The Role of Sponsorship Fit for Changing Brand Affect: A Latent Growth Modeling Approach

Marc Mazodier, Assistant Professor, University of Nottingham Ningbo, Ningbo, 315100, China, and Adjunct Professor at ISG Business School, Paris, France. Ph: +86 574 8818 3042. E-mail: marc.mazodier@nottingham.edu.cn

Pascale Quester, Professor, University of Adelaide Business School, Adelaide, SA 5005, Australia. Ph: +61 8 8303 3986. E-mail: pascale.quester@adelaide.edu.au

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Abstract

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Keywords: sponsorship, congruence, event involvement, attitudes toward sponsorship, latent growth modeling

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The Role of Sponsorship Fit in Changing Brand Affect: A Latent Growth Modeling Approach

Abstract

Using a latent growth modeling (LGM) approach, this study examines the controversial role of perceived sponsor–event fit with respect to inducing changes in brand affect. Using two longitudinal studies that are related to the 2010 FIFA World Cup and the 2012 London Olympics, the authors determine that fit and brand affect increase linearly over time. The results of this study address an existing conflict in the marketing literature and demonstrate that the initial level of fit relates positively to the initial level of brand affect but relates negatively to the subsequent increase in brand affect. Moreover, the results demonstrate that a significant and positive association emerges between the change trajectories, and the resulting steep increase in perceived fit implies a faster rate of brand affect improvement. Moreover, the initial level of brand affect is not associated with subsequent increases in brand affect or fit. Therefore, incongruence resolution will ensure that sponsorship improves brand affect. Finally, both consumer attitude toward the sponsorship and the level of event involvement have positive impacts on subsequent increases in both brand affect and perceived fit.
Keywords: sponsorship, congruence, event involvement, attitudes toward sponsorship, latent growth modeling
1. Introduction

The vast majority of major sporting events are sponsored in some way. In the past 40 years, sponsorship has evolved from the traditional, short-term corporate donations that were designed to boost management egos into long-term, economic-based relationships between sponsor and sponsored properties and that are typically grounded by complex legal agreements (Quester & Thompson, 2001). Sponsorship spending has increased significantly from $2 billion worldwide in 1984 (Sponsorship Research International, 1996) to an estimated $48.6 billion in 2011 (International Events Group, 2012).

Extensive research has therefore sought to establish how sponsorship affects brand awareness, affect, trust, and loyalty, in addition to consumer purchase intention (for a review, see Cornwell, 2008). However, the majority of research refers to sponsorships in static terms, whereas the cumulative nature of sponsorship effectiveness suggests the need for a longer-term perspective and the use of longitudinal methodologies. The relevant data should be collected periodically to record the changes in consumer brand affect over time (Pham, 1991).

Research confirms that attitudes toward sponsorships (Quester & Thompson, 2001), event involvement (Lardinoit & Derbaix, 2001; Meenaghan, 2001), and sponsor–event fit (Johar & Pham, 1999; Olson & Thjomoe, 2011) are critical factors of sponsorship effectiveness. Fit is a powerful predictor of sponsorship persuasion, which is consistent with schema theory. Sponsorships exhibit high levels of fit when they are consistent with the consumer expectations for a firm, increase the likelihood that spectators will identify the sponsors correctly (Johar & Pham, 1999; Johar, Pham, & Wakefield, 2006), encourage positive brand attitudes (Becker-Olsen & Simmons, 2002; Gwinner & Eaton, 1999), induce favorable purchase intentions (Olson & Thjomoe, 2009), and increase brand equity (Simmons & Becker-Olsen, 2006). However, Olson and Thjomoe (2009), using realistic sponsorship stimuli, and Trendel and Warlop (2007), using implicit measures, demonstrate that sponsors with a low level of fit may enjoy stronger identification than sponsors with a high level of fit,
primarily because people find some degree of incongruence interesting. Low fit sponsorships can generate positive effects (Meyers-Levy & Tybout, 1989), particularly among spectators with a high need for cognition (Masterson, 2005) and those who view the sponsorship as philanthropic (D’Astous & Bitz, 1995) and consider the event to be significant (Speed & Thompson, 2000) or the association to be entertaining and creative. However, Prendergast, Poon, and West (2010) find no influence of image congruence on brand affect.

These conflicting results may arise because fit changes over time, even though congruence literature conceptualizes it as a generally static variable. Prior research offers a wealth of knowledge regarding the fit construct, its antecedents and its consequences, but a fundamental premise remains untested: Does a person’s perception of congruence change over time? If so, is that change indicative of a subsequent change in the brand affect caused by sponsorship? The potential impact of these questions is significant. Academics and practitioners have long relied on fit to explain sponsorship (Olson & Thjomoe, 2011; Quester & Thompson, 2001). If fit perceptions can change, then certain interventions could enhance the perception of this fit. Therefore, this study examines the effect of incongruence resolution that might result from an acceptance of incongruent brand–event associations. A study by Cornwell and colleagues (2005) calls for the empirical validation of a sponsorship’s ability to resolve initial incongruence and the testing of the positive attitudes that could result. Many companies seek to improve their brand image by sponsoring an event that might not fit with their current brand image but that offers beneficial associations (Smith, 2004). The decision to sponsor events that do not share a natural fit with the brand is both common and intentional. Therefore, we study the effect of sponsorship on perceived brand–event fit and examine the impacts of two individual variables, attitudes toward the sponsorship and event involvement, on the process of incongruence resolution. This study also examines the relationship between changes in perceived fit and brand affect over the course of a sponsorship. Using latent
growth modeling (LGM), we disentangle the static (initial status) and dynamic (change) components of these variables. To achieve greater external validity, we also conducted two studies to collect data from the 2010 FIFA World Cup and the 2012 Olympics for three successive occasions in each case (i.e., before the event, at the beginning of the event, and at the conclusion of the event). Specifically, we studied Sony’s sponsorship of the 2010 FIFA World Cup and EDF’s sponsorship of the 2012 London Olympics. This study elucidates the role of fit in defining the change in brand affect that can result from sponsorship.

This study provides an overview of the sponsorship and congruence literature that serves as the foundation for our hypotheses development. We then present the results and conclude with a discussion of the theoretical and methodological implications of our findings.

2. Conceptual background

2.1. The sponsorship-linked marketing activities

The sponsorship involves an exchange between a sponsor and the event property; the property sells the right to associate with the event to the sponsor, thereby providing leverage opportunity to the sponsor to exploit its communications to consumers (Simmons & Becker-Olsen, 2006). Sponsorship-linked marketing is a subset of event-related marketing and is distinguished by the presence of sponsorship contracts that authorize certain entities to associate with the event in an official way (Cornwell et al., 2006). Keller (2003) suggests that sponsorship, through an association with an event, builds brand equity more effectively than traditional marketing communications such as advertising. Cornwell and colleagues (2005) also emphasize the importance of examining sponsorship-linked marketing and recommend theoretically grounded research into sponsorship processing.

