to capture potential unobserved longitudinal and cross-sectional heterogeneity.

Descriptives

Table 2 shows descriptive statistics and correlations, while Fig. 2 plots the five key variables on average

⁵ Note that in German professional soccer, the number of seasonal tickets sold is never higher than the demand for a single match. Clubs intentionally restrict the number of seasonal tickets holders to a particular share of stadium capacity to offer access for new fans and to avoid potentially empty seats. Therefore, the observed demand at a match day is a true reflection of the market interest in the respective match and so is the attendance aggregate that we use. Please note that capturing attendance annually means that match-level factors such as timing of wins or weather will average out.

⁶ Some clubs share the same city. We calculate the cross-team correlations of clubs from the same city (using the residuals from the attendance model) to test whether observations can still be treated as well-separated. Indeed, we find no significant correlation ($r = .11$, $p > .10$). Thus, no specific account for covariances in error terms is required.

Table 2 Descriptive statistics

	Mean	SD	Skewness	$r_{t/t-1}$	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Attendance (in 1000)	308.63	248.07	1.22	.92	1.00										
2. SBBE	-2.11	180.62	.15	.84	.74	1.00									
3. Recruitment spend (in €1 m)	.51	1.52	5.68	.69	.56	.44	1.00								
4. Winning percentage	.40	.14	.39	.14	.04	.03	.10	1.00							
5. Publicity (in 100)	2.97	2.62	2.69	.89	.69	.52	.66	.05	1.00						
6. Brand age (in seasons)	24.13	13.48	.12	.88	.37	.06	.36	-.04	.39	1.00					
7. Promotion (dummy)	.10	.30	2.65	-.06	.03	.06	-.05	-.24	.00	.08	1.00				
8. Relegation (dummy)	.12	.32	2.37	-.04	-.18	-.21	-.10	.19	-.14	.07	-.12	1.00			
9. Goals scored	55.34	15.53	.87	.28	-.05	.00	.01	.74	-.03	-.26	-.22	.19	1.00		
10. Youth players	5.61	3.32	.77	.35	.14	.04	.16	-.03	.13	.39	-.07	.10	-.13	1.00	
11. Host city's population (in 100,000)	5.86	6.20	2.64	.97	.28	.00	.09	.07	.17	.04	-.01	-.02	.06	-.15	1.00

Correlations greater than or equal to .05 in absolute value are significant ($p < .10$, two-tailed)

across all clubs over brand life. As Panel A shows, clubs initially attract an average of 275,000 spectators per season, but the average grows into the 600,000 range in more recent times, reflecting the growth of the sports market in general. Recruitment spend is, on average, €.51 million, with a strong surge in the most recent 20 years (Panel B). Winning percentage is .40 on average, which means that clubs win on average 40% of their games (Panel C). Publicity amounts to 297 articles per year on average, but is lower when brand age is low than when it is high (Panel D). Average SBBE shows ups and downs but grows toward the end (Panel E). As is reflected in the low correlation between the two variables ($r = .06$, $p < .10$), Panel E also underlines that SBBE is substantially different from brand age. Brand age is a pure trend variable that only develops in one direction (upward). SBBE, in contrast, describes a sports brand's worth at a given point in time and can diminish or grow over time. As such, there is a high variance in SBBE, for sports brands both at a young and at an old age. [Web Appendix A](#) lists the 40 clubs in the sample together with the club-level descriptives for each variable, and [Web Appendix C](#) plots the variables over time for five prototypical clubs.

Modeling approach

General model specification

We specify a set of equations that incorporate the relationships between value drivers, SBBE, and attendance. We account for endogeneity of recruitment spend and autocorrelation. The framework implies two main regressions: (1) a regression of SBBE on value drivers to capture their brand building effects and (2) a regression of attendance to capture (a) the transactional

effects of the value drivers, (b) the brand leverage effect of SBBE, and (c) the moderating role of brand age to untangle the evolution of both effects over time. The first equation captures the expectation that recruitment spend, winning percentage, and publicity have a brand building effect in that they drive SBBE. The SBBE model is defined as follows.

$$\begin{aligned}
 SBBE_{it} = & \beta_0 + \beta_1 RecruitSpend_{it} + \beta_2 WinPerc_{it} \\
 & + \beta_3 Pub_{it} + \beta_4 Prom_{it} + \beta_5 Rel_{it} + \beta_6 Goals_{it} \\
 & + \beta_7 YouthPlay_{it} + \beta_8 CityPopu_{it} + \sum_i \alpha_i Club_i \\
 & + \sum_t \delta_t Season_t + u_{it},
 \end{aligned} \tag{1}$$

where $SBBE_{it}$ is the SBBE of club i at season t , $RecruitSpend_{it}$ is recruitment spend, $WinPerc_{it}$ indicates the winning percentage, and Pub_{it} describes publicity. $Prom_{it}$, Rel_{it} , $Goals_{it}$, $YouthPlay_{it}$, and $CityPopu_{it}$ refer to the covariates promotion, relegation, goals scored, youth players, and host city's population. $Club_i$ and $Season_t$ are club dummies and season dummies, respectively. The club dummies control for time-invariant differences between clubs. The season dummies offer a flexible approach to capture changes over time. Including these dummies implies that it is not necessary to control for the main effect of a trend or brand age. It is not even possible to include these because they are a linear combination of the time dummies. Finally, β_0, \dots, β_8 are the model coefficients, α_i are club fixed effects, δ_t are the season fixed effects, and u_{it} is the error term.

