PRICE PROMOTIONS AND POPULAR EVENTS

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PRICE PROMOTIONS AND POPULAR EVENTS

Abstract

Managers often use popular events, such as the Olympics, to advertise their brands more heavily. But can manufacturers and retailers also capitalize on these events to enhance the response to their price promotions? This study empirically examines whether the sales response to price promotions is stronger or weaker around events than at non-event times, and what factors drive this relative promotion response. Studying 242 brands from 30 CPG categories in the Netherlands over more than four years, the authors find that a price promotion offered around a popular event often generates a stronger sales response than the same promotion at non-event times, with a price promotion elasticity that is 9.3% larger, on average, during events. Still, the variance in relative promotion response across brands and events is high, and the authors identify several drivers that managers should consider before shifting promotions towards event times. Currently, managers often do not take these drivers into account. This study provides guidelines how to improve promotional timing decisions in relation to popular events.

Keywords: price promotion, popular event, promotion calendar, sales response
Introduction

Marketing campaigns linked to popular events, such as soccer championships, the Olympics, or the Eurovision Song Contest, are quite common. The events draw attention and provide entertainment, and thus, present an opportunity for firms to engage in marketing activities that seek to generate larger profits. Many firms use this opportunity to intensify advertising for their brands. For instance, Gijsenberg (2014a) finds that advertising spendings for national brands of consumer packaged goods (CPG) in the U.K. are 25% higher around major sport events, even though advertising elasticities are smaller than at non-event times. Some firms also use popular events for more intense promotion activities. Kellogg’s, for instance, launched the “Feast of Football” campaign in the U.K., featuring price promotions on product packages, to capitalize on the 2010 Soccer World Championship. In Germany, Haribo offered “Fan Gums Brazil” around the 2014 Soccer World Championship, and Powerade heavily promoted their sports-bottle during the 2012 London Summer Olympics.

Sales promotions constitute large parts of CPG manufacturers’ total marketing budget, e.g., 55% in the U.S. (Cadent Consulting Group 2017), and extant research shows that price promotions lift brand sales substantially (Bijmolt, van Heerde, and Pieters 2005). But should companies concentrate their price promotions around such events, or focus instead on other periods? And how does this vary across brands and events? To the best of our knowledge, the sales response to promotions around popular events relative to non-event times has not been analyzed systematically so far.

In this study, our key focus is on the difference between the sales response to price promotions during events and the response at non-event times, which we refer to as ‘relative promotion response’. Upfront, it is not obvious whether relative promotion response is positive (i.e., stronger response during events) or negative (i.e., weaker response during
events). On the one hand, promotions can benefit from an association with the event. E.g., the event theme can draw attention to the promotion and the brand, transfer the positive image and emotions of the event to the brand, and provide opportunities for targeting specific customer groups. On the other hand, it may be harder for promotions to stand out around popular events. Consumers are exposed to even larger amounts of commercial and non-commercial information that time (Gijsenberg 2014a), making it more difficult for an individual marketing action to get noticed. Moreover, relative promotion response likely varies across brands and events, so it is interesting to understand what factors drive these differences. For instance, relative promotion response may differ according to the fit between the event and the brand’s product category, and integration of price promotions with advertising may work differently during events (when they are linked by a common event theme) than at non-event times.

This study addresses two main research questions. First, we examine if short-term sales response to price promotions is stronger or weaker around popular events than at non-event times (relative promotion response). Second, we study which factors drive this relative promotion response. We focus on temporary price reductions as the most frequently used type of promotion in the CPG industry. To answer these research questions, we analyze household panel data for 242 brands from 30 CPG categories over more than four years at the four largest HiLo grocery retailers in the Netherlands. We examine these brands’ promotions in relation to the five most popular sports and cultural events as perceived by the Dutch population during that period. These events are featured intensively in the national media.

In the next section, we review relevant literature, after which we present our research framework and derive hypotheses about the drivers of relative promotion response in relation to events. Next, we describe our data, model-free evidence and method, before reporting the
results. We close with a summary and discussion of implications for managers and researchers.

**Literature**

While popular events have been the focus of many studies in the area of advertising and sponsoring (e.g., Cornwell, Pruitt, and Clark 2005; Yelkur, Tomkovich, and Tracyk 2004), few studies have linked these events to price promotions. Still, two streams of research on price promotions are particularly relevant to our work. First, research on the *timing of promotions* or the ‘promotion calendar’ offers insights into how retailers and/or manufacturers should schedule price promotions for a brand relative to promotions (i) by competing brands (e.g., Anderson and Song 2004; Freimer and Horsky 2008; Tellis and Zufryden 1995), (ii) at competing retailers (Guyt and Gijsbrechts 2014), and (iii) in related product categories (Mehta and Ma 2012; Mulhern and Leone 1991). It shows that sales response to promotions is lower when more competing brands or retailers promote at the same time (e.g., Anderson and Song 2004; Guyt and Gijsbrechts 2014). But it does not study promotion timing and competitive effects in the context of popular events. Accordingly, these studies report on the negative effect of promotion clutter, which is likely stronger during events, but do not capture potential positive effects of events due to, for instance, the opportunities for gaining attention, improving brand image, and better targeting.

Second, the promotion literature has examined price patterns and sales response in relation to *seasonal or holiday demand cycles*. It finds that prices tend to fall during demand peaks related to weekends, holidays, and weather-related seasons (e.g., Chevalier, Kashyap, and Rossi 2003; MacDonald 2000; Warner and Barsky 1995). Warner and Barsky (1995) argue that in periods with high demand, like weekends, consumers are more vigilant and better informed about prices since they have more time to shop, which makes them more
responsive to prices that time. Another explanation for lower prices during peak demand seasons are more retailer-advertised discounts (Chevalier, Kashyap, and Rossi 2003). Only Chevalier, Kashyap, and Rossi (2003) empirically measure consumer price sensitivity during seasonal demand peaks (i.e., over Thanksgiving and Christmas) and compare it to the sensitivity at other times. For the majority of their products, the authors find no difference in price response between these periods. Unlike Chevalier and colleagues (2003), our study focusses on popular media events. Price promotion response around popular events likely differs from that during (regular) seasonal occasions: Intensive media coverage draws more attention to the event, emotional and affective response to events is stronger, and more precise targeting opportunities exist around events than for regular seasonal promotions. At the same time, consumers do not necessarily have more shopping time during popular events as with traditional holiday periods to look out for deals, and not all product categories experience demand peaks around popular events.

So far, only Gijsenberg (2014a) measured relative sales response to prices in relation to popular events. But his focus is on advertising (not price), and his analysis at the aggregate (national) level is less suited for evaluating promotion response where most of the activity and competitive effects occur at the retail level. Furthermore, he studies only category-event fit as a potential driver of relative advertising response around events, but no drivers of relative price response.