Certain studies demonstrate that sponsorship can enhance a sponsor’s brand affect (Simmons & Becker-Olsen, 2006; Speed & Thompson, 2000). The mere exposure effect (Olson & Thjomoe, 2003) that spreads activation through an associative network (Pham &
Vanhuele, 1997) and transfer models (Gwinner & Eaton, 1999; Keller, 2003) attempt to explain how sponsorships improve brand attitudes. However, none of these studies elucidate the relationship between sponsorship-linked marketing and any brand affect *improvement*. For example, the role of repetition for communication effectiveness has gained considerable research attention, and the leading theory advocates a curvilinear relationship between message repetition and message effectiveness (Anand & Sternthal, 1990; Batra & Ray, 1986). However, Campbell and Keller (2003) demonstrate that brand affect increases linearly with message repetition for familiar brands. Additional processing, as a result of repetition and brand unfamiliarity, may lead to fewer positive thoughts over time. Moreover, consumers may use more extensive processing to consider the inappropriateness of advertising tactics for unfamiliar brands when the advertisements appear to be repeated more frequently (Campbell & Keller, 2003). The sponsors of large events are often familiar brands (e.g., Adidas, HSBC, and Sony). We hypothesize the following:

**H1:** The consumer brand affect, over time and at the individual level, increases linearly as a result of sponsorship-linked marketing from familiar brands.

### 2.2. Fit and sponsorship effects

Sponsorship research focuses on the idea of fit (or congruence, relatedness, or match) between a sponsor and the sponsored event or activity. Congruence refers to the extent to which the sponsor and the event are perceived as similar, whether on the basis of functionality, attributes, images, or other key associations (Simmons & Becker-Olson, 2006). Congruence appears in many studies across different areas of marketing, including some early definitions in the brand extension literature. For example, Park, Milberg, and Lawson (1991) define perceived fit as a process of categorization by consumers that determines the suitability of a new product introduced under a given brand name. Most literature conceptualizes congruence as uni-dimensional (Simmons & Becker-Olson, 2006; Speed & Thompson, 2000),...
though certain scholars suggest a multi-dimensional approach (Fleck & Quester, 2007; Zdravkovic, Magnusson, & Stanley, 2010). For this research, we adopt a dominant, uni-dimensional conceptualization for parsimony and simplicity (Speed & Thompson, 2000).

According to Becker-Olson and Simmons (2002), the link between a sponsor and an event can be apparent from the mere juxtaposition of their names (“native fit”), or the association may require some explanation in dedicated communication (“created fit”). This study investigates both native and created fit with respect to the sponsorship-related impact on brand affect. The potential negative effects of incongruence represent another important issue for managers of sponsoring companies that lack a logical or natural link to the sponsored events. Hoeffler and Keller (2002) suggest that high levels of company–cause fit bolster a company's existing brand associations, but low levels of fit are more conducive to both augmenting current associations and creating brand differentiation. Finally, certain firms may engage in sponsorships simply to support a worthy (though ill-fitting) event (Brown & Dacin, 1997; Cornwell et al., 2006; Olson & Thjomoe, 2011; Simmons & Becker-Olson, 2006).

2.2.1. Fit and sponsorship effects in the short term

The effect of congruence and its various definitions have been examined extensively to produce a range of documented effects. For example, many studies demonstrate that high levels of native fit lead to more favorable responses to sponsorship, including sponsor recall and recognition (Johar & Pham, 1999), image transfer from event to sponsor (Gwinner & Eaton, 1999), and brand equity (Simmons & Becker-Olson 2006). To account for these positive effects of congruence, most prior research employs spreading activation theory (Anderson, 1983) or Heider’s (1958) balance theory. According to Heider’s (1958) balance theory, incongruent information tends to be ignored (Aaker & Sengupta, 2000). When people are exposed to sponsorship information, they access event and brand schemas from memory and compare them, which determines their judgment with respect to the appropriateness of the
sponsorship (McDaniel, 1999). A match leads to more positive evaluations because affect moves from the event schema to the brand schema (Perrachio & Tybout, 1996). Additionally, when consumers elaborate on the sponsorship and discover a level of congruence, they experience a sense of cognitive satisfaction that influences their evaluation of the sponsoring brand (Meyers-Levy & Tybout, 1989). Because the prior studies are static and do not consider potential changes in perceived fit, their findings are limited to the short-term effects of sponsorship. Therefore, we posit the following:

\[ H_2 \]: At the initial level, the perceived sponsor-event fit and brand affect are positively related.

2.2.2. Fit and sponsorship effects over time

Sponsorship-linked marketing activities often span many days, weeks or years and imply repeated exposure to sponsor messages. One objective of these messages is to communicate the meaning of the association between the sponsor and the event to leverage the benefits of sponsorship (Quester & Thompson, 2001). Zdravkovic and colleagues (2010) highlight that managers should not rely on natural fit but should proactively attempt to communicate their brand’s fit with the event to consumers. It is ultimately the marketer’s responsibility to explain the link between the event and the brand, using advertising, public relations, promotion, and merchandising. Therefore, 78% of sponsorship managers invest as much in sponsorship activation as they do in fees to acquire the official rights (IEG, 2013). The congruence can be enhanced or created if the brand explicitly articulates the basis and meaning of its sponsorship relationship. When salient event associations are not relevant but non-salient associations are, the communication strategy should emphasize the non-salient associations. The articulation of the associations can create a link between the existing schemas held with respect to the event and the brand in addition to imbuing an otherwise incongruent sponsorship relationship with meaning (Cornwell et al., 2006). Simmons and
Becker-Olsen (2006) demonstrated that created fit, which they achieved by explaining how the sponsor and incongruent sponsor recipient relate, can improve evaluations of incongruent sponsorships. Therefore, a clear articulation may increase overall sponsor-event fit perceptions (Olson & Thjomoe, 2011; Simmons & Becker-Olsen, 2006). Similarly, repeated exposure increases elaboration and evaluations of incongruent extensions (Lane, 2000). For the first time, this research measures repeated exposure to sponsorship over time and examines its impact on the relationship between sponsorship fit and brand affect change.

According to Mandler (1982), incongruent information can lead to superior recall and positive evaluations because incongruent messages can stimulate consumer interest. The congruent associations can thus be overlooked or regarded as not stimulating because they conform to expectations (Jagre et al., 2001). However, initial or native incongruence must be resolved before it can have positive brand influences. If sponsorship articulation leads to incongruence resolution, the brand generates arousal, is interesting, and is valued positively (Mandler, 1982). The process of resolution leads to greater positive evaluations. In contrast, unsuccessful incongruence resolution may generate unfavorable thoughts and negative attitudes toward the sponsor (Jagre et al., 2001). Olson and Thjomoe (2009, 2012) confirm a negative impact of the initial level of fit between a sponsor and an event on sponsor recognition when sponsorship activation takes place. The articulation of the sponsorship is likely to remove the initial advantage of a congruent sponsorship, namely, the presence of pre-existing links in the memory between the event and the brand (Cornwell et al., 2006). Because higher level attitudinal and image transfer communication effects depend on accurate sponsor recognition (Johar et al. 2006), the incongruent sponsorship with activation should more positively influence brand affect than congruent sponsorship. Moreover, Halkias and Kokkinaki (2011) indicate that incongruence resolution generates favorable attitudes because consumers enjoy intellectually challenging processes such as incongruence resolution. The
authors also suggest that “successfully resolving incongruity seems to provide consumers a sense of satisfaction and fulfillment that is intuitively transferred to their evaluations” (Halkias & Kokkinaki, 2011, p. 148). Consistent with congruence theory (Mandler, 1982; Jagre et al., 2001), we expect that initial incongruence should lead to a greater sponsorship-induced change in brand affect. Over time, as consumers are exposed to and become aware of sponsorship activation, the initial sponsorship incongruence is resolved, generating positive attitudes. Therefore, we hypothesize the following:

H3: The low initial perceived sponsor–event fit produces a greater subsequent increase in brand affect than high initial fit over time.