The second equation captures the expectation that recruitment spend, winning percentage, and publicity have transactional effects on attendance and that SBBE has a brand leverage effect on attendance as well. It also tests the proposition that the brand leverage effect of SBBE increases with increasing brand age whereas the

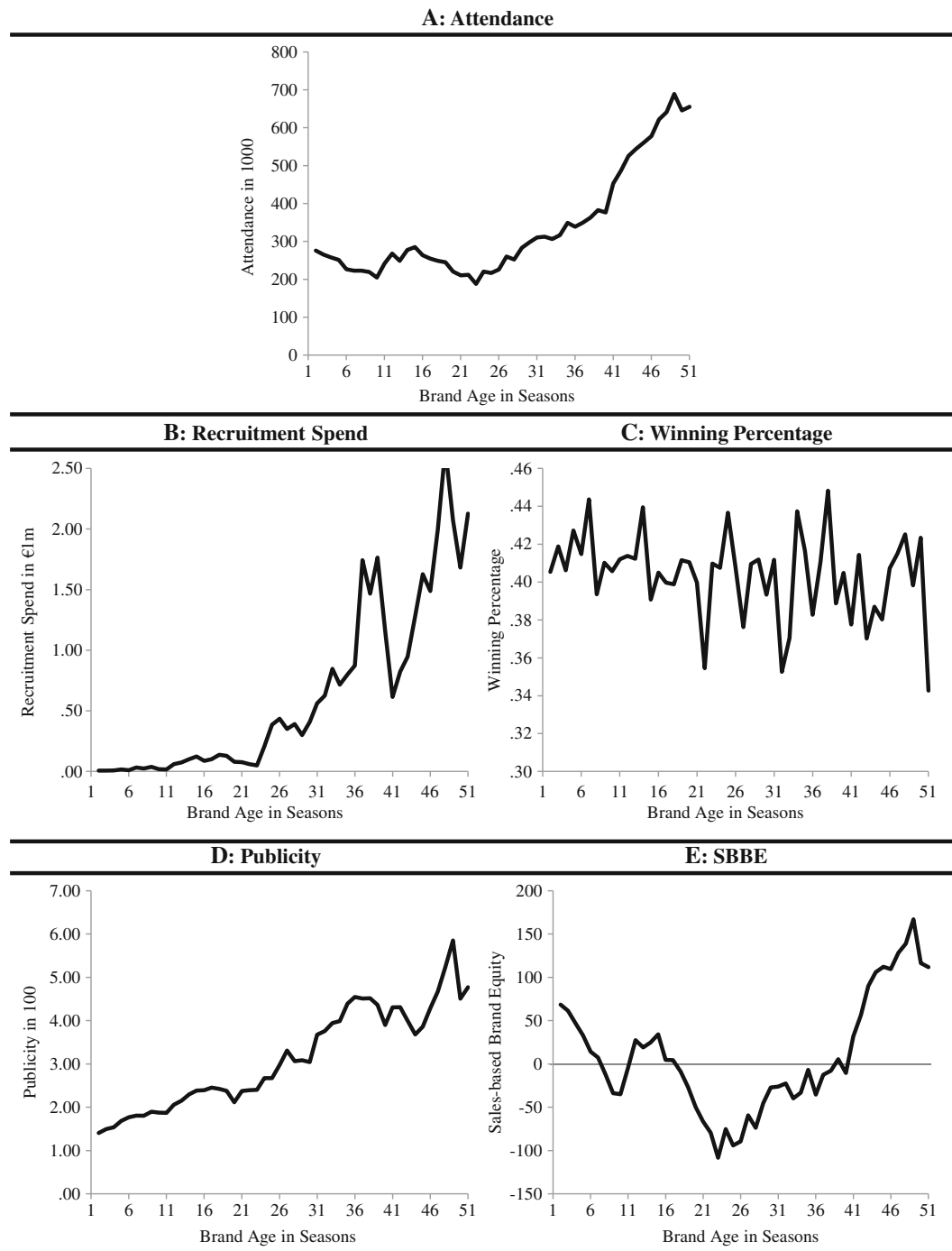


Fig. 2 Evolution of average attendance, recruitment spend, winning percentage, publicity, and SBBE over time. *Notes:* These are averages across clubs. The lowest maximum brand age across the 40 clubs in the sample is 25 seasons (including all seasons a club was in first, second,

third, and minor leagues from entrance into professional soccer to the end of 2014), and the highest is 51 seasons. Thus, the set of clubs that we use to calculate yearly averages decreases after a brand age of 25

transactional effects of the value drivers decrease. Thus, we allow the attendance effects of recruitment spend, winning percentage, publicity, and SBBE to vary over time (i.e., to interact with brand age). We start with the following regression.

$$\begin{aligned}
 Attend_{it} = & \gamma_0 + \gamma_{1,it}RecruitSpend_{it} + \gamma_{2,it}WinPerc_{it} \\
 & + \gamma_{3,it}Pub_{it} + \gamma_{4,it}SBBE_{it-1} + \gamma_5Prom_{it} \\
 & + \gamma_6Rel_{it} + \gamma_7Goals_{it} + \gamma_8YouthPlay_{it} \\
 & + \gamma_9CityPopu_{it} + \sum_i \theta_i Club_i \\
 & + \sum_t \psi_t Season_t + v_{it}.
 \end{aligned} \tag{2}$$

In Eq. 2, $Attend_{it}$ is attendance of club i at season t . The explanatory variables are the same as described in Eq. 1 but now include lagged SBBE ($SBBE_{it-1}$). The rationale for the lag ($t - 1$) is that theory says that the accumulated SBBE just prior to period t (at the end of period $t - 1$) can be leveraged to drive attendance in period t (Bruce et al. 2012). That is, changes in brand differentiation need time to trickle through to consumer purchase decisions and thus should be modeled with a time lag (Ho-Dac et al. 2013). The time lag also avoids correlated errors that would arise from the use of SBBE as both a dependent variable in the first and an independent variable in the second equation (Hanssens et al. 2014). The coefficients $\gamma_5, \dots, \gamma_9$ capture the attendance impact of the covariates. Finally, θ_i are club fixed effects, ψ_t are the season fixed effects, and v_{it} is the error term.