Overall, previous research offers little guidance whether and how promotion response differs around popular events compared to non-event times, and for what brands and events this is the case. We therefore follow the call by Gijsenberg (2014b) for more research into the differential effectiveness of marketing activities in relation to popular events.
Research Framework

Relative Promotion Response in Relation to Popular Events

Whether sales response to promotions is stronger or weaker around popular events than at other times is not obvious and arguments exist in both directions. On the one hand, brands can take advantage of unique event association opportunities when scheduling their promotions at the time of an event. The event theme provides a “hook” that grabs consumers’ attention, and brands can integrate this theme into their promotions through supporting materials like displays, feature ads, and/or packaging. The association with an event provides several opportunities. First, the intense atmosphere and feelings surrounding an event enables a transfer of both the attention and the event’s image to the promoted brand (Escalas, Moore, and Edell Britton 2004; Keller 2003). This strengthens the position of the brand in consumers’ mind, resulting in a higher purchase intention (Morris et al. 2002) and more salience of its promotion messages (Gijsenberg 2014a). Second, better possibilities arise around a popular event to reach specific target groups, because it appeals to particular audiences that are heavily involved in the event. For example, Beiersdorf intensively promotes its ‘Nivea for Men’ line of cosmetics around soccer championships, to target adult men, who are otherwise hard to reach (personal interview with Beiersdorf manager). Third, demand in some categories expands during an event, e.g., consumers buy more beer and chips during soccer championships. When category demand increases, there is more to gain from shifting promotions towards the event because the same (percentage) lift in sales will result in a larger absolute sales gain, which does not necessarily come at the expense of competing brands or retailers (Chevalier, Kashyap, and Rossi 2003). Moreover, when demand peaks, shoppers with a weaker attachment to the category who have a larger responsiveness to price cuts may enter the market (MacDonald 2000).
On the other hand, around events, it may be harder for promotions to *stand out.* Consumers are overwhelmed by impressions and information related to the event, stemming from both intensive media coverage of the event and the numerous event-related marketing messages that time (Eastlick, Feinberg, and Trappey 1993; Gijsenberg 2014a). This may result in information overload (Edmunds and Morris 2000; Schick, Gordon, and Haka 1990). In such an environment, it is harder for a brand to grab consumers’ attention with promotions. Moreover, when a large number of brands associate with the same event theme, consumers can be confused and it is more difficult for brands to create a distinct and clear message. Whether the benefits from event associations outweigh these negative effects from difficulties to stand out during events is hard to predict upfront, and we leave it as an empirical question.

**Drivers of Relative Promotion Response**

Previous research has extensively studied drivers of *absolute* promotion response (see Bell, Chiang, and Padmanabhan 1999 for a review). However, our main interest is in drivers of *relative* promotion response, i.e., the difference in promotion response between event and non-event times. We examine four drivers that are stable characteristics of events and brands: category-event fit, event sponsorship by a brand, brand leadership, and brand price premium. In addition, we study two context factors – promotion clutter and supporting advertising by the manufacturer – that vary over time (and over retailers). Sales response to promotions likely changes as a function of the context in which a promotion is offered. In this study, we evaluate if (and how) the impact of the context factors on promotion response differs between event versus non-event times. Table 1 summarizes our expectations about the six drivers. A driver is associated with a ‘higher’ ('lower') relative promotion response if the difference between price promotion response during events and its response at non-event times becomes larger (smaller) with larger values of the driver, irrespective of its sign (e.g., a negative...
difference – signaling weaker promotion response during events than at other times – may
become smaller or even turn positive with higher relative promotion response).

--- Insert Table 1 about here ---

Category-event fit. If the fit between a brand’s product category and the event is higher,
the brand has better event association opportunities. It should be easier for brands from
categories with a better event fit to link promotions to the event and transfer the event image
to the brand. Also better opportunities arise for targeting specific consumer segments
interested in both the event and the category, and demand expansion in the category is likely
stronger with a better category-event fit. Previous research shows that better fit improves
consumer response in many contexts, including brand extensions (e.g., Aaker and Keller
1990; Bhat and Reddy 2001), advertising with testimonials (e.g., Kamins and Gupta 1994),
cause-related marketing (e.g., Pracejus and Olsen 2004), and sponsoring (e.g., Speed and
Thompson 2000). Similarly, we expect:

H1: Relative promotion response is higher when there is a better fit between the
category and the event.

Event sponsorship. We expect brands that are an official sponsor of an event to benefit
more from promoting around the respective event. Relative promotion response should be
larger than for non-sponsoring brands because of better event association opportunities and
an enhanced ability to stand out. Event sponsorship is not only communicated through
various marketing activities by the brand itself, but the event also prominently features its
official sponsors repeatedly in the media and at the event itself. The strong connection
between a sponsoring brand and an event may facilitate a transfer of the event image to the
promoted brand (Cornwell, Pruitt, and Clark 2005; Keller 2003). Sponsoring also makes the
brand and its promotion activities more salient and consumers are more likely to notice the
sponsoring brand’s promotion in the store among similar competing offerings of non-
sponsoring brands (Bal, Quester, and Plewa 2009). Since these benefits only arise at event times, we expect:

\[ H_2: \text{Relative promotion response is higher when the brand is an official event sponsor.} \]

**Brand leadership.** Brand leaders have the largest market share in the product category. We expect brand leaders to have a higher relative promotion response than non-leading brands due to their enhanced ability to *stand out*. Brand leaders acquire more and better shelf space (Hoch, Dreze, and Purk 1994) and possess greater market power over retailers (Ailawadi et al. 2006). This materializes in preferred promotion support by the retailer compared to smaller competitors. Such a preferential treatment is especially important during popular events, when consumers are overwhelmed with different commercial and non-commercial messages resulting in information overload (Jacoby 1984). Thus, brand leaders are in a better position to benefit from popular events, and we expect:

\[ H_3: \text{Relative promotion response is higher when the brand is a brand leader.} \]

**Brand price premium.** We expect brands with a higher price premium over private labels in the product category to have a higher relative promotion response because of better *event association opportunities* and a higher ability to *stand out*. Such brands enjoy higher brand equity (Ailawadi, Lehmann, and Neslin 2003). They can be clearly distinguished from competing offerings, and enjoy a more exclusive image to target high-end market niches (Pauwels 2007). Therefore, premium-priced brands should find it easier to stand out during events. Moreover, their exclusive brand image may be more congruent with the unique event image, and premium brands should derive more opportunities for image transfer from event associations (Ailawadi, Lehmann, and Neslin 2003). Thus, we expect:

\[ H_4: \text{Relative promotion response is higher for brands with a larger price premium.} \]
Promotion clutter. Clutter in this study refers to the promotion activity by competing brands in the product category at the same retailer. In line with Danaher, Bonfrer, and Dhar (2008), it captures both promotion frequency (i.e., the number of competing brands with promotions) and promotion depth (i.e., the depth of these competitive price cuts). In an advertising context, several studies affirm that advertising clutter lowers recall and recognition (e.g., Burke and Srull 1988; Kent and Allen 1993; Riebe and Dawes 2006) as well as the sales impact of advertising (e.g., Danaher, Bonfrer, and Dhar 2008). Similarly, more and/or deeper promotions by competitive brands at the same retailer can diminish the response to the focal brand’s price promotions (Guyt and Gijsbrechts 2014). But are these clutter effects different around events than at non-event times? We expect the effect of clutter on promotion response to be especially problematic during events because a promotion’s ability to stand out is lower due to the abundance of event-related (commercial and non-commercial) communications that time. Also, often other brands and categories build on the same event theme for their promotions, which may lead to contextual interference, and in turn, to brand confusion (Kumar 2000, Kumar and Krishnan 2004, Poiesz and Verhallen 1989). In contrast, even with many competing promotions, brands engage in more unique marketing actions and can better differentiate their promotions at non-event times. Therefore, we expect:

H5: The interaction between promotion clutter and price promotions is less favorable around popular events than at non-event times.