2.3. Control variables

Spector and Brannick (2011) advocate the use of control variables to eliminate the possibility that any observed relationships are the result of extraneous variables in the tested hypotheses. However, the authors also indicate that researchers should provide theoretical evidence for including particular control variables and predict the sign of their relationship.

The schema congruence and sponsorship literature provide certain insights into the factors that moderate incongruence resolution and sponsorship effects. The consumers likely respond to incongruence according to their levels of long-term involvement. Petty and Cacioppo (1984) suggest that highly involved people may be more motivated to process incongruence because they are already engaged in product evaluation. De Pelsmacker, Geuens, and Anckaert (2002) confirm that context–advertising incongruence has a positive influence on advertising effectiveness for respondents with high involvement. Therefore, consumers involved in the event should be more likely to resolve brand–event incongruence.

The intention a receiver attributes to the source could also constitute a facilitator of incongruence resolution. When incongruence prompts suspicion, it can erode evaluative responses (Friestad & Wright, 1994). The consumer attitude toward sponsorships may
influence the response to brand–event incongruence. If a consumer has a negative predisposition toward a sponsorship, they may perceive an incongruent sponsorship as manipulative. This tendency could explain why sponsorships are more effective when consumers perceive their intentions as philanthropic rather than commercial (d’Astous & Bitz, 1995). We expect that positive attitudes toward sponsorship motivate people to resolve incongruence.

The previous research suggests that event involvement (Lardinoit & Derbaix, 2001) and attitudes toward sponsorship (Olson, 2010) positively influence the sponsorship’s impact on brand affect. Therefore, we introduce event involvement and attitudes toward sponsorship as control variables that should increase the rate of improvement in perceived brand event fit and brand affect.

3. Operationalizing change

3.1. Limitations of traditional approaches

The longitudinal changes in variables and their dynamic effects have long fascinated academics, including those in the marketing realm. To assess change, scholars have used various operationalizations such as difference scores, repeated analyses of variance, regression, or time-series models. However, as Chan and Schmitt (2000) and Steenkamp and Baumgartner (2000) note, intra-individual change cannot be conceptualized or empirically examined appropriately with such approaches. Time-series models, most likely the most commonly used longitudinal data analysis technique, cannot model inter-individual differences in intra-individual changes, which “make[s] it impossible to study the differential effectiveness of marketing actions at the micro level” (Steenkamp & Baumgartner, 2000, p. 199).

Moreover, traditional techniques assume, rather than test, measurement invariance in intra-individual repeated responses over time (Chan, 1998). However, the validity of data
analysis depends on whether the analyst adequately considered measurement error when specifying the model or estimating its parameters. Chan (1998) noted that a common assumption in many analysis procedures is that the error terms are independent, but this assumption may not hold for longitudinal studies that track change, especially if the data collection points are proximate in time and rely on identical measures or scales.

3.2. Advantages of latent growth modeling

Latent growth modeling (LGM) offers a promising methodological response to these concerns. It is increasingly accepted in many disciplines for its capacity to describe, measure, and analyze longitudinal change (Lance, Vandenberg, & Self, 2000), and LGM overcomes many challenges that have stymied previous attempts to operationalize intrapersonal change including repeated measures, regressions, or difference scores (Chan, 1998; Duncan, Duncan & Strycker, 2006; Kher & Laurenceau, 2011). Unlike these methods, LGM can track the measures of several focal constructs for each respondent in addition to the starting level of each variable (Steenkamp & Baumgartner, 2000; Willet & Sayer, 1994). Doing so demands repeated measures on three or more sequential occasions to allow for the calculation of second-order or higher latent constructs, the initial status, and the change (i.e., slope) of each variable under consideration. A first-order latent construct that represents the variable of interest (e.g., latent constructs at Times 1, 2, and 3) would produce a separate loading on the second-order latent factors (in this research, brand affect and perceived fit constructs). The second-order latent factor “initial status” then represents the initial value of the first-order variable, and the second-order latent factor “slope” measures the rate of change in the first-order variable. As a special application of structural equation modeling, LGM provides access to an array of model fit indices (Little et al., 2009) and offers several key benefits.

First, LGM statistically quantifies the variations in sample elements on both intra-individual (e.g., changes in each individual’s brand affect over time) and inter-individual (e.g.,
changes in brand affect across a sample) levels (Duncan et al., 2006; Preacher et al., 2008). Moreover, LGM can describe a single entity’s change trajectory and then capture individual differences in these trajectories.

Second, LGM accounts explicitly for both cross-sectional and longitudinal measurement errors (Chan, 1998). It is fundamental to determine whether the changes are in absolute terms or are affected by variability in the measurement instrument or conceptual domain. Accounting for measurement error increases both the reliability and the power of the relationship among the variables of interest (Duncan et al., 2006).

Third, LGM can assess the form of growth (e.g., linear, optimal) in a process referred to as second-order (SOF) LGM. This advantage addresses the issue of the reversibility of change over time. It also assists scientists to assess whether the change of the variable is gradual or linear.

Fourth, LGM provides an estimate of covariance among the constructs that define the form of growth. A significant positive covariance between the intercept and the slope thus reveals that high initial brand affect is associated with greater brand affect change. Moreover, investigators can study the predictors and consequences of change separately from the correlates of initial status (Duncan et al., 2006).

Fifth, LGM provides estimates of variance in the constructs for the form of growth across individual entities. Thus researchers can determine whether a distinct trajectory of longitudinal changes in the latent construct is needed for different individuals in the sample (Bollen & Curran, 2006). For example, statically significant variability in the intercept and slope for linear LGM would suggest that the starting point and rate of change in brand affect for each individual may differ from the starting point and rate of change in brand affect that fits the entire sample.
Sixth, LGM can test whether the same form of growth exists across multiple groups. Different groups may vary in terms of the specific facets of their intra-individual changes. Because LGM can test the similarity and invariance of key parameters across groups, it provides useful information concerning the growth and covariates of growth across co-varying populations (Duncan et al., 2006).

Finally, growth parameter variances can be explained by covariates; that is, LGM is able to identify the predictors of change in trajectories for different cases (Kher & Laurenceau, 2011). For example, if a linear model fits changes in individual brand affect over time, and the variance indicates that different members of the sample have different linear trajectories, researchers should investigate the reasons for the different trajectories concerning the different members of the sample. The identification of these variations may clarify whether certain participants exhibit a higher increase in brand affect over time. Moreover, LGM can test whether growth in one domain affects growth in another (Kher & Laurenceau, 2011). Changes in one focal variable may relate systematically to changes in another focal variable, a finding that is relevant to our research objectives.

This study therefore attempts to answer the following questions: Is the rate of improvement in sponsorship-induced brand affect greater for the consumers who initially perceive the sponsor-event association as congruent? Is the rate of brand affect change greater for those who resolve any incongruence over the same time periods? Using LGM, we test whether the rate of change in brand affect relates to its initial level or to the rate of change in perceived fit that is achieved with sponsorship-linked marketing activities. The application of SOF LGM to the examination of sponsorship persuasion processes offers exciting opportunities by isolating change in perceived fit from any concomitant change in individual brand affect. Therefore, using SOF LGM in this study provides an initial empirical test of the hypothesized association between changes in constructs that result from sponsorships.
We present in the following sections the empirical context and data collection methods that were implemented in this research. We describe two studies that employed longitudinal methods to collect responses from a large sample of consumers with respect to the 2010 FIFA World Cup and the 2012 London Olympics.