We allow for time-varying parameters of the three value drivers (recruitment spend, winning percentage, and publicity) and SBBE, moderated by brand age: $\gamma_{1, it} = \lambda_1 + \lambda_2 BrandAge_{it}$, $\gamma_{2, it} = \lambda_3 + \lambda_4 BrandAge_{it}$, $\gamma_{3, it} = \lambda_5 + \lambda_6 BrandAge_{it}$, and $\gamma_{4, it} = \lambda_7 + \lambda_8 BrandAge_{it}$, leading to the actual estimation equation for attendance.

$$Attend_{it} = \gamma_0 + \lambda_1 RecruitSpend_{it} + \lambda_2 RecruitSpend_{it} \times BrandAge_{it} + \lambda_3 WinPerc_{it} + \lambda_4 WinPerc_{it} \times BrandAge_{it} + \lambda_5 Pub_{it} + \lambda_6 Pub_{it} \times BrandAge_{it} + \lambda_7 SBBE_{it-1} + \lambda_8 SBBE_{it-1} \times BrandAge_{it} + \gamma_5 Prom_{it} + \gamma_6 Rel_{it} + \gamma_7 Goals_{it} + \gamma_8 YouthPlay_{it} + \gamma_9 CityPopu_{it} + \sum_i \theta_i Club_i + \sum_t \psi_t Season_t + v_{it}. \tag{3}$$

In Eq. 3, $\lambda_1, \lambda_3, \lambda_5$, and λ_7 capture the direct main effects of recruitment spend, winning percentage, publicity, and SBBE on attendance and $\lambda_2, \lambda_4, \lambda_6$, and λ_8 are the moderated (by brand age) effects. H1 through H4 imply that the direct attendance effect of the three value drivers decline with increasing brand age, whereas the attendance effect of SBBE increases with brand age. Parameters λ_7 and λ_8 account for the brand leverage effect. While λ_7 (expected > 0) captures the brand leverage effect commonly ascribed to strong brands (Keller 1993), λ_8 (expected > 0) suggests that strong brands are increasingly rewarded over time due to the formation of a brand community. We estimate all models with variables measured in units (instead of logarithms or other transformations). This allows us to compare effect sizes across equations and to linearly decompose the total effect of a driver on attendance into a direct effect and an indirect effect via SBBE.

The system of Eq. 1 and Eq. 3 captures dynamic indirect effects as the value drivers in period $t - 1$ affect SBBE in period $t - 1$, which drives attendance in period t . The model also captures contemporaneous direct (transactional) effects of the value drivers in period t on attendance in period t . The evolving nature

of the effects is captured through the interaction effects with brand age. As we discuss next, we also account for the potential endogeneity of recruitment spend, which is the only variable under direct control of a club in this setting.

Correction for endogeneity of recruitment spend

Since we are interested in estimating consistent effects of recruitment spend on SBBE and attendance, we need to safeguard against three potential endogeneity issues. First, endogeneity may arise from a cross-sectional correlation across clubs between recruitment spend and demand shocks. Unobserved, time-invariant club factors such as the wealth of the region where a club is located or a club's financial capacity can make a club more popular (create higher ticket demand) as well as richer (raise the budget for recruitment), leading to a noncausal correlation between recruitment spend and the error term of attendance. To address this type of endogeneity, we include club fixed effects in both Eq. 1 and Eq. 3 using the dummy variable $Club_i$.

The second type of endogeneity involves temporal correlation of recruitment spend with unobserved demand shocks. Industry-wide time-varying shocks may occur, such as new TV contracts or the introduction of the Euro in 2002. To safeguard against this type of endogeneity, we include season fixed effects in Eq. 1 and Eq. 3 using the $Season_t$ dummies. These dummies also account for growth of the professional soccer market over time.

Third, club-season-specific demand shocks may also drive recruitment spend. For instance, if a club anticipates a demand shock in a certain season, the recruitment spend may be adapted strategically, either downward (because it is expected that the spectators are attending anyway) or upward (because a club wants to showcase the best possible team to counter the demand shock). Then, recruitment spend and the error term of SBBE (u_{it}) or attendance (v_{it}) may be correlated. To address this possible remaining source of endogeneity, we adopt two alternative approaches: instrumental variables (IVs) and Gaussian copulas.

IVs isolate the exogenous variation in the endogenous variable by regressing it on the IVs and the exogenous variables in the system (Ebbes et al. 2011). A good instrument should be correlated with the recruitment spend variable (instrument strength) but not with the error term of the dependent variable (instrument validity or exclusion restriction). We propose that the one-season lagged *competitor recruitment spend* describes a first strong and valid IV. As good players are rare, the recruiting activities of competitors inform about the current demand for and the availability of skilled candidates (Ployhart et al. 2009). Therefore, competitor recruitment spend is a relevant (strong) IV for the recruitment spend

necessary to acquire new candidates. The model controls for winning percentage, which is the net outcome of the comparison of the strength of the home team and the visiting teams. Hence, competitors' recruitment spend is a valid IV because it is unlikely to be a relevant omitted variable affecting the dependent variable after controlling for winning and own recruitment spend. In other words, it satisfies the exclusion restriction.

The second IV is the one-season lagged *wins* and *losses*. Past success requires a club to invest further to defend its position. Similarly, clubs that previously lost often need to invest to improve future performance. These arguments underline the relevance (strength) of this IV. As for the exclusion restriction (instrument validity), the wins and losses from one season ago are likely to be uncorrelated with the error term of the dependent variable because demand depends more on recent outcomes than on past outcomes (Bolton et al. 2006). Any remaining carryover of past wins and losses for attendance should be captured by the included variable SBBE.

The attendance model includes an interaction between the potentially endogenous variable recruitment spend and brand age. Thus, we also include the interaction effects of all IVs introduced previously with brand age in the attendance model (Wooldridge 2002). We formally test the adequacy of the instruments in the results section.

To corroborate the findings, we also employ an alternative, instrument-free approach to address the endogeneity problem, namely Gaussian copulas (Park and Gupta 2012). Copulas build on the joint distribution function to capture the correlation between the endogenous regressor and the error term. Specifically, we calculate a copula term that we add to both Eq. 1 and Eq. 3. In a first step, the density of the endogenous regressor recruitment spend is estimated by applying a nonparametric method, which serves to compute the marginal distribution of the endogenous variable. This marginal distribution is then used to construct the likelihood function. Formally, the copula term is:

$$RC_{it} \sim \Phi^{-1}[H(\text{RecruitSpend}_{it})], \quad (4)$$

where Φ^{-1} is the inverse of the normal cumulative distribution function and $H(\text{RecruitSpend}_{it})$ represents the empirical distribution function of recruitment spend.⁷ For parameter estimation, we use bootstrapping with 5000 replications to obtain the correct standard errors.