Supporting advertising. Previous research has shown that there can be positive or negative interaction effects when combining price promotions and advertising in the same period (e.g., Naik, Raman, and Winer 2005). Either way, price promotion response likely changes with supporting advertising by manufacturers. We expect that the interaction between the two tools is more favorable around popular events than at non-event times as
both marketing instruments can build on the same event theme. When manufacturers advertise their brands during events, they typically also pick up the event theme (McKelvey, McDonald, and Cramer 2005). With both advertising and promotions building on the event theme, better event association opportunities arise, in the sense that, for example, affective response to the event and the event image can be transferred more easily (Keller 2003). Moreover, advertising for a brand makes the corresponding price promotion more salient to consumers and hence, helps the brand stand out against many other promotions without advertising support. This is especially important during event times. We therefore expect:

$$H_6:$$ The interaction between advertising and price promotions is more favorable around popular events than at non-event times.

**Data**

We study price promotions in the Dutch CPG sector between January 2007 and April 2011, combining information from various data sources. First, we use Dutch consumer panel data collected by GfK. Our data contains detailed purchase records from all household panel members made at the four largest HiLo retailers in the Netherlands between January 1, 2007 and April 1, 2011. The retailers vary in price positioning, service level, and extent of promotion activity, with Albert Heijn (33.6% value market share in 2010) scoring high on price and service, Plus (6%) having intermediate price and service levels, and C1000 (11.5%) as well as Jumbo (5.5%) having relatively low prices but reasonable service (Sotgiu and Gielens 2015; van Lin and Gijsbrechts 2016). They collectively cover 56.6% of the Dutch grocery market in 2010, based on value sales (Distrifood 2013).

We examine 30 CPG product categories that include various food and non-food products. These categories are not dominated by discounter (i.e., discounter have a combined volume market share in the Netherlands < 30%), and have at least two brands that meet our brand selection criteria. In Table 2, we present the categories, arranged in broad
category groups. Within these 30 categories, we examine 242 brands whose volume market shares during the data period exceed 3%, that were available for purchase in at least two retailers,\(^1\) and for which we could gather at least one observation (brand-retailer-week combination) with a price promotion during a quarter in which an event occurs. Following Nijs, Srinivasan, and Pauwels (2007), we define a brand-retailer-week combination as a promotion if the actual brand price in a week shows a negative price shock of at least 5% below the brand’s regular (non-promoted) price (defined as the maximum price observed in the most recent four weeks; see Table 4).

--- Insert Table 2 about here ---

A second key data input for this study is the choice of popular events. We consider large sports and cultural events with the following characteristics: (i) the event is featured in the Dutch national media; (ii) it is highly popular among the Dutch as determined by TV viewing rates (all events have >10% viewers among the total population); and (iii) it is recurring yearly or over multiple years. Based on these criteria, we identify five popular events that took place between January 2007 and April 2011 (see Web Appendix W1): speed skating championships (European and World Championships), soccer championships (European and World Cup), the Summer Olympics, the Winter Olympics, and the Eurovision Song Contests. We combine the soccer championships (European and World) and speed skating events (European and World) into one event each, but treat the Summer and Winter Olympics as separate events because of their different seasonal timing and their potential to attract a different target audience. Soccer Cups are the most popular events in the Netherlands, and the

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1 When we observed no transactions for a brand in a given week at a given retailer, we dropped this brand-retailer-week combination from the analysis. Further, we dropped brands with more than 100 retailer-week combinations where no sales were observed.
Summer Olympics and the European Song Contest the least popular among our five events. Except for the Summer and Winter Olympics, the events repeat during our data period.

Third, we acquired weekly TV advertising expenditures (in Euro) by manufacturers in the Netherlands from Nielsen for each brand over our four-year data period.

Fourth, to measure category-event fit, we designed a questionnaire that was completed in May 2012 by over 1,000 participants in the GfK online panel. Each respondent evaluated two product categories, randomly chosen out of the 30 categories. Per category, we received between 45 and 82 responses from consumers who had made at least one purchase in the category during the previous six months.

Finally, we collected information on brands’ event sponsorship from the event organizers’ websites and other sources, such as company and brand websites.

**Model-Free Evidence**

We provide first insights into promotion response by comparing the average lift in brand sales due to promotions during events to the lift in non-event times. To distinguish between event versus non-event weeks, we take into account that an event’s atmosphere and attention builds up even before the actual event, and brands may already capitalize on this increased media attention to offer promotions. Specifically, we use the term “event weeks” to refer to the weeks in which the event takes place plus the two weeks prior to it. All other weeks are “non-event weeks”. This approach is consistent with earlier work on advertising and popular events (see Gijsenberg 2014a) and avoids an underestimation of relative promotion response (Doyle and Saunders 1985).

Table 3 provides model-free evidence on the promotional lift across all events and for each of the five events separately. We determine the sales lift for each brand-retailer combination as the brand’s average weekly sales volume at the retailer during weeks with a
promotion divided by its average weekly sales volume at that retailer in non-promotion weeks. It is derived separately for event weeks and non-event weeks during the same quarter. The values reported in Table 3 are means across the brand-retailer-week combinations.

--- Insert Table 3 about here ---

Table 3 shows that during non-event weeks, price cuts are very effective. The average lift in brand sales is 3.45. I.e., on average, sales during a promotion week are 3.45 times the sales in comparable weeks (in the same quarter) without a promotion. More interestingly, the promotional sales lift is 3.90, on average, in event weeks, which is 13% higher than in non-event weeks. But there are clear differences across events. Sales lifts range from 2.68 for promotions during the Summer Olympics to 5.44 during Winter Olympics. Table 3 further shows that supporting advertising and promotion clutter are not always higher during events, although we see an increase in both during soccer cups. To formally compare sales response to promotions in both periods while controlling for these and other drivers of brand sales and promotion response, we build a hierarchical linear model (HLM) (Bryk and Raudenbush 1992) where promotion response is allowed to differ between event and non-event times.