4. Study 1

4.1. The Method

4.1.1. The participants and the procedure

To enhance the external validity of our results, this study relied on quota sampling and real sponsorship activities that were associated with the 2010 FIFA World Cup in South Africa—a well-known, highly visible event with a positive image. Among its many sponsors we selected Sony, a new entrant that intended to leverage its sponsorship in France. Following the event, Kantar Media (2010) revealed that Sony spent more than any other company on its World Cup communications in France (5,376,000 euros). Prior to the study, the results of a pre-test (n=63) demonstrated that the variance of the perceived fit between Sony and the FIFA World Cup was higher than the variance of the perceived fit for most other sponsors.

We used a Web panel to recruit 1,064 French participants and achieved sample representativeness with respect to age and gender through quota sampling. Our study questions included a variety of topics to avoid demand effects. The questions were mostly related to branding variables (with respect to Sony, Samsung and Philips), the Olympics, individual characteristics and demographics. The questionnaire took approximately fifteen minutes to complete. The first data collection wave (T1) was conducted prior to the 2010 FIFA World Cup, in week 20 of 2010. The World Cup was in progress for the next two waves, and we collected subsequent data in week 23 (T2) and week 26 (T3). All of the questionnaires included measures of fit and brand affect and were completed online. Of the 1,064 respondents initially recruited for T1, a total of 834 completed the questionnaire for T2.
(78.4%), and a total of 494 (59.2%) completed the questionnaire for T3. The average age of respondents in the final sample was 40.86 years (SD=11.86), and the sample was composed of 69% female and 31% male participants. The sample size is satisfactory because sample sizes of approximately 100 are used to fit latent growth models (Curran, Obeidat & Losardo, 2010). Moreover, MacCallum, Browne and Sugawara (1996) present a framework that determines the minimum sample size that is required to achieve a given level of power in the assessment of fit of covariance structure models. According to this framework, the overall statistical power for the following analyses is acceptable.

4.1.2. Measures

We measured all of the constructs (brand–event fit, brand affect, and event involvement) using previously validated scales that were derived from prior literature. The brand affect items (e.g., “I have good feeling about Sony”; “I feel favourable about Sony”; “I feel positive about Sony”; 1 = “strongly agree”; 5 = “strongly disagree”) originated from Chaudhuri and Holbrook (2001). With respect to the fit between the brand and the event, we followed the scale used by Speed and Thompson (2000) (e.g., “Sony and the FIFA World Cup fit together well”; “The image of Sony and the image of the FIFA World Cup are similar”; 1 = “strongly agree”; 5 = “strongly disagree”). To avoid revealing Sony’s sponsorship, we modified one item (e.g., “It makes sense to me that Sony associates itself with the FIFA World Cup” instead of “Sony sponsors the FIFA World Cup”). These three-item scales were administered in all three waves of the survey.

To measure the long-term involvement in the event, we used the three-item scale developed by Strazzieri (1994) (e.g., “I’m very interested in the FIFA World Cup”; “I give a particular importance to the FIFA World Cup”; “The FIFA World Cup is a domain that interests me”). The attitudes toward the sponsorship were measured using a three-item scale that was adapted from Quester and Thompson (2001) (e.g., “The FIFA World Cup is better
because of sponsors”; “The FIFA World Cup would not be possible without sponsorship”; “I would be inclined to give my business to firms that sponsor the FIFA World Cup”

Appendix A demonstrates that all of the variables exhibited excellent reliability, ranging from .94 to .98.

4.1.3. Attrition analyses

It is not uncommon for the longitudinal field studies to experience a drop in response rates between the first and last measurement occasions (Chan, 1998). The respondents who drop out of the study would typically be eliminated from all subsequent data analyses because the use of complete cases avoids overestimating the results (McArdle, 2009). We conducted certain analyses to assess whether non-responses in our data were systematic.

First, we compared the demographic characteristics and all of the variables that were included in the model between respondents who remained in the study and those who did not (Goodman & Blum, 1996; Ployhart & Vandenberg, 2010). We repeated this comparison for the multiple measurement occasions. We used dummy variables to classify respondents into three groups: Group 1 included participants who only completed the measures at T1 (n=230); Group 2 represented those who completed measures at both T1 and T2 (n=340); and Group 3 was composed of the respondents who completed all three measurement waves (n=494). We first determined, for the three waves of analysis, whether the groups differed in age, gender, or residence. Although we found no differences with respect to age or residence, more females answered the T3 questionnaire.

Second, we considered any differences in perceived congruence for each survey wave. We conducted a multiple analysis of variance (MANOVA) to determine overall response biases across the T1 measures as a function of group membership. A second MANOVA was conducted on the T2 responses with respect to the fit measures included only in Groups 2 and 3. Neither MANOVA was significant (F(6, 2118)=1.715 and F(3, 830)=.406, respectively).
Third, we tested for differences in the brand affect at each wave. The first MANOVA included the T1 measures of brand affect for all three groups; the second featured the T2 measures of brand affect for Groups 2 and 3. Again, both MANOVAs yielded non-significant results ($F(6, 2118)=.457$ and $F(3,830)=1.372$).

Fourth, we evaluated whether the missing data mechanism was “ignorable” or “informative” (Diggle & Kenward, 1994)—that is, if the reason for the missing data was related to the study’s purpose. Little and Rubin (2002) emphasize a distinction among data that are missing completely at random (MCAR), missing at random (MAR), or not missing at random (NMAR). Specifically, MCAR data occur when the missing data are completely unrelated to any covariates or outcomes in the study, and MAR implies that the likelihood of missing variable data does not relate to the participant’s score on the variable after controlling for other variables in the study. Both MCAR and MAR are ignorable forms of dropout (Schaefer & Graham, 2002). If we cannot demonstrate either MCAR or MAR, the data must not be missing at random (NMAR), and these non-responses are therefore informative. Only NMAR is an issue for LGM (Little et al., 2009; Ployhart & Vandenberg, 2010). For a longitudinal study with attrition, the missing data must be ignorable at every occasion. Little’s (1988) MCAR test examines the null hypothesis that missing values of a given variable are independent of all observed variables in the data set; we conducted this test separately for non-respondents at both T2 and T3 for all measures of interest. The MCAR tests were not significant ($\chi^2(13)=14.75, p=.32$ at T2; $\chi^2(32)=41.85, p=.11$ at T3), and the dropouts therefore appear completely random. The observed variables, including gender, do not influence participation at T2 and T3; therefore, we can safely proceed with the LGM because respondent attrition does not create any bias in the focal variables for this study.

4.2. Results
Consistent with Chan (1998), we undertook tests for measurement invariance in addition to two waves of LGM analyses. All of the analyses were conducted using structural equation modeling with LISREL 8.5. Invariance in an LGM context exists if the nature of the construct that is operationalized by the measured variables remains unchanged across measurement occasions (configural invariance) and the relations between measures and their corresponding constructs are invariant across measurement occasions (metric invariance). We performed nested model comparisons to test for measurement equivalence. The results confirm the predictions of configural and metric invariance for both perceived fit and brand affect. Thus, we retained the invariance constraints for the LGM analyses.