Model estimation

We use three different estimation procedures to establish model robustness: (1) fixed effects only, (2) fixed

⁷ The empirical distribution function represents the probability that a random variable takes on a value less than the respective value of recruitment spend.

effects with instrumental variables (i.e., two-stage least squares (2SLS)), and (3) fixed effects with Gaussian copulas. However, there is potential for autocorrelation in the error terms u_{it} and v_{it} because time-varying omitted predictors might affect SBBE and attendance. In the presence of autocorrelation, ordinary least square (OLS) estimates have been shown to be inefficient (Wooldridge 2002). Therefore, we use generalized least square (GLS) estimates that allow for contemporaneous correlation between the errors.

Results

Specification tests

We use several specification tests. We inspect the correlations between the explanatory variables (see Table 2) and the variance inflation factors to test for discriminant validity and multicollinearity. The maximum correlation is .74, which is below .8 (Hair Jr. et al. 2010). Correlations among these variables are less than one by an amount greater than twice the respective standard error. This provides evidence for discriminant validity (Bagozzi and Warshaw 1990). The variance inflation factors (VIFs) are on average 1.46 (2.15) with a single highest value of 2.05 (5.33) for the SBBE (attendance) model, which is well below 10 (Hair Jr. et al. 2010). Thus, multicollinearity does not constitute an issue.

Hausman–Wu tests (Wooldridge 2002) call for endogeneity correction of recruitment spend both in the SBBE model ($p < .05$) and the attendance model ($p < .01$). We test the strength of the IVs used in 2SLS-GLS by applying incremental F-tests. The tests show that the IVs are sufficiently strong (SBBE model: $F(3, 1668) = 163.21, p < .01$; attendance model: $F(6, 1661) = 66.55, p < .01$). With respect to the Gaussian copulas, a Shapiro–Wilk test confirms that the endogenous regressor is nonnormally distributed ($W = .58, p < .01$), which is required for identification purposes. Thus, using Gaussian copulas is appropriate.

Finally, we test for autocorrelation through Durbin-Watson tests. The test statistics show that after OLS, autocorrelation exists in SBBE ($DW = .67, p < .01$) and attendance ($DW = 1.35, p < .01$) suggesting GLS estimates being the most suited—which are the ones we report.

Model comparison

Table 3 reports the results of the SBBE and the attendance models for each of the three estimation approaches (fixed effects GLS, fixed effects 2SLS-GLS, fixed effects Copula-GLS). All effects highlighted in the framework are stable in terms of direction and significance across all estimation procedures, pointing to model robustness.

Table 3 Parameter estimates for SBBE and attendance models

Variable	SBBE Model			Attendance Model			Hypotheses
	Fixed Effects GLS	Fixed Effects 2SLS-GLS	Fixed Effects Copula-GLS	Fixed Effects GLS	Fixed Effects 2SLS-GLS	Fixed Effects Copula-GLS	
Value drivers' effects							
Recruitment spend	4.53** (2.04)	12.96*** (2.70)	7.26** (3.59)	26.63*** (4.58)	36.29*** (3.68)	32.98*** (4.67)	
Winning percentage	80.08*** (19.05)	74.73** (31.43)	81.41*** (30.99)	98.90*** (17.85)	67.36*** (21.59)	69.15*** (20.28)	
Publicity	24.23*** (2.22)	40.45*** (2.03)	37.69*** (3.02)	28.84*** (2.55)	16.75*** (1.99)	16.77*** (2.20)	
Brand effects							
SBBE				.22*** (.02)	.54*** (.02)	.54*** (.02)	
Moderating effects							
SBBE × brand age				.01*** (.00)	.01*** (.00)	.01*** (.00)	H ₁ ✓
Recruitment spend × brand age				-1.21*** (.27)	-1.68** (.24)	-1.58*** (.33)	H ₂ ✓
Winning percentage × brand age				.16 (.86)	.41 (1.07)	.55 (1.13)	H ₃
Publicity × brand age				-.45** (.18)	-.56*** (.16)	-.54*** (.19)	H ₄ ✓
Controls							
Promotion	60.68*** (5.69)	59.98*** (9.56)	53.93*** (9.57)	71.44*** (5.48)	91.05*** (6.63)	89.14*** (8.41)	
Relegation	-50.46*** (5.36)	-47.53*** (9.10)	-47.54*** (8.86)	-56.88*** (5.21)	-66.90*** (6.32)	-66.70*** (6.12)	
Goals scored	.06 (.19)	-.36 (.31)	-.22 (.30)	-.03 (.18)	-.07 (.21)	-.05 (.20)	
Youth players	-.25 (.59)	-1.30 (1.01)	-.81 (.99)	-.00 (.56)	-.17 (.70)	-.06 (.67)	
Host city's population	-18.50 (12.07)	13.67* (7.05)	14.63 (10.15)	-.00 (8.71)	6.58 (4.93)	6.34 (6.38)	
Dummies for season	Included	Included	Included	Included	Included	Included	
Dummies for club	Included	Included	Included	Included	Included	Included	
Copula term			18.71*** (2.30)			3.93** (1.58)	
Constant	23.19 (66.79)	-5.96 (40.25)	-9.44 (47.74)	289.20*** (44.97)	287.25*** (27.98)	288.15*** (29.50)	
R ²	.53	.63	.61	.88	.91	.91	
Adjusted R ²	.50	.61	.59	.87	.90	.90	
BIC (lower is better)	17,037.78	16,597.37	16,762.42	15,720.80	15,260.54	15,276.78	

The standard errors appear in parentheses. We mean-center the explanatory variables in the moderation analysis to enhance the interpretability of the results. For Gaussian copula analyses, we report bootstrapped standard errors with 5000 replications. The direct effect of brand age on SBBE and attendance is fully explained by the dummies for season and is therefore excluded from the analyses. The coefficients for the club and season dummies are listed in [Web Appendix D](#)

* $p < .10$, ** $p < .05$, *** $p < .01$ (two-tailed)

Limiting the number of results for discussion is now a matter of choosing the focal estimation method. Thus, we compare the R²s and BICs between the approaches. Significant Hausman–Wu tests and significant copula terms point to endogeneity-corrected models instead of GLS without endogeneity correction. Comparing the R²s and BICs between the endogeneity-corrected approaches, the 2SLS-GLS models have a superior fit compared to the Copula-GLS models. Consequently, we focus on the 2SLS-GLS models for further discussion. Please note that the substantive insights are very similar for the GLS and the Copula-GLS models.