**Method**

**Model specification**

We pool all observations across weeks, brands, and retailers, and estimate a HLM with two levels. At level 1, the HLM includes all time-varying independent variables that are nested within brands and events. In line with the promotion literature (e.g., Macé and Neslin 2004, van Heerde, Leeﬂang, and Wittink 2004), we model a brand’s volume sales by week and retailer as a multiplicative function of the brand’s own and competitive prices, events and other independent variables that vary across time (and retailers). The multiplicative model allows us to interpret the price coefficients as elasticities. At level 2 of the HLM, we add
independent variables that are constant over time and retailers but vary across brands and events to explain the variance in the key parameters of the level 1 model. To test our hypotheses on drivers of relative promotion response, we include the four drivers that are constant over time in level 2 of the model, while the context factors advertising and promotion clutter that vary over time (and retailers) are part of the level 1 equation.

For expositional clarity, we present the model in separate equations for each level before integrating them into the actual estimation equation (cf. Raudenbush and Bryk 2002). Also, in Equation 1, we split up the exponent of the price index variable PI into two separate terms to make clear which estimates capture relative promotion response, i.e., how price elasticity is different at event versus non-event times. We provide details on all variables in the model in Table 4 and Web Appendix W2. Following Raudenbush and Bryck (2002), we group-mean-center all continuous level 1 predictors by brand and grand-mean-center all continuous level 2 predictors.

\begin{equation}
S_{irt} = e^{\beta_{0,i}} \cdot \prod_{n=1}^{n} P_{1,n}^{\text{Devent}_{nt}} \cdot P_{irt}^{[\beta_{2,i} + \beta_{3} \ln(\text{ADV}_{it}) + \beta_{4} \ln(\text{CLUT}_{irt})]} \cdot P_{irt}^{[\beta_{5,i} \ln(\text{Devent}_{t}) + \beta_{6} \ln(\text{ADV}_{it}) \cdot \text{Devent}_{t} + \beta_{7} \ln(\text{CLUT}_{irt}) \cdot \text{Devent}_{t}]} \cdot \text{ADV}^{\beta_{8}} \cdot \text{CLUT}^{\beta_{9}} \cdot \text{Preg}_{irt}^{\beta_{10}} \cdot \text{cPIrets}^{\beta_{11}} \cdot \text{ASS}_{irt}^{\beta_{12}} \cdot \prod_{w} (P_{irt-w}^{\beta_{13,w}}) \cdot \text{Dxmas}^{\beta_{14}} \cdot \text{Deaster}^{\beta_{15}} \cdot \text{trend}^{\beta_{16}} \cdot \text{Pret}^{\beta_{17}} \cdot \prod_{q} (\beta_{18,q}^{\text{Dquart}_{qt}}) \cdot \prod_{r} (\beta_{19,r}^{\text{Dret}_{rt}}) \cdot \prod_{c} \text{copPRI}_{cirt}^{\beta_{20,c}} \cdot e^{u_{irt}}.
\end{equation}

where the indices \(i, r,\) and \(t\) represent brands, retailers, and weeks, respectively. The random error term \(u_{irt}\) is assumed to be normally distributed with zero mean and variance \(\sigma^2\).

\textit{Price promotion response.} A focal independent variable in the level 1 model is the price index \(PI\). To determine \(PI\), we divide a brand’s actual price by its regular (baseline)
price at the respective retailer, so that PI is comparable across retailers. The index captures
price promotions and not price differences across brands, since we control for regular price,
Pred (Jedidi, Mela, and Gupta 1999). This regular price is derived over a four week rolling
window to account for gradual changes in the non-promoted price over time (see Table 4 and
Web Appendix W2). The first PI term in Equation 1 captures promotion response during non-
event times. The coefficient $\beta_{2,i}$ is the short-term promotional price elasticity when $\ln(ADV)$
and $\ln(CLUT)$ are at their means (which is zero given mean-centering), and all variables in
Equation 2b are zero (see later). $\beta_{2,i}$ should be negative if price cuts (i.e., lower PI) raise brand
sales. This baseline promotion elasticity can change for different values of ADV and CLUT
through the coefficients $\beta_3$ and $\beta_4$. Positive (negative) estimates reflect a weaker (stronger)
response to promotions for higher values of ADV or CLUT.

Our main interest is in the difference in promotion response between event and non-
event times. This relative promotion response is captured by the interactions between PI and
the event dummy Devent in the second PI term in Equation 1. Devent is 1 for event weeks, and
0 in all non-event weeks. The interaction coefficient $\beta_{5,in}$ informs on the difference in price
promotion elasticity around popular event $n$ (compared to non-event times) when $\ln(ADV)$ and
$\ln(CLUT)$ are at their means (i.e., zero), and the predictors in Equation 2b are also zero. A
negative (positive) value for this baseline relative promotion response indicates that sales
response to price promotions is stronger (weaker) during events than at non-event times, i.e.,
the absolute value of the negative price elasticity becomes larger (smaller). We hypothesized
in H5 and H6 that the effects of supporting advertising and promotion clutter on promotion

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2 Unlike the main effects of ADV and CLUT, the interactions between PI and ADV / CLUT in Equation 1
include the log-transformed variables $\ln(ADV)$ and $\ln(CLUT)$. This way, the variables are consistent after we
linearize our multiplicative function for estimation (see also model estimation). For example, the advertising
terms become: $\ldots + \beta_3 \cdot \ln(ADV) \cdot \ln(PI) + \beta_6 \cdot \ln(ADV) \cdot \ln(CLUT) \cdot \ln(PI) + \ldots + \beta_8 \cdot \ln(ADV) \ldots$
response are different around events than at non-event times. This is captured by the coefficients $\beta_6$ and $\beta_7$ where positive (negative) values indicate that the interaction effects between price promotions and supporting advertising ($\beta_3$) or promotion clutter ($\beta_4$) are less (more) favorable around events than at non-event times. Note that we study the difference in short-term price promotion response between event and non-event times, and only control for the effect of promotions on future sales (see next).

**Control variables.** We control for the main effect of the events on brand sales through $\beta_{1n}$, $\beta_8$ captures the main effect of brand advertising on that brand’s sales, and $\beta_9$ is the main effect of (in-store) promotion clutter on brand sales. We also control for the impact of regular prices through $P_{\text{reg}}$, where the estimate $\beta_{10}$ is negative if higher prices lower brand sales. While our clutter variable already accounts for promotions by competing brands within the retailer (see Table 4), we further account for promotions by the focal brand at competing retailers through a competitive price index, $c_{\text{PIrets}}$ (Kopalle, Mela, and Marsh 1999; van Heerde, Leeflang, and Wittink 2004). The coefficient $\beta_{11}$ is positive if price cuts for the focal brand at other retailers (i.e., lower PI) hurt the brand’s sales at the focal retailer. The effect of retailers’ assortment breadth (ASS) on brand sales is captured by $\beta_{12}$. In line with van Heerde, Leeflang, and Wittink (2000), we account for potential stockpiling behavior and post-promotion dips in the weeks after a promotion by including a lag specification for PI over $w$ weeks. In order to capture these dynamic effects with the smallest possible number of lags, we set the maximum lag length to $w^* = 6$ and iteratively exclude the last lag if it is non-significant.\(^3\) Van Heerde, Leeflang, and Wittink (2000; 2004) find that a six-week lag length is sufficient for the vast majority of brands. Positive values for $\beta_{13}$ are consistent with a post

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\(^3\) The first $w$ weeks of our sample are dropped from the estimation sample as we cannot compute all lag variables for these observations.
promotion dip. We further use dummy variables to account for major holidays (Dxmas, Deaster), seasons (Dquart), and adverse economic conditions (Drec), and we add a trend variable (trend). Finally, differences in sales across retailers are captured by retailer fixed effects (Dret) and the copPRI terms refer to the copula-based variables to control for potential endogeneity in the price variables (see model estimation).