4.2.1. Changes in perceived fit and brand affect

To ensure that our data collection did not condition participant responses, we measured sponsorship recognition only at the end of the third wave. A total of 38% of the final sample recognized Sony as a sponsor of the 2010 FIFA World Cup. Kantar Media (2010) similarly found that 34% of French people were aware of Sony’s sponsorship. Thus, our longitudinal data collection did not appear to significantly increase awareness of Sony’s sponsorship. We applied the two-phase SOF LGM procedure to test the hypotheses pertaining to longitudinal changes in perceived fit and brand affect in addition to their relationships (for a full description of SOF LGM, see Chan, 1998; for application examples, see Chan & Schmitt, 2000; Lance et al., 2000).

With respect to the first phase, we performed univariate SOF LGM analyses to determine the basic shape of the growth curves for perceived fit and brand affect. To establish a final model that most adequately depicts the change trajectory, we then fitted a series of nested univariate SOF LGM models to the data for each variable. To do so, we compared a no change model (no slope factor), a linear model (the slope factor loadings are respectively

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1Because of space constraints, certain results are not presented or detailed in this paper, but the authors may be contacted for a written description of the details and outcomes.
fixed to 0, 1 and 2) and an optimal model (the first two slope factors loadings are respectively fixed to 0 and 1, and the remaining slope factor loading is freely estimated). The free estimation of the remaining loading is equivalent to modeling unspecified trajectories, where the shape of the trajectory may be determined by the data. In such a model, the slope factor is better interpreted as a general shape factor. Because we had previously established metric invariance, all the univariate models included equality constraints on the first-order factor loadings for like items across the three measurement waves. Additionally, we allowed the same-item residuals to co-vary across measurement occasions (Chan, 1998).

Table 1 presents the results of an analysis that fit the univariate LGM models separately for each variable. For both variables, the nested model comparisons demonstrated that a linear change model (Models 1 or 2) provided a significant improvement over a no-growth model (Model 0). Additionally, the comparison between Models 1 and 2 and between Models 3 and 4 demonstrated that allowing the residuals to display a heteroscedastic structure significantly improved the model fit for brand affect. The superiority of the heteroscedastic model for brand affect may result from the sensitivity of brand affect to even minor changes in consumer attitude toward a brand over time, which makes it difficult for consumers to report their own brand affect reliably over time. However, the homoscedastic and heteroscedastic residual structure models for perceived fit exhibited almost equivalent fit, and we therefore adopted the more parsimonious homoscedastic structure in this case. Overall, the results indicate that the optimal change model did not improve the model fit significantly over the linear change function for either variable. For the sake of parsimony, a linear trajectory of change model thus was deemed the best depiction of intra-individual change over time for both our focal variables.

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Insert Table 1 about here

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To precisely determine the shape of growth trajectories for the variables, we examined the SOF LGM parameter estimates (factor means and variances) for both initial status and change factors in the selected models. In support of H₁, the mean for the change factor was positive and significant for brand affect (μ₁=0.15, p<0.001). Similarly, the mean for the change factor was positive and significant for perceived fit (μ₁₀=0.14, p<0.001). These variables both increased in a linear fashion over time. Furthermore, the slope (change) factor variances of both variables were statistically significant (perceived fit σ²₁₀=0.11, p<0.05; brand affect σ²₁=0.21, p<0.05). Certain respondents experienced change at a much faster rate than others over the same period.

The intercept factor variances for both variables were statically significant (perceived fit σ²ₙ=2.16, p<0.001; brand affect σ²ₙ=1.24, p<0.001), which revealed systematic individual differences in initial perceived fit and brand affect (i.e., some people reported higher mean levels than others at T1). Finally, the factor covariance between the intercept and slope for perceived fit was negative and statistically significant; respondents who reported low levels of perceived fit at T1 (initial status) increased their perceptions of fit at a faster rate than those who began with a higher level of fit. However, the covariance between the initial status and change for brand affect was not statistically significant. Note that, regardless of a respondent’s initial level of brand affect, the respondent experienced an increase in brand affect over the duration of this study.

4.2.2 Explaining the factors of growth in perceived fit and brand affect

With respect to the second phase, we used the multivariate SOF LGM model that is depicted in Figure 1 to test the hypothesis related to brand affect and perceived fit improvements. This multivariate model combines the two univariate latent growth models previously identified with two additional predictors: event involvement and attitudes toward sponsorship. Figure 1 demonstrates the model for the variables measured at three points in
time and equally spaced at three-week intervals. Using LISREL notations, the first growth factor, labeled Intercept $\eta_I$, is a constant for any given respondent over time, leading to fixed values of 1.0 for factor loadings (i.e., $\beta_{1I}, \beta_{2I}, \beta_{3I}$) on the repeated measures. The intercept factor represents information concerning the mean $\mu_I$ and the variance $\sigma^2_I$ of the collection of individual intercepts of each respondent’s growth curve. The second growth factor, labeled slope or change $\eta_{CH}$, represents information concerning the mean $\mu_{CH}$ and the variance $\sigma^2_{CH}$ of the collection of individual slopes of each respondent’s growth curve. Both factors, as estimated from the data, may co-vary (estimated as $\Psi_{I-CH}$), as indicated by the double-headed curved arrow between the factors (Chan & Schmitt, 2000). Because we want the intercept factor to represent the initial status at T1, the intercept should be located at T1, which can be achieved by fixing the slope factor loadings of $\beta_{1CH}$ and $\beta_{2CH}$ to 0 and 1, respectively. The remaining slope factor loading $\beta_{3CH}$ is fixed to equal 2 for both variables to assess linear change models. The mathematical details of the structural model appear in Appendix B.

We first examined the association between the initial status and the change factors for the focal variables, including brand affect and perceived fit between the event and the sponsor. This model incorporated the retained specifications of both variables’ univariate LGM models and allowed the co-variances among initial status and change factors to be freely estimated. The model exhibited a good fit with the data ($\chi^2(222) = 948.37, p = .00$, confirmatory fit index [CFI] = .94, non-normed fit index [NNFI] = .92, square root mean residual [SRMR] = .14, root mean square error of approximation [RMSEA] = .081). The within-domain co-variances were virtually identical to their corresponding values in the univariate models. Therefore, no abnormality affected the results when we combined the univariate models. The R-square values for latent change factors were .38 for brand affect and .47 for perceived fit.
The results provided support for H2, which predicted that the initial fit status was positively related to the initial level of brand affect (ψ_{9,4}=.49, \( p<.001 \)). With respect to H3, we also predicted a negative association between the initial level of perceived fit and the rate of improvement of brand affect and we found conclusive support for that prediction (ψ_{9,5}=-.50, \( p<.001 \)). Several other findings were also noted. First, the rate of increase in perceived fit and the improvement of brand affect were positively related (ψ_{10,5}=.13, \( p<.001 \)). Second, the initial level of brand affect was not associated with greater perceived fit (ψ_{10,4}=.09, \( p>.05 \)).