Sales-based brand equity model

The SBBE model has reasonable fit (R² = .63). The results reported in Table 3 show that recruitment spend ($\beta_1 = 12.96, p < .01$), winning percentage ($\beta_2 = 74.73,$

$p < .05$), and publicity ($\beta_3 = 40.45, p < .01$) have the expected significant positive impact on SBBE. Promotion ($\beta_4 = 59.98, p < .01$), relegation ($\beta_5 = -47.53, p < .01$), and host city's population ($\beta_8 = 13.67, p < .10$) have (marginally) significant effects on SBBE, in the expected directions. We found no significant impacts for goals scored ($\beta_6 = -.36, p > .10$) and number of signed youth players ($\beta_7 = -1.30, p > .10$).⁸

Attendance model

The attendance model has a good fit (R² = .91). As shown in Table 3, recruitment spend ($\lambda_1 = 36.29, p < .01$), winning percentage ($\lambda_3 = 67.36, p < .01$), and publicity ($\lambda_5 = 16.75,$

⁸ We test the impact of number of signed youth players on SBBE for lags up to five seasons. However, we find no significant effect of any coefficient.

$p < .01$) significantly increase attendance via the transactional route.

In line with our expectation, we find a positive and significant brand leverage effect of SBBE on attendance ($\lambda_7 = .54, p < .01$). On top of that, there is a positive and significant interaction between SBBE and brand age ($\lambda_8 = .01, p < .01$), suggesting that the effect of SBBE on attendance gains further leverage when brand age is higher, confirming H1. This is an important finding because it explains the hitherto unexplained variance in the overperformance of strong brands that cannot be explained by SBBE alone.

Further, we also examine interaction effects between the value drivers and brand age. We find evidence for H2: the effect of recruitment spend on attendance decreases as a brand becomes more established ($\lambda_2 = -1.68, p < .01$). H3 is not confirmed as there is no evidence for a decreasing transactional effect of winning percentage on attendance ($\lambda_4 = .41, p > .10$). However, the direct effect of publicity significantly decreases when brand age increases ($\lambda_6 = -.56, p < .01$), confirming H4. The control variables promotion ($\gamma_5 = 91.05, p < .01$) and relegation ($\gamma_6 = -66.90, p < .01$) have significant effects on attendance, suggesting that promoted clubs sell more tickets while relegated clubs sell fewer, as expected. No significant effects are found for goals scored ($\gamma_7 = -.07, p > .10$), number of signed youth players ($\gamma_8 = -.17, p > .10$),⁹ and host city's population ($\gamma_9 = 6.58, p > .10$).

Indirect effects testing

The proposed framework suggests that recruitment spend, winning percentage, and publicity affect attendance directly ($\omega_{Variable, direct}$) and indirectly (through SBBE). In line with Preacher and Hayes (2008), we calculate the indirect effect ($\omega_{Variable, indirect}$) as the product of the effect of value drivers on SBBE times the effect of SBBE on attendance. Formally,

$$\omega_{RecruitSpend, indirect} = \beta_1 \times \gamma_{4, it} \tag{5}$$

$$\omega_{WinPerc, indirect} = \beta_2 \times \gamma_{4, it} \tag{6}$$

$$\omega_{Pub, indirect} = \beta_3 \times \gamma_{4, it} \tag{7}$$

Further, the total effect ($\omega_{Variable, total}$) is the sum of the direct and indirect effects. For instance, based on the values reported in Table 3, the direct effect of recruitment spend on attendance is $\omega_{RecruitSpend, direct} = \gamma_{1, it} = 36.29$ and the indirect effect is $\omega_{RecruitSpend, indirect} = 12.96 \times .54 = 7.00$. Adding both results in a total effect of $\omega_{RecruitSpend, total} = 36.29 + 7.00 =$

43.29.¹⁰ To test changes over time, we calculate the difference of the effect sizes for low (fifth percentile) and high (ninety-fifth percentile) values of brand age. Bootstrapping provides the standard errors to test for statistical significance of these effects (Preacher and Hayes 2008).

The results in Table 4 reconfirm the significantly positive direct effects on ticket attendance of recruitment spend ($\omega_{RecruitSpend, direct} = 36.29, p < .01$), winning percentage ($\omega_{WinPerc, direct} = 67.36, p < .01$), and publicity ($\omega_{Pub, direct} = 16.75, p < .01$). We find significant and positive indirect effects of all three variables on attendance that operate through SBBE ($\omega_{RecruitSpend, indirect} = 7.03, p < .01$; $\omega_{WinPerc, indirect} = 40.55, p < .05$; $\omega_{Pub, indirect} = 21.95, p < .01$) as well as significant positive total effects on attendance ($\omega_{RecruitSpend, total} = 43.33, p < .01$; $\omega_{WinPerc, total} = 107.91, p < .01$; $\omega_{Pub, total} = 38.70, p < .01$). In sum, the results further support the conceptual framework proposed.

Considering the evolution of these effects, we find evidence for a strong shift from a dominance of direct effects when brand age is low to a dominance of indirect effects (via SBBE) when brand age is high. As brands evolve from the fifth to the ninety-fifth percentile of age, we find a significantly increasing indirect effect ($\Delta\omega_{RecruitSpend, indirect} = 6.72, p < .01$) and a significantly decreasing direct effect ($\Delta\omega_{RecruitSpend, direct} = -67.39, p < .01$) for *recruitment spend*. This means that for young brands, 5% of the total recruitment effect is indirect (and the balance is direct), whereas for more established brands, 80% is indirect. For *winning percentage*, the indirect effect increases significantly ($\Delta\omega_{WinPerc, indirect} = 38.72, p < .05$), but the direct effect on attendance does not change significantly ($\Delta\omega_{WinPerc, direct} = 16.31, p > .10$). As a result, 26.4% of the total effect of winning percentage is indirect for young brands and 44.2% is indirect for brands of higher age. For *publicity*, we also find a significantly increasing indirect effect ($\Delta\omega_{Pub, indirect} = 20.96, p < .01$) and a significantly decreasing direct effect ($\Delta\omega_{Pub, direct} = -22.45, p < .01$). While 29.1% of the total publicity effect is indirect for young brands, for old brands 85.4% is indirect.