**Level 2** includes predictors that vary across brands and/or events:

(2a) \[ \beta_{0,i} = \gamma_{00} + v_{0,i}, \]

(2b) \[ \beta_{2,i} = \gamma_{20} + \gamma_{21} \cdot D_{.LEADER_i} + \gamma_{22} \cdot PRIPREM_i + \gamma_{23} \cdot D_{.NFOOD_i} + v_{2,i}, \]

(2c) \[ \beta_{5,in} = \Sigma_n (\gamma_{50,n} \cdot D_{.EVENT_i^n}) + \gamma_{51} \cdot EVTFIT_{in} + \gamma_{52} \cdot D_{.EVTPON_{in}} + \gamma_{53} \cdot D_{.LEADER_{i}} + \gamma_{54} \cdot PRIPREM_i + \gamma_{55} \cdot D_{.NFOOD_i} + v_{5,in}, \]

with indices \( i \) for brands and \( n \) for events. In Equation 2a, we account for the nested structure of the data and for unobserved brand-specific effects by including the random intercept \( v_{0,i} \).

Equation 2b models promotion response at non-event times (\( \beta_{2,i} \)) as a function of three drivers: (1) brand leadership (D.LEADER), (2) brand price premium (PRIPREM), and (3) differences between food and non-food categories (captured by D.NFOOD). More interesting is the effect of these drivers on relative promotion response, i.e., on the interaction between PI and events. Therefore, Equation 2c models \( \beta_{5,in} \) as a function of our drivers, i.e., characteristics of events and brands that are constant over time. In addition to the variables in Equation 2b, we include category-event fit (EVTFIT) and event sponsoring (D.EVTSPON), and the five event dummies (D.EVENT) allow relative promotion response to differ across our five events.

**Model estimation**

By substituting the level 2 equations into the level 1 equation, we arrive at a single estimation equation. To linearize this model, we take the logs of both sides of the equation (cf. Andrews
et al. 2008; van Heerde, Leeflang, and Wittink 2000). We then estimate the HLM with a maximum likelihood approach as implemented in the software R. Prices may be endogenous if managers adjust them based on expected demand, which may also differ around event times. To formally address endogeneity concerns for the price variables PI and Preg, we implement the instrument-free Gaussian copula approach that directly models the joint distribution of the potentially endogenous regressors and the error term through the control function term (see Park and Gupta 2012, Datta, Ailawadi, and van Heerde 2017). This approach requires that the price variables are non-normally distributed, which is the case for both price variables, as indicated by a Shapiro-Wilk test ($W_{PI} = .756, p < .01$ and $W_{Preg} = .998, p < .01$). We find that PI is endogenous, while the copula coefficient for Preg is not significant ($p > .10$), so we retain only the copula term for PI in our model.

**Model validity**

To test the validity of the model results, we consider multicollinearity issues, non-linear effects, and the explanatory power of our focal predictors.

*Multicollinearity.* All bivariate correlations among the predictors within each level are modest with no absolute value exceeding .3. This suggests that multicollinearity is not a problem.

*Non-linearity.* We test for non-linearity in the effects of the continuous event-related drivers in Equation 2c by adding squared terms. Likelihood ratio tests (Wooldridge 2010, p. 481) show a significant improvement in model fit when we add a squared term for the category-event fit variable ($\chi^2(1) = 8.39; p < .01$). We include this term in the final model.

*Model fit and predictive validity.* To test the explanatory power of our focal predictors, we build our model by successively adding blocks of predictors and comparing model fit. We start with a base model (Model 0) that includes only control variables and the main effects of
price promotions and events, but not the interactions between them. I.e., all coefficients of the second PI term in Equation 1 (β₆, and β₇, and all coefficients in Equation 2c that constitute β₅ₙₙ) are set to zero. Next, in Model 1, we add the interaction between PI and events (β₅ₙₙ), which we allow to vary by event type (D.EVENTₙ), but not by the hypothesized drivers of relative promotion response (β₆, β₇, and the coefficients in Equation 2c except for γ₅₀ₙ remain zero).

Finally, to arrive at our full model (Model 2), we introduce the effects of the potential drivers of relative promotion response, i.e., β₆, β₇, as well as the other predictors in Equation 2c. We apply likelihood ratio tests to check if model fit improves significantly when we add the predictors and move from Model 0 to Model 1, and from Model 1 to Model 2. We find significant improvements (p < .01) in both steps ($\chi^2(5) = 46.437$ if we add event-specific promotion effects in Model 1; and $\chi^2(8) = 98.301$ if we add the remaining drivers in Model 2).

This indicates that price promotion response indeed differs between event and non-event times, and that our drivers make a significant contribution to explaining the variance in relative promotion response.

To compare the predictive validity of the three models, we use three product categories as holdout and re-estimate our models on the remaining 27 categories. We use the model parameters to predict sales for the brands in our holdout categories. Overall, predictive validity is good, with a mean absolute percentage error (MAPE) of 13.187% for the full model (Model 2). Again, we find that prediction accuracy improves when we move from Model 0 to Model 1, and from Model 1 to Model 2. For more details, see Web Appendix W3.

**Model Results**

We present our model estimates in Table 5.⁴

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⁴ In Table 5 and in the text, we report our estimates for the linearized model. For dummy variables, these estimates correspond to the ln-transformed coefficients, which can easily be retransformed into the multipliers in
Control variables

The estimates for the event dummies, ln(β₁₅), capture the main effect of events on sales, i.e., the expansion (>0) or contraction (<0) in brand sales around the respective events for the mean level of ln(PI) (which is zero due to mean-centering). We find evidence for differences in brand sales levels between event and non-event times only for the skating events and the Winter Olympics (ln(β₁₁) = -.031, p < .01; ln(β₁₄) = -.061, p < .01). The respective multipliers β₁₁ and β₁₄ are .969 and .941, indicating that brand sales volume is 3.1% and 5.8% lower during these events than at non-event times.