To evaluate the optimal level of incongruence, we developed a multivariate SOF LGM model for respondents who reported low initial fit levels (less than the median of 4). Among these 186 respondents, we found good fit with the data (χ²(104)=205.46, \( p=.00 \), CFI=.97, NNFI=.96, SRMR=.010, RMSEA=.073). Both brand affect and perceived fit increased significantly (μ₅=.38, \( p<.001 \); μ₁₀=.59, \( p<.001 \), respectively). Moreover, the initial level of fit did not relate significantly to the rate of brand affect improvement, which suggests that extreme and moderate incongruence exerted similar influences on the change in brand affect caused by sponsorship, at least with high sponsorship articulation. Finally, we assessed a multivariate SOF LGM model for respondents who indicated a high level of fit (>4). With respect to this group, brand affect did not change significantly over time. Therefore, sponsorship-linked marketing may resolve incongruence but not improve congruence for people who already perceive the event–sponsor association as congruent.

To facilitate the interpretation of these findings, we also tested the role of sponsorship fit in changing brand affect by using a repeated measure analysis of variance (RANCOVA) with one within-subject factor (i.e., prior to the event, at the beginning of the event, and at the end of the event) and one between-subject factor (i.e., the dichotomized perceived fit between the event and the sponsor). Figure 2 illustrates the results of this analysis.

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Insert Figure 2 about here
We can also examine the role of event involvement and attitude toward sponsorship in sponsorship effects. The event involvement relates positively to the change in perceived fit ($\gamma_{10,1} = .05, p < .001$). The event involvement also exerts a positive influence on the rate of improved brand affect ($\gamma_{5,1} = .07, p < .001$). Finally, the attitudes toward sponsorship relate positively to the change in perceived fit ($\gamma_{10,2} = .17, p < .001$) and exert a positive influence on the rate of improved brand affect ($\gamma_{5,2} = .09, p < .001$).

5. Study 2

5.1. Method

To enhance the generalizability of our results, we replicated Study 1 by investigating the effects of EDF’s sponsorship activities in association with the 2012 London Olympics. Similar to Sony in the context of the 2010 FIFA World Cup, EDF was a new entrant that intended to leverage its sponsorship heavily in the United Kingdom. It spent several million pounds emphasizing its role in “powering” the Olympics (Marketing Magazine, 2012a) and supported its “Energy of the Nation” campaign with multi-media advertising, including advertorials and editorials in the Daily Mail, a website, an “Energy2012” mobile application, and an Energy of the Nation Facebook page. Prior to the study, a pre-test (n=45) demonstrated that the variance in perceived fit between EDF and the London Olympics was higher than the variance in perceived fit for most other sponsors.

We used a Web panel to recruit 903 U.K. participants and achieved sample representativeness through quota sampling with respect to age and gender. The first wave (T1) took place prior to the 2012 London Olympics, in week 29 of 2012. The next two waves took place during the 2012 Olympics: T2 in week 31, and T3 in week 33. All of the questionnaires included measures of all variables and were completed online. Of the 903 respondents recruited at T1, 694 completed the questionnaire at T2 (76.8%), and 577 (63.9%) responded to the T3 survey. To control for any mere measurement effect, we also solicited 302 new
respondents to complete the questionnaire at T3 only. The average age of respondents in the final sample was 42.16 years (SD=13.17), and the sample was composed of 65% female and 35% male participants. All of the variables were measured with scales identical to those used in Study 1 and exhibited excellent reliability, ranging from .89 to .97 (see Appendix A). In comparison to Study 1, the branding variables were related to EDF, E.On and ScottishPower and we added some new socio-psychological variables to the questionnaire. Therefore, the questionnaires took approximately twenty minutes to complete.

To determine whether attrition produced any outliers in the responses or stemmed from demographic differences in the sample, we performed the same analyses that we described for Study 1. The groups did not differ in age, gender, or residence ($p>.05$). All MANOVAs yielded non-significant results ($p>.05$), indicating that there was no difference in brand affect or perceived fit at each measurement interval for all three groups. Finally, the MCAR tests were not significant ($p>.05$), and the respondent attrition appeared random with reasonable certainty.\(^2\)

5.2. Results

Following the third wave, 45% of the final sample could recognize EDF as a sponsor of the 2012 London Olympics, consistent with the results published by Interbrand (Marketing Magazine, 2012b), which indicated that 40% of British people were aware of EDF’s sponsorship. Moreover, we introduced a control group of respondents who completed the questionnaire at T3 only, to examine the potential for a mere measurement effect. To verify the comparability between the experimental and control groups, we conducted chi-square tests of the socio-demographic variables (gender, income, age), as well as ANOVAs to compare the means with respect to involvement in the event and attitude toward the sponsorship. No significant differences emerged between groups for either variable. We then compared brand

\(^2\)Because of space constraints, we excluded some details of these results here, but they are available on request.
affect and perceived fit between the experimental and control groups using MANOVAs; we found no significant differences (brand affect F=1.003, p=.39; perceived fit F=1.026, p=.38). The measuring of brand affect and perceived fit three times over a six-week period did not affect consumer perceptions of EDF. Moreover, we compared the different groups in terms of their awareness of EDF’s sponsorship and found no significant difference ($\chi^2=2.77$, p=.60). These findings affirm the validity of our study.

Similar to Study 1, we applied the recommended two-step SOF LGM process to analyze the data. First, the results confirmed both forms of invariance for perceived fit and brand affect and we therefore retained the invariance constraints during the LGM analyses. In Table 2, we present the results of the nested univariate LGM model comparisons. The change over time was well represented for both variables by a linear growth function, and the heteroscedastic residual structure represented the sample data appropriately. The resulting univariate LGM produced good overall fit statistics.

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Insert Table 2 about here
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First, the univariate SOF LGM models estimated values for all parameters. Similar to Study 1, the mean for the change factor was positive and significant for perceived fit ($\mu_{10}=12$, $p<.001$) and brand affect ($\mu_{15}=14$, $p<.001$), in support of $H_1$. The significant intercept and slope factor variances of both variables also indicated substantial inter-individual differences in both the initial level of brand affect ($\sigma^2_1=1.25$, $p<.001$) and perceived fit ($\sigma^2_2=0.83$, $p<.001$) and their changes over time (perceived fit $\sigma^2_{10}=1.5$, $p<.01$; brand affect $\sigma^2_{15}=1.5$, $p<.001$). The covariance between the initial status and change for brand affect again was not statistically significant, nor was the factor covariance between the intercept and slope for perceived fit (cf. Study 1, where it was negative and statistically significant). Thus, all respondents appear to have increased their perceptions of fit between EDF and the Olympics at a similar rate, regardless of their initial level of perceived fit at T1.
Second, we used the multivariate SOF LGM model to test the predictors of brand affect and perceived fit improvements. The model indicated an adequate fit with the data ($\chi^2_{(220)}=875.70$, $p=.00$, CFI=.92, NNFI=.90, SRMR=.044, RMSEA=.072). The results confirmed our findings from Study 1. Study 2 revealed a positive relationship between the initial level of perceived fit and the initial level of brand affect ($\psi_{9,4}=.20$, $p<.001$), supporting H2. It also confirmed a negative effect of initial fit status on brand affect growth ($\psi_{9,5}=-.16$, $p<.001$) in support of H3. We also found a positive association between the rate of increase in perceived fit and the improvement of brand affect ($\psi_{10,5}=.06$, $p<.001$). The multivariate SOF LGM model for respondents who reported low initial levels of fit (less than the median of 4) demonstrated that both brand affect and perceived fit increased significantly ($\mu_5=.25$, $p<.001$; $\mu_{10}=.30$, $p<.001$). The results related to these 281 respondents indicated adequate fit ($\chi^2_{(102)}=174.47$, $p=.00$, CFI=.99, NNFI=.98, SRMR=.067, RMSEA=.050). Surprisingly, the initial level of fit related significantly to the rate of brand affect improvement ($\psi_{10,5}=-.07$, $p<.05$), suggesting that extreme incongruence had a greater influence on the change in brand affect caused by sponsorship. In conjunction with the lack of relationship between the initial level of fit and change in fit, these findings suggested that extreme incongruence directly influenced change in brand affect in Study 2; extreme incongruence instead indirectly influenced brand affect increase through perceived fit improvement in Study 1. We discuss these results below. The multivariate SOF LGM model for respondents who reported a high level of fit (>4) indicated that brand affect did not change significantly over time. These results thus confirmed that incongruent sponsorships increased the rate of brand affect improvement. Figure 3 presents these results.