Overall, the indirect versus direct effects testing and their comparison over time provides further evidence for the important role that the increasing brand leverage effect plays for the long-term market performance of sports brands. The fact that the indirect effects do not only grow over time due to the evolution of the brand leverage effect but that these impressive gains are also mirrored by significantly diminishing direct effects of value drivers (apart from winning percentage) shifts the relative means by which sports brands are successful in the market.

⁹ We also test the impact of number of signed youth players on attendance for lags up to five seasons. Again, none of the respective estimates appears significant.

¹⁰ We use the rounded values reported in Table 3 for exemplification. The actual values reported in Table 4 differ slightly due to consideration of all decimal places.

Table 4 Direct, indirect, and total effects of recruitment spend, winning percentage, and publicity on attendance

Variable	Effect size		Changes in effect size due to brand age				
			Effect size for low brand age		Effect size for high brand age		Change (Δ) in effect size going from low to high brand age (SD)
	Absolute (SD)	Relative	Absolute (SD)	Relative	Absolute (SD)	Relative	
Recruitment spend							
Direct effect	36.29*** (4.67)	83.8%	69.99*** (10.92)	95.0%	2.60 (3.56)	20.0%	-67.39*** (13.30)
Indirect effect	7.03*** (2.54)	16.2%	3.68*** (1.41)	5.0%	10.39*** (3.78)	80.0%	6.72*** (2.58)
Total effect	43.33*** (5.78)		73.66*** (11.16)		12.99** (5.55)		-60.67*** (13.31)
Winning percentage							
Direct effect	67.36*** (20.62)	62.4%	59.21** (29.54)	73.6%	75.51** (31.39)	55.8%	16.31 (44.91)
Indirect effect	40.55** (16.98)	37.6%	21.19** (9.35)	26.4%	59.91** (25.10)	44.2%	38.72** (16.80)
Total effect	107.91*** (32.82)		80.40** (33.70)		135.42*** (47.14)		55.02 (49.06)
Publicity							
Direct effect	16.75*** (2.25)	43.3%	27.98*** (5.13)	70.9%	5.53 (3.47)	14.6%	-22.45*** (7.52)
Indirect effect	21.95*** (1.78)	56.7%	11.47*** (1.71)	29.1%	32.43*** (2.77)	85.4%	20.96*** (2.92)
Total effect	38.70*** (3.03)		39.45*** (4.95)		37.96*** (4.59)		-1.49 (7.37)

The standard errors appear in parentheses. We report bootstrapped standard errors with 5000 replications. As brand age is captured using mean-centered values in the interaction terms, we use -20 years (fifth percentile) for low brand age, and for high brand age we use +20 years (ninety-fifth percentile)

* $p < .10$, ** $p < .05$, *** $p < .01$ (two-tailed)

Robustness checks

Validity of the SBBE measure In this research we focus on SBBE as an established, up-to-date, and objective measure of brand equity (Datta et al. 2017) because it is most appropriate to address our research question and also because it is the only one available for all observations across 40 clubs and 51 years. Theoretically, there are alternative approaches and we need to check the robustness of the findings.

First, the SBBE measure and hence the results might be sensitive to the set of variables that were used to isolate SBBE from other factors as described in the measurement section. We therefore also ran three variants where we reduced the set of variables used to calculate the residual. The resulting measures are all highly correlated with our measure ($r \geq .73$, $p < .01$). When we replace the SBBE measure chosen with any of the alternative versions, the results for the SBBE model and the attendance model remain stable. [Web Appendix E](#) provides details.

Second, choosing a consumer-based brand equity (CBBE) rather than an SBBE measure may affect the results, because CBBE reflects brand equity’s origins in the hearts and minds of consumers. Sportfive, a sports marketing agency, provides multiple waves of survey data on three mind-set metrics commonly used to capture CBBE (brand awareness, brand familiarity, and brand appeal). We average the mind-set metrics as a measure for CBBE and impute missing observations (see [Web Appendix F](#)). The correlation between SBBE and the Sportfive measure is .62, around what can be expected for the correlation between SBBE and CBBE (Datta et al. 2017). When we run the brand equity model and the attendance model using the Sportfive measure as an alternative to SBBE, all results remain similar, both in terms of direction and significance of effects. We provide detailed results in [Web Appendix G](#).

Third, we also correlate our measure with other brand equity measures that are only available for the most recent years, including the shareholder-focused measure of Brand Finance, the consumer-based measures adopted by the Facebook brand popularity ranking and other social media brand ratings (Hanssens et al. 2014). We find correlations between .48 and .86 (all $p < .01$), which are within the common range (Ailawadi et al. 2003; Datta et al. 2017). Together with the other checks presented above, these correlations point to a satisfactory convergent validity of the SBBE measure with alternative measures.

Model validation The attendance model captures the evolution of the brand leverage and transaction effects. To reassure this evolution, we undertake several model validation checks.

First, we conduct subsample testing. Specifically, we compare the proposed model’s fit between the full sample and ten randomly chosen subsamples, each of which contain 70% of the full sample. We find no significant difference between each subsample analysis and the full sample analysis as indicated by the R^2 s (min: .91, max: .92, $p > .10$). As is shown in [Web Appendix H](#), the effects are stable in direction and significance across all subsamples.

Next, we perform holdout sample validation. As our research goal is descriptive and the estimation method corrects for endogeneity, holdout sample validation serves to show estimation consistency rather than to obtain the best possible forecasts (Ebbes et al. 2011). We split the sample into a 45-season estimation sample and a 5-season holdout sample (10% of the data). We then use the estimation sample to calibrate the model. We find a correlation of .96 for the holdout sample, which is even better than that for the estimation sample (.95).

We further compare the fit of the proposed linear model against four alternative nonlinear models. First, we consider decreasing incremental effects of the value drivers and SBBE on attendance by replacing the linear terms in Eq. 3 by the natural logarithm and by a square-root transformation of these variables. We also test the possibility of increasing incremental effects by using exponential transformations of the value drivers replacing their linear terms. Moreover, we account for decreasing returns on brand age by replacing it with a natural logarithm transformation. However, R^2 comparisons suggest that the chosen linear model ($R^2 = .91$) has superior power to explain attendance compared to the logarithmic ($R^2 = .88$), the square-root-based ($R^2 = .90$), and the exponential ($R^2 = .78$) attendance models as well as to the model with the logarithmic brand age transformation ($R^2 = .90$).