Our results for the other control variables in level 1 of the HLM are plausible. The main effect of brand advertising on sales is significant and positive, but small (β₈ = .020, p < .01), which is common in CPG categories (Sethuraman, Tellis, and Briesch 2011). More clutter, i.e., more and/or deeper promotions by competing brands at the focal retailer, significantly reduces brand sales (β₀ = -.007, p < .01). We find a negative response to regular price (β₁₀ = -.987, p < .01). Also, price promotions for the focal brand at competing retailers (i.e., a lower competitive PI) reduce sales (β₁₁ = .037, p < .01). When the retailer’s assortment expands, the focal brand’s sales are lower (β₁₂ = -.173, p < .01). Furthermore, to examine post-promotion sales dynamics, we choose a lag specification with 4 weeks, since the lags for weeks 5 and 6 turned out insignificant (p > .10). Consistent with consumer stockpiling behavior and post-promotion dips, we find significant positive coefficients for the lagged PI variables that decay over time (β₁₃,₁ = .268, p < .01; β₁₃,₂ = .259, p < .01; β₁₃,₃ = .044, p > .10; β₁₃,₄ = .103, p < .01). The Christmas and Easter dummies have significant negative effects

--- Insert Table 5 about here ---

Equation 1. E.g., for the skating event dummy, the estimate is ln(β₁₁) = -.031, and the respective multiplier β₁₁ is exp(-.031) = .969.
\[ (\ln(\beta_{14}) = -0.059, p < 0.01; \ln(\beta_{15}) = -0.033, p < 0.05), \] indicating lower sales during those weeks. This is not surprising as many stores close for the holidays and families have time to travel and eat out. There is evidence for a negative trend in brand sales \((\beta_{16} = -0.035, p < 0.01)\), but sales do not vary systematically with aggregate economic conditions \((p > 0.10)\). Finally, there is some evidence for seasonal patterns \((\ln(\beta_{18,2}) = 0.033, p < 0.01; \ln(\beta_{18,4}) = -0.012, p < 0.10)\), and sales levels differ across retailers, with the highest sales at market leader Albert Heijn \((\ln(\beta_{19,2}) = 0.731, p < 0.01)\).

**Sales response to promotions during non-event times**

The response to price promotions during non-event times is captured by the first PI term in Equation 1. In our log-log specification, the intercept \(\gamma_{20}\) in Equation 2b captures the baseline promotional price elasticity during non-event times when all drivers of promotion response, i.e., \(\ln(\text{ADV})\) and \(\ln(\text{CLUT})\) as well as the independent variables in Equation 2b, are zero. Consistent with earlier work for CPG brands (Bijmolt, Van Heerde, and Pieters 2005), the estimate \(\gamma_{20}\) is negative and amounts to 

\[-1.226 (p < 0.01).\] Thus, a promotional price cut of 20% raises brand sales in the store by almost 25%, for mean values of \(\ln(\text{ADV})\), \(\ln(\text{CLUT})\), and \(\text{PRIPREM}\) in Equation 2b (given mean-centering), and for non-leading brands \((D.\text{LEADER}=0)\) that belong to a food category \((D.\text{NFOOD}=0)\).

However, the promotional price elasticity during non-event weeks varies according to some of our moderating variables. We find that the interaction between PI and advertising is insignificant \((p > 0.10)\). So while advertising has a positive main effect on brand sales, it does not make promotions at non-event times more or less effective. The interaction between PI and promotion clutter is negative and significant \((\beta_{4} = -0.094, p < 0.01)\). Thus, although higher clutter hurts sales (see before: negative main effect of CLUT on brand sales), more intense
promotion activity by competitors at the store makes consumers more responsive to the focal brand’s own promotions. With more intense promotions, the category receives considerable attention and becomes more salient, especially when a retailer emphasizes these promotions in its flyer and/or in the store through merchandising support. This may entice indirect store switching behavior such that more consumers buy the focal category at the promoting retailer rather than at competing retailers (Bucklin and Lattin 1992; van Heerde, Leeflang, and Wittink 2004). Several brand-related variables also influence the promotional price elasticity at non-event times. Price promotion response is stronger for category leaders (γ21 = -2.343, p < .01), which is consistent with results of Pauwels (2007), and weaker for more expensive brands (γ22 = .164, p < .01) and in non-food categories (γ23 = .487, p < .01).

**Differences in sales response to promotions around popular events**

The second PI term in our HLM model captures relative promotion response through the interactions of PI with the event dummy. Again, this difference in promotion response during events compared to non-event times is a function of various moderating variables, as hypothesized in H1-H6. The estimates γ50,1 to γ50,5 capture the difference in promotion response during each event compared to non-event weeks when all these drivers are zero (i.e., with ln(ADV), ln(CLUT) and all continuous drivers in Equation 2c at their means, and for non-leading, non-sponsoring brands in food categories). We find negative coefficients γ50,n, ranging between -1.060 and -2.297, which are significant for all events (p < .05), except one (Summer Olympics). This indicates that promotions have a stronger promotion response during events than at non-event times.

The pattern of the γ50,n estimates across the five events is in line with the model-free evidence in Table 3 in the sense that skating events and the Winter Olympics show the highest relative promotion response, and the Summer Olympics the lowest. The correlation
between the difference in promotional sales lift between event and non-event times (Table 3) and the $\gamma_{50,n}$ estimates in our model is .93, suggesting very high convergent validity. Yet, all $\gamma_{50,n}$ estimates indicate stronger promotion response during events, while for two out of five events, model-free evidence suggest a weaker promotion response compared to non-event times (Table 3). Note, however, that our $\gamma_{50,n}$ parameters do not capture the mean relative promotion response in our sample, but rather the effect in a specific situation (e.g., for non-leading brands in food categories). To derive the overall mean relative promotion response, we need to calculate it for each brand-event combination based on our model parameters and the brand- and event-specific values for the drivers of relative promotion response. We present the respective calculation later (see section ‘Are managers on target?’), after testing our hypotheses in the next sub-section.

**Drivers of relative promotion response**

To test our hypotheses, we examine the coefficients associated with the six drivers of relative promotion response that are part of the second PI term in Equation 1 and of Equation 2c.

First, we find only partial support for $H_1$. The effect of category-event fit is U-shaped: The coefficient for fit is positive ($\gamma_{51,1} = 1.221, p < .01$), and the coefficient for its squared term is negative ($\gamma_{51,2} = -.215, p < .01$). Hence, promotion response weakens up to a fit level of 2.83 (which is well within our observed data range of (mean-centered) category-event fit), after which it increases again. The positive effect for high fit levels is in line with our hypothesis. Examples for very high category-event fit in our study (above the turning point) are beer during soccer cups or wet soup during ice skating events. Although on average, demand does not expand across all brand-event combinations, these specific cases likely benefit from higher category sales during these events. At the other extreme, when fit is very low as with, for instance, toilet refreshers during ice skating events, the low fit may help promotions stand
out. Such a promotion may draw more attention since the link with the event is unexpected. A similar argument about the role of fit with events has arisen in some recent studies on advertising and sponsoring effectiveness. Gijsenberg (2014a) reports a mean (short-run) advertising elasticity around sport events that is slightly smaller in high-fit categories, and Mazodier and Quester (2014) posit that sponsors with a low level of fit enjoy stronger identification, because people find some degree of incongruence interesting, such that low fit is more conducive to augmenting current associations and creating brand differentiation. Thus, the impact of category-event fit might not only be driven by better event association opportunities as we expected, but also by difficulties to stand out.