Finally, event involvement related positively to the change in perceived fit ($\gamma=.02$, $p<.01$) and enhanced the rate of improved brand affect ($\gamma=.02$, $p<.01$). The consumer attitude
toward the sponsorship related positively to the change in perceived fit ($\gamma=.08, p<.001$) and positively influenced the rate of improved brand affect ($\gamma=.05, p<.05$). These results are consistent with Study 1.

6. Discussion and conclusions

With the application of SOF LGM, we have revealed several important findings. The initial levels of brand affect and fit are positively associated with increases in brand affect but negatively correlated with increases in brand affect. Although the initially perceived brand–event fit is positively related to initial brand affect, incongruence is more effective than high levels of congruence as a tactic to improve brand affect. The results also demonstrate that brand affect and perceived fit increase linearly with sponsorship-linked marketing during the event, but only when people initially perceive the sponsor–event association as incongruent. Incongruence resolution generates positive affect, whereas congruence enhancement does not improve affect toward the sponsor. We have also identified a significant positive association between the change trajectories, and the steeper the increase in perceived fit, the greater the rate of increase in brand affect. The initial level of brand affect is not associated with subsequent increases in fit or brand affect, and sponsors therefore cannot rely on initial brand affect; rather, they must help consumers resolve any incongruence to generate favorable attitudes. Finally, event involvement and attitudes toward sponsorship have positive impacts on improvements in both brand affect and perceived fit. These results confirm that long-term involvement and the intentions attributed to the sponsor facilitate incongruence resolution.

These findings expand our current understanding of the sponsorship persuasion process. Specifically, we establish important connections between constructs that are often considered in isolation. To establish these connections, we used a method that examined change at the individual level rather than through cohort means and scores. By assessing individual consumer responses to sponsorship, our results offer direct managerial implications
pertaining to the need to measure initial levels of perceived fit and then to target consumers who are more likely to respond to a communicated association. Because sponsorship-linked marketing improves brand affect for consumers who initially perceive the association as incongruent, managers should sponsor events that do not share a natural fit with the brand without jeopardizing their marketing performance. However, we recommend that they reserve a substantial budget to explicate their fit with the sponsored event and that they should do so early in the campaign. Finally, our results encourage sponsors to focus their efforts on consumers involved in the event or those with a positive attitude toward sponsorship. Sponsors and event organizers should implement early communication activities to boost consumer involvement and attitudes toward sponsorship in a similar manner as efforts by the International Olympic Committee to place press advertisements that extoll the principles of Olympians and their support by sponsors (Mazodier, Quester, & Chandon, 2012).

Despite the validity of the benefits offered by LGM and the robustness of the results it yields, to the best of our knowledge, this study represents its first application in a marketing communications context. This study offers a potentially critical methodological contribution. Beyond sponsorship research, we find no reported studies that use LGM to investigate changes in consumer attitude or beliefs in response to other types of marketing communications such as advertising, promotions, or public relations. Although it is a resource-intensive methodology, particularly in terms of sample requirements, conclusive results can emerge from the application of LGM to data collected over several consecutive dates. We hope our successful research application prompts a richer, more prolific body of empirical work with respect to LGM in marketing communications contexts.

7. Limitations and directions for further research

This research focuses on sponsorship-linked marketing effects and does not compare the impacts of different sponsorship-linked marketing activities, such as televised
commercials, print advertisements, or packaging. This type of comparative assessment represents a clear avenue for ongoing research. This study does not compare other event-related communication strategies, such as advertising or ambush marketing. The lack of research that compares the returns with respect to communication alternatives is a common criticism (Olson & Thjomøe, 2009).

LGM is not without limitations. The nature of the data that it demands restricted our study to two events in two countries with two familiar brands. This restriction clearly and intrinsically limits the external validity of our findings. For example, Dahlen and Lange (2004) suggest that incongruent advertising–media associations have a more positive influence than congruence among individuals who are familiar with the source, but Zdravkovic et al. (2010) demonstrate that brand familiarity does not moderate the relationship between fit and brand attitude. We hope further investigations confirm the role of incongruence resolution for sponsorship effectiveness in relation to unfamiliar brands.

Our results also demonstrate that Sony and EDF’s sponsorship activation improved the initial levels of perceived incongruence. Further research should assess the effects of several different communication strategies (number of repetitions, creative content) that are used to resolve perceived incongruence. Moreover, researchers might study the effects of sponsorship activation that fails to resolve incongruence. Jagre and colleagues (2001) suggest that unsuccessful incongruence resolution leads to negative attitudes toward the sponsor. Finally, due to resource constraints, we collected data at three consecutive times only, precluding the use of more sophisticated logistic or quadratic models to describe and explain intra-individual changes over time. Memory decay following a change in sponsor (Quester & Farrelly, 1998) might be tracked more effectively and elucidated more fully with additional data collections following the event.
Both studies exhibited a high degree of convergence in support of our hypothesized model. The two studies concur in their demonstration that extreme incongruence enhances changes in brand affect. However, in Study 1, this process occurred through a change in perceived fit, whereas in Study 2, the effect was direct, from initial fit to brand affect. Although these findings might be a result of our use of co-variances to determine the effects, the issue of low initial perceived fit translation into greater brand affect, either directly or indirectly through fit, represents an interesting avenue for research. Sponsors would benefit from an awareness of a minimum threshold of initial fit that must exist to ensure an eventual impact of their incongruent sponsorships. Controversial sponsors, such as tobacco or whiskey brands, may not achieve the formation of positive evaluation (Ruth & Simonin, 2003). The examination of cases with an initial fit that is lower than the values we identified in this study (i.e., slightly below the median on a 1 to 7 scale) would help clarify this issue.

Other applications of LGM to marketing contexts include a closer examination of the variables that influence the link between fit and brand affect. This application would provide marketing insights concerning the long-term effects of different types of advertising appeals, from brand positioning to consumer responses to marketing campaigns, all of which can be answered more rigorously through the use of LGM.