Moreover, the effect of recruitment spend on attendance may depend on the quality of the current team. Therefore, we run an alternative model that includes the interaction between the quality of the current team and recruitment spend as an additional variable. We use the last season's winning percentage as a proxy to measure the team's quality. The results reveal no significant interaction effect ($\beta = 17.43$, $p > .10$). All other effects remain stable, as shown in [Web Appendix I](#). In sum, these additional results suggest that the presented model is robust.

Discussion

Implications for researchers

This paper adds to the nascent stream of research that provides empirical guidance for branding decisions in nontraditional contexts such as gaming (Nair et al. 2017), hospitality (Yi-Lin et al. 2015), movies (Carrillat et al. 2018), music (Saboo et al. 2016), or sports (Hartmann and Klapper 2017; Yang et al. 2009). With a focus on sports, we find that the brand leverage effect of SBBE on attendance gains traction when brand age increases. The finding is substantial. It means that two sports brands that are *exactly the same* in terms of SBBE can still vary widely in terms of their ability to attract consumers depending on their age: the long established brand will attract more consumers than the young brand, because its SBBE translates better into attendance. The finding explains why rich sports clubs are getting richer, widening the gap between strong and weak sports brands over time. To capture the gap it is necessary to account for a constant effect of SBBE on attendance (which is the common assumption in brand research) *and* a time-varying effect, both of which add up to a double advantage of strong sports brands when their age increases.

We also provide longitudinal insight on the implications of the increasing brand leverage effect for the value drivers' attendance effects that are at the core of sports brand managers' daily business. By uncovering the value drivers' routes to

attendance over time, we answer calls for empirical research into the role of brands for sports clubs' market performance (e.g., Gladden et al. 1998; Ross 2006). We show that recruitment spend serves to drive attendance, both directly and indirectly through SBBE. However, when brand age is high, 80% of the effect of recruitment spend on attendance operates through SBBE as compared to only 5% for a young brand. For winning percentage, the direct effect remains more important than the indirect effect, although it declines from 74% of the total effect for young brands to 56% for old brands. We also observe a shift from direct to indirect effects for publicity. Its indirect effect on attendance through SBBE grows from 29% of the total effect on attendance for young brands to 85% for brands at a high age, a development that is accompanied by a decreasing direct effect of publicity on attendance.

While sports markets have some idiosyncrasies such as the role of transfer fees, there are also many similarities to experience services such as events, entertainment, or traveling and many other industries that have to manage fixed, perishable inventory (Lewis 2008; Lovett and Staelin 2016). Thus, the findings of this paper also point toward insights that are worth further consideration in brand and service research in general.

Most brand research implicitly assumes that a brand's relevance for driving market performance is stable over time (Fischer et al. 2010). Several researchers, however, have called for study of the role that brand age might play for the brand value creation process (Ataman et al. 2008; Borkovsky et al. 2017; Slotegraaf and Pauwels 2008; Srinivasan et al. 2010). Addressing their calls, our study suggests that brand leverage has two components, a static component that is stable over time and a dynamic component that grows as brand age increases.

Linking value drivers to market performance both directly and indirectly through the brand and demonstrating their evolution allows us to align the findings of market response research and brand research. Market response research suggests that over time value drivers (such as advertising; Sethuraman et al. 2011) become steadily less relevant for driving firm performance. However, brand research implies that firms should increase their investments in the same value drivers. How do these recommendations align? We argue that both highlight different effects. Market response research focuses on transactional effects but tends to ignore brand building and brand leverage effects. Brand research focuses on brand building and leverage effects but tends to neglect transactional effects. Focusing on the moderating role of brand age, this study's results suggest that both go hand in hand, such that early on in brand life, transactional effects are relatively more important, while later on, the brand-centered route is more important.

The implication for theory is that the market response and the brand literature need to converge. We urge new research on the interface of these domains to account for both direct (transactional) effects and indirect (via SBBE)

effects of value drivers on brand performance in their models as well as for the brand age moderation. The results also imply that samples dominated by young brands should exhibit relatively strong transactional effects, whereas samples dominated by old brands most likely produce stronger brand leverage effects. We thus recommend that marketing researchers consider (and report) brand age when collecting an appropriate sample.

The study’s results are also relevant for service research. The service profit chain—the key chain-link framework in service marketing—relates the human factor and service quality to market outcomes (Heskett et al. 1994; Kamakura et al. 2002), which we do in this study as well. While we take a broader scope than is implied by the service profit chain (e.g., by accounting for publicity and SBBE), the findings hold potential to stimulate service research. First, in line with the recent observation that several key links are missing in the various versions of the service profit chain adopted by marketing researchers so far (Hogreve et al. 2017), our results suggest that brands might have a role to play in the framework. For instance, brands might funnel the translation from objective service quality into consumer-perceived measures of service quality and consumer reactions subsequently, leading to an incomplete understanding (or even biased estimates) of the effect when the brand is not accounted for. Second, the results also fortify the legitimacy of calls for more longitudinal examinations of the service profit chain (Bowman and Narayandas 2004; Hogreve et al. 2017). Given the significant changes in the effects of recruitment spend and winning percentage on attendance that we find over time, longitudinal examinations might help to isolate the sources of the large heterogeneity in the findings across the various studies that test the service profit chain (Hogreve et al. 2017).