Consistent with H2, official event sponsors are more likely to benefit from popular events than non-sponsors, given the negative coefficient for sponsorship in Equation 2c ($\gamma_{52} = -1.488, p < .01$). This effect of sponsoring occurs over and above the effect of event advertising for which we control in the model. With respect to the brand characteristics, we find no effect on relative promotion response from the brand leader dummy ($p > .10$), and thus, H3 is not supported. H4 is supported as premium priced brands have more to gain from shifting their promotions towards events, as indicated by the negative coefficient for price premium ($\gamma_{54} = -.511, p < .01$).

Finally, the context in which promotions take place has a different impact during events than at non-event times, both for in-store promotion clutter and supporting advertising. Our findings support H5, given a positive interaction between promotion clutter, PI, and the event dummy ($\beta_7 = .064, p < .05$). Thus, while clutter increases promotion response at non-event times (see previous sub-section), this is no longer the case during popular events. The effect of clutter on sales response to promotions is not significant around popular events ($\beta_4 + \beta_7 = -.030; p > .10$). Consistent with H6, the 3-way interaction between advertising, PI, and
events is negative ($\beta_6 = -0.137, p < .10$). I.e., *supporting advertising* enhances promotion response more during events than at non-event times, presumably because both marketing tools can benefit from the common event theme.

**Are Managers’ Promotion Strategies on Target?**

If promotion response is stronger (weaker) around events than at non-event times, managers should consider this in their promotion timing decision and promote more (less) during event weeks. But do they actually do so? To evaluate this, we contrast relative promotion response with relative promotion activity.

We determine *relative promotion response* for every brand-event-combination using the estimates of the second PI term in our HLM (see Equations 1 and 2c) in combination with the respective brand- and event-specific values for its predictors (for details see Web Appendix W4). Negative (positive) values imply that the promotion elasticity has a larger (smaller) negative value, and hence, promotion response is stronger (weaker) during events than at other times. We calculate relative promotion response for the 1,198 brand-event combinations for which our estimation dataset contains at least one observation during the event. The mean relative promotion response across these brand-event combinations is -0.119, indicating that, on average, promotions are more effective during events than at other times. Compared to an average promotion elasticity for our brands at non-event times of -1.283$^5$, the elasticity around popular events is -1.402, i.e., 9.3% larger. This is in line with the model-free evidence, where the average sales lift due to promotions increases by 13% during events (Table 3). Moreover, consistent with Table 3, we find that relative promotion response is

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$^5$ To determine the mean price elasticity in non-event times of -1.283, we compute the price elasticity for each brand based on the parameter estimates in Table 5 and brand-specific values for the drivers in Equation 2b, and take the mean across brands.
highest for ice skating events (-.672) and the Winter Olympics (-.546), and lowest for the Summer Olympics (.571).

We also compute relative promotion activity for the 1,198 brand-event combinations, by dividing the mean PI at non-event times by the mean PI during event weeks (for details see Web Appendix W4). A value greater than 1 indicates that brand i’s promotion activity is more intense during event n than at comparable non-event times, while a value between 0 and 1 reflects less intense promotion activity during the event window. Across our 1,198 brand-event combinations, we find that 47.5% of the relative promotion activity measures are greater than 1, and the mean value is 1.001. I.e., on average, promotion activity is highly similar across event and non-event times, and managers do not systematically shift promotions towards event times. Limited in-store space could prevent a boost in the overall number of promotions around popular events. Still, we find considerable variation (standard deviation of .024). For some brand-event combinations, there is less promotion activity around events (minimum .936), while for others, it is clearly more intense (maximum 1.511).

The correlation between relative promotion activity and relative promotion response is .058. This low value indicates that managers’ timing of promotion activities in relation to popular events is not well aligned with relative promotion response. Moreover, among the 1,198 brand-event combinations, less than half (48.6%) are “on target”, i.e., promotion activity more (less) intense during events than at non-event times when promotion response is stronger (weaker) during events. For 23.4% of the brand-event combinations, promotion activity is more intense during events than at non-event times, even though sales response to

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6 Note that our measure of relative promotion activity indicates more intense activity during events if brands promote more often and/or if they offer deeper price cuts. In our data, we observe very little variance in promotion depth, but relative promotion activity is mostly driven by differences in promotion frequency. Details are available upon request.
promotions is weaker around events. These are cases of “spoiled arms” (Leeflang and Wittink 1996). The remaining 28.0% of the cases represent “missed opportunities”, as the sales response to promotions is stronger during events than at non-event times, but promotion activity is less intense.

Note that these findings do not account for differences in promotion costs and should be interpreted with caution. Promotion costs might be higher around events because price cuts are supported with more non-price promotions, e.g., features and displays, and for manufacturers, pass-through could become more difficult (Meza and Sudhir 2006). Thus, managers should carefully balance any additional promotion costs against the benefits of a higher sales response around event times when shifting their promotions to popular events.

Robustness Checks

We performed a series of robustness tests to ensure the stability of our results. First, instead of the two lead weeks before the event, we re-estimated our model with two alternative event windows: (i) a one week lead, and (ii) a three week lead. Second, not all of our events repeat during our observation period, and we re-estimated our model omitting the Summer and Winter Olympics which occurred only once. Third, to account for different dynamics around events, we added four interactions to the model between the lagged PI variables and the event dummy Devent. Fourth, to allow price promotion response to vary across retailers, we added interactions between the promotion index PI and the retailer dummies, as well as three-way interactions between PI, the retailer dummies, and the event dummy. Our main results are robust to these changes (see Web Appendix W5 for details). Finally, to test the stability of our parameters, we implemented a jackknife procedure where we randomly dropped 10% of our
brands and re-estimated the HLM model on 218 brands. We repeated this procedure 10 times. Our results were highly stable in all analyses in terms of sign, significance and magnitude.⁷

Discussion and Implications

Popular events such as the World Soccer Cup or the Olympics have become very attractive platforms for firms to advertise their brands. Not only sport events but also many cultural events like music contests and festivals are broadcasted internationally and have become important occasions for brands to communicate with their target audience. But do these events also offer opportunities for promotions? Several manufacturers and retailers have picked up event themes when promoting their brands. Yet, there is hardly any research evidence about promotion response in relation to popular media events and what brands benefit most in relation to what events.

Overall, we find that popular events provide interesting opportunities for many CPG brands to enhance the effectiveness of their price promotions: on average, the (absolute) price promotion elasticity is 9.3% larger around an event than at other times. Relative promotion response in the Netherlands is the largest during ice skating events and the Winter Olympics with elasticities in our sample that are 52.4% and 42.6% larger, respectively, during these events than at non-event times. At the other extreme, the price promotion elasticity is 44.5% smaller during the Summer Olympics than at non-event times.