This research broadens the understanding of the fit construct and its role in sponsorship-linked marketing. Incongruence resolution appears critical to sponsorship effectiveness, and sponsorship-linked marketing must communicate to consumers the sponsor’s fit with the event. Further research should determine the most efficient marketing communications to increase fit perceptions according to consumer characteristics. These findings can assist managers to create more effective sponsorship programs that translate into stronger brand affect.
REFERENCES


Figure 1
Multivariate SOF LGM model

Notes: B.A. = brand affect; A.S. = attitudes toward sponsorship; E.I. = event involvement.
In this figure, we do not show the covariances between error terms for the y values.
Figure 2
The role of sponsorship fit in brand affect change caused by sponsorship-linked marketing activities (study 1)
Figure 3
The role of sponsorship fit in brand affect change caused by sponsorship-linked marketing activities (study 2)
<table>
<thead>
<tr>
<th>Variable</th>
<th>Model</th>
<th>Change Function</th>
<th>First-Order Function</th>
<th>Residual Structure</th>
<th>$\chi^2$</th>
<th>df</th>
<th>CFI</th>
<th>NNFI</th>
<th>SRMR</th>
<th>RMSEA</th>
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<td>.98</td>
<td>.071</td>
<td>.091</td>
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<td>.99</td>
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* Retained (most parsimonious model).

*** $p<.001$. ** $p<.01$. * $p<.05$.

Notes: CFI = confirmatory fit index; NNFI = non-normed fit index; SRMR = square root mean residual; RMSEA = root mean square error.
### Table 2
Univariate SOF latent growth models: Test of alternative specifications (study 2)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model</th>
<th>Change Function</th>
<th>First-Order Function</th>
<th>Residual Structure</th>
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<th>df</th>
<th>CFI</th>
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<td>Model 4</td>
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$^a$ Retained (most parsimonious model).

*** $p<.001$. ** $p<.01$. * $p<.05$.

Notes: CFI = confirmatory fit index; NNFI = non-normed fit index; SRMR = square root mean residual; RMSEA = root mean square error.
## Appendix A. Descriptive statistics and correlations of study variables.

### Study 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
<th>SD</th>
<th>Rho</th>
<th>AVE</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<tr>
<td><strong>2. Brand affect/T1</strong></td>
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<td>1.54</td>
<td>.96</td>
<td>.90</td>
<td></td>
<td>.21**</td>
<td>1.00</td>
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</tr>
<tr>
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<td>2.22</td>
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<td>.95</td>
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<td></td>
<td>.25**</td>
<td>.14**</td>
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<tr>
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**p<.01, *p<.05.**

### Study 2

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<td>.04</td>
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**p<.01, *p<.05.**
Appendix B. Equations of the model

Measurement model: Equations for $x$ and $y$.

\[
x_i = \tau_i^x + \xi_1 \left( \frac{\lambda_{i=2.1}}{\lambda_{i=3.1}} \right) + \delta_i \quad i = 1, \ldots, 3
\]

\[
x_i = \tau_i^x + \xi_2 \left( \frac{\lambda_{i=5.1}}{\lambda_{i=6.1}} \right) + \delta_i \quad i = 4, \ldots, 6
\]

\[
y_i = \tau_i^y + \eta_1 \left( \frac{\lambda_{i=2.1}}{\lambda_{i=3.1}} \right) + \epsilon_i \quad i = 1, \ldots, 3
\]

\[
y_i = \tau_i^y + \eta_2 \left( \frac{\lambda_{i=5.1}}{\lambda_{i=6.1}} \right) + \epsilon_i \quad i = 4, \ldots, 6
\]

\[
y_i = \tau_i^y + \eta_3 \left( \frac{\lambda_{i=8.1}}{\lambda_{i=9.1}} \right) + \epsilon_i \quad i = 7, \ldots, 9
\]

\[
y_i = \tau_i^y + \eta_6 \left( \frac{\lambda_{i=11.1}}{\lambda_{i=12.1}} \right) + \epsilon_i \quad i = 10, \ldots, 12
\]

\[
y_i = \tau_i^y + \eta_7 \left( \frac{\lambda_{i=14.1}}{\lambda_{i=15.1}} \right) + \epsilon_i \quad i = 13, \ldots, 15
\]

\[
y_i = \tau_i^y + \eta_8 \left( \frac{\lambda_{i=17.1}}{\lambda_{i=18.1}} \right) + \epsilon_i \quad i = 16, \ldots, 18
\]

In these equations, $x$ and $y$ refer to observed variables; $\xi$ and $\eta$ represent latent variables; $\tau$ indicates means or intercepts; $\lambda$ refers to regression coefficients for the effects of the latent variables on the observed variables; and $\delta$ and $\epsilon$ are (random) error terms.
Structural model: equations for $\xi$ and $\eta$

$$\xi_i = \kappa_i + \phi_{bi} \quad i = 1, 2$$

$$\eta_i = \alpha_i + \eta_i + \xi_1$$
$$\eta_2 = \alpha_2 + \eta_4 + \eta_5 + \xi_2$$
$$\eta_3 = \alpha_3 + \eta_4 + 2\eta_5 + \xi_3$$
$$\eta_4 = \alpha_4 + \xi_4$$
$$\eta_5 = \alpha_5 + \gamma_{5,1}\xi_1 + \gamma_{5,2}\xi_2 + \xi_5$$
$$\eta_6 = \alpha_6 + \eta_9 + \xi_6$$
$$\eta_7 = \alpha_7 + \eta_9 + \eta_{10} + \xi_7$$
$$\eta_8 = \alpha_8 + \eta_9 + 2\eta_{10} + \xi_8$$
$$\eta_9 = \alpha_9 + \xi_9$$
$$\eta_{10} = \alpha_{10} + \gamma_{10,1}\xi_1 + \gamma_{10,2}\xi_2 + \xi_{10}$$

In these equations, $\xi$ and $\eta$ are latent variables; $\kappa$ and $\alpha$ represent means or intercepts; $\gamma$ refer to regression coefficients for the effects of $\xi$ on $\eta$; $\xi$ indicate (random) error terms; and $\phi$ are variances associated with $\xi$.

The four covariance matrices are

$$\Theta_\delta = \begin{bmatrix}
\theta_{1,1}^\delta & 0 & 0 & 0 & 0 & 0 \\
0 & \theta_{2,2}^\delta & 0 & 0 & 0 & 0 \\
0 & 0 & \theta_{3,3}^\delta & 0 & 0 & 0 \\
0 & 0 & 0 & \theta_{4,4}^\delta & 0 & 0 \\
0 & 0 & 0 & 0 & \theta_{5,5}^\delta & 0 \\
0 & 0 & 0 & 0 & 0 & \theta_{6,6}^\delta
\end{bmatrix}$$

where $\Theta_\delta$ is the variance/covariance matrix of error terms in the equations for $x$;
where $\Theta_y$ is variance/covariance matrix of error terms in the equations for $y$;

$$
\Phi = \begin{bmatrix}
\phi_{1,1} \\
0 & \phi_{2,2}
\end{bmatrix}
$$

where $\Phi$ is the variance/covariance matrix of $\xi$ and $\eta$.

$$
\Psi = \begin{bmatrix}
\varphi_{1,1} \\
0 & \varphi_{2,2} \\
0 & 0 & \varphi_{3,3} \\
0 & 0 & 0 & \varphi_{4,4} \\
0 & 0 & 0 & 0 & \varphi_{5,5} \\
0 & 0 & 0 & 0 & 0 & \varphi_{6,6} \\
0 & 0 & 0 & 0 & 0 & 0 & \varphi_{7,7} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \varphi_{8,8} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \varphi_{9,9} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \varphi_{10,10}
\end{bmatrix}
$$

where $\Psi$ is the variance/covariance matrix of error terms in the equations for $\eta$.

The fifth variance/covariance matrix, $\Theta_{\delta\delta}$, is a zero matrix.