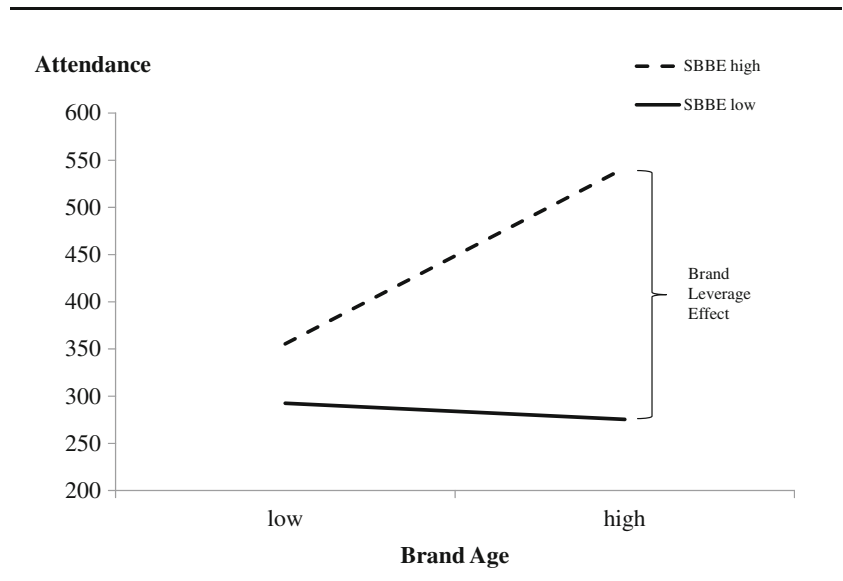
Implications for practitioners

Our findings serve to improve sports clubs’ marketing plans by accounting for the role of three important value drivers previously overlooked in marketing research: recruitment spend, winning percentage, and publicity. Table 4 shows that club managers need to consider the role that these factors play for their market performance. The total (direct + indirect) effect of recruitment spend on attendance is 43.33. That is, for every €1 million spent on attracting new players, a club attracts 43,330 extra visitors to games across the season. This is a substantial amount given that on average, a club attracts an annual crowd of 308,630. Winning also drives attendance, as the total effect of 107.91 means that a 10 percentage point increase in winning rate attracts additional 10,791 spectators annually. Publicity’s total effect size is 38.70, implying that 100 additional media mentions leads to 38,700 more visitors through the gates per season. While the media are certainly not under the control of the clubs, recent research provides interesting findings suggesting that they can be influenced, for example through paid advertising or professional public relations (van Heerde et al. 2015; Hewett et al. 2016). We therefore recommend that club managers account for these factors in their marketing plans.

Sports brand managers can also capitalize on the increasing brand leverage effect of SBBE on attendance. Figure 3 compares the attendance of high and low SBBE brands when they are young and when they have matured. Figure 3 visualizes the gap between strong and weak brands that widens due to the increasing brand leverage effect.

The increasing brand leverage effect highlights the need for professional and long-term oriented sports brand management. The findings imply that brand age establishes SBBE

Fig. 3 As brand age increases, the attendance gap between high and low SBBE-brands widens due to an increasing brand leverage effect



as a major driver of market performance, increasingly funneling the indirect effects of value drivers on attendance while their direct effects diminish. At a young age, due to value drivers' direct effects on attendance, clubs will be able to compete in terms of market performance without a strong brand and might therefore be tempted to delay brand building efforts to the future. In the long run, however, the attendance gap between weak and strong sports brands will widen and cannot be closed anymore by directly impacting on attendance. As a result, clubs with high SBBE will be uplifted in an upward spiral of market performance with increasing returns on their brand, while clubs with low SBBE will struggle to move forward. Overall, because of the growing brand leverage effect, the results not only cement the importance of long-term brand management in general, but they also emphasize the need to manage sports brands right from the start because this will not only be rewarded in the short run but will increasingly pay off in the long run.

With respect to the changing effects of value drivers on club attendance, club managers should consider the following recommendations worthwhile to implement. Regarding recruitment spend, the focus of young clubs should be to acquire star players that help to build the brand and attract more consumers. Later on, recruitment spend should be guided by considerations about forming a team that represents the brand image. Winning games keeps on having strong direct effects on attendance. However, if a club has been able to build the brand early on, long periods of underperformance can still come along with strong attendance rates due to the brand leverage effect. When it comes to publicity, young clubs should design their public relations such that they reach many potential fans, while later on in club life it pays off to design public relations to account for the needs of a loyal fan base.

The Dallas Mavericks are an example of a club that is managed in this way. Founded in 1980, they initially relied strongly on recruiting star players such as Mark Aguirre and Derek Harper (Smith 2011). In their early years, they further delivered strong performance on the court, reached the play-offs in almost all seasons and continuously improving winning percentage (NBA 2018). Also, at a young brand age, the Mavericks' public relations approach focused on "rumbling the drum" to gain awareness and drive attendance, for example, by signing Dennis Rodman as a genius publicity stunt, regularly pulling media appearances (MacMahon 2010). Nowadays, being on the market for a significant amount of time, the Mavericks are renowned as one of the strongest brands in the NBA, having seen the longest sell-out streak in the four major sport leagues (Dawson 2018). With Dirk Nowitzki reaching the end of his career, the Mavericks now keep attendance rates at record levels without relying on purchasing new star players. Rather, they now look for "a legacy team that sells a unique, emotional brand experience" (Bondarenko 2015), a strategy that includes developing rookie players like Dennis Smith Jr.

Importantly, the club's performance in terms of attracting attendance is hardly affected by their highly volatile performance on the court (Ourand and Lombardo 2017). And their public relations are designed to speak to a loyal fan base. Among others, their efforts involve organizing training camps, summer leagues, NBA draft parties, all-star games, and basketball academies and leveraging the media to spread information about these efforts (Karalla 2015).

Limitations and avenues for further research

This study has limitations that provide opportunities for further research. We contribute to the brand literature by providing the first longitudinal examination of the unique drivers and consequences of *sports brands* and by uncovering their growing brand leverage effect. We believe, however, that many of the arguments put forward may hold in other, more traditional settings where a long grown history may play a role for capitalizing on a strong brand as is reflected in the growing brand leverage effect. One might think of the strong communities that surround brands like Apple, Harley-Davidson, Porsche, and many others. Assessing the evolution of the brand leverage effect and its implications in such traditional settings as well as considering classical marketing instruments might be fruitful undertakings. Next, we suggest that adopting SBBE as a measure for brand equity (Datta et al. 2017) is appropriate for the purpose of this research because it builds on objective data and is the only one available for the full sampling period. Further, we show that it strongly correlates with several other established measures and that the results are consistent with those found when we adopt other measures. Yet, we acknowledge that one might opt for another brand equity measure, particularly if the data were available. Finally, our sample covers 87% of all tickets sold in in the world's most attended professional soccer league up to 2014. While the German market has many similarities to other international leagues, an international sample might help to further guarantee generalizability. Overall, we hope that future research will expand and refine the insights.

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