Apart from differences between events, there is considerable variation in relative promotion response across brands, suggesting that shifting promotion budgets to event times is more appropriate for some brand-event combinations than for others. Several of our hypothesized drivers contribute significantly to explaining these differences. Interestingly, at present, managers do not increase their promotion activity systematically during events when

⁷ Detailed results are available from the authors upon request.
promotion response is stronger and there is room for improvement.

**Managerial Implications**

To enhance promotion response, managers should carefully choose the right brand-event combinations and reallocate promotions towards an event only if brands have a stronger promotion response that time. To guide managers in this choice, we provide them with the following recommendations.

*Avoid being stuck in the middle.* Managers should promote their brands more during events where category-event fit is either low or high, while promotions during events are less suited when category event-fit is intermediate. In the case of intermediate fit levels, event promotions may be seen as part of the event itself and it becomes harder to get noticed with many other promotions around the event building on the same event theme. This is less of a problem for low-fit categories where brands may ‘surprise’ consumers with an event link. Promotions in high-fit categories may be especially effective if category demand is higher around event times.

*Integrate your event marketing.* We encourage manufacturers to integrate event promotions into a broader marketing campaign. In our data, we do not often observe that managers combine advertising and/or sponsoring investments with promotion activities around events. While 10.79% of the price promotions during non-event times are supported by advertising, only 8.71% are during events. However, according to our results, beneficial advertising-promotion interaction effects only emerge during popular events, presumably due to the common theme on which both marketing tools can build. Moreover, brands that are official event sponsors achieve a stronger relative promotion response than brands that are not. So we advise brand manufacturers to further integrate price promotions into their broader advertising and sponsoring activities in relation to popular events, as it offers a unique
opportunity to capitalize on these expensive investments.

Choose the right brands. Brand leaders do not gain more than other brands, but premium priced brands benefit relatively more from shifting their promotions towards events than brands with a lower price premium. Hence, managers should select brands for event promotions based on brand equity (reflected in relative price) rather than brand popularity.

Tailor your decisions to the context. Since in-store promotion clutter is not favorable during events, managers need to pick their events carefully. While very popular events with high category fit may seem attractive because they expand category sales, these events likely attract intensive promotions from competing brands, and this clutter makes events less attractive for promotions.

These implications are relevant for retailers, who decide on price promotions in their stores and who are in the position to select brands for promotion, as well as for manufacturers, who seek to influence those decisions through their trade marketing and who are in control of supporting brand advertising and sponsoring activities.

Limitations and Future Research

Our study has some limitations that provide opportunities for future research. First, we focus on relative promotion response for CPG brands following temporary price reductions. In our data, other types of promotions are rare. We lack details about displays, in-store signage and other promotional support, and feature activity is highly correlated with price, which makes it impossible to separate out its effects in our model. Still, it would be interesting to study the effects of such non-price promotions that support price cuts by alerting consumers to them. They likely play an important role around popular events, because they allow brands to communicate the event theme and we expect relative promotion response to be larger when non-price promotions are combined with price cuts.
Second, out-of-store promotions like coupons, features, sampling, and sweepstakes may work differently than the in-store promotions we study. In the store, it is particularly difficult to stand out, because promotion activity may be more intense than at other times, and many promotions will use the event theme. Outside the store, it may be easier to find locations where the promotion stands out. Or else, managers may try to place their promotion in close proximity to the event, which would make it harder to stand out, but it might increase event association opportunities.

Third, popular events could also be an attractive platform for promotions for durable products, and relative promotion response may be different for durables than for CPGs. On the one hand, price cuts are larger in absolute value so that consumers may focus more on price and be less responsive to promotion communication that picks up the event theme. Purchase decisions for durables are also less impulsive and based on more extensive information search. On the other hand, durables can use different promotion tools that may provide additional event association opportunities and help the promotion stand out. For example, managers may use conditional promotions where consumers buy a durable product at full price before an event and get a discount later only if an event-related condition is fulfilled (e.g., a football team winning a championship) (Ailawadi et al. 2014).

Fourth, we have examined five events highly popular among the Dutch between 2007 and 2011. Especially for infrequent events that occur only every few years, future work should replicate our analyses. Studying price promotions in relation to other popular events like cycling (e.g., Tour de France) or tennis cups, and investigating events popular in other countries like the famous U.S. Super Bowl would also represent important steps toward more generalizable results, and offer opportunities for studying additional drivers of relative promotion response.
Fifth, our model could be extended, for example, by allowing price sensitivity to vary over time. Also, the main effect of advertising could vary between event versus non-event times. Similarly, it would be interesting to compare relative price promotion response around popular media events to that around seasonal events like Christmas or Thanksgiving.

Finally, to measure the sales response of promotions, we relied on pure sales data as is common in promotion research (Dekimpe et al. 2005). In the absence of cost data, we refrain from recommending optimal promotion strategies and encourage future research on the profitability of promotions around events.
References


Table 1
Expected Effects of the Drivers on Relative Promotion Response

<table>
<thead>
<tr>
<th>Variables</th>
<th>Event association opportunities</th>
<th>Ability to stand out</th>
<th>Expected net effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category-event fit (H₁)</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Event sponsorship (H₂)</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Brand leadership (H₃)</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Brand price premium (H₄)</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Promotion clutter (H₅)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supporting advertising (H₆)</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

Notes: + (-) indicates that the driver makes relative promotion response higher (lower), i.e., sales response to promotions becomes stronger (weaker) during events compared to non-event times.
## Table 2
### Product Categories

<table>
<thead>
<tr>
<th>Product Group</th>
<th>Product Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>dry soup, wet soup, wet sauce, dry meal mix sauces, chewing gum, gum alikes,</td>
</tr>
<tr>
<td></td>
<td>candy bars, chocolate pills, chocolate bars, drops, toffees, cutting cake, other</td>
</tr>
<tr>
<td></td>
<td>cookies, chips, peanuts, responsible snack</td>
</tr>
<tr>
<td>Beverages</td>
<td>beer, fruit juices, soft drinks</td>
</tr>
<tr>
<td>Household care</td>
<td>laundry powder, laundry powder amplifier, laundry softener, detergent</td>
</tr>
<tr>
<td></td>
<td>machine, liquid cleaner, liquid toilet cleaner, toilet refresher, toilet tissue</td>
</tr>
<tr>
<td>Personal care</td>
<td>shampoo, toothpaste, other bath products</td>
</tr>
</tbody>
</table>
### Table 3

**Brand Sales Lift Due to Promotions in Event and Non-Event Weeks**

<table>
<thead>
<tr>
<th></th>
<th>Brand sales lift</th>
<th>Supporting advertising</th>
<th>Promotion clutter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>no event</td>
<td>event</td>
<td>no event</td>
</tr>
<tr>
<td>Overall</td>
<td>3.45</td>
<td>3.90</td>
<td>2.462</td>
</tr>
<tr>
<td>Event Skating</td>
<td>3.66</td>
<td>4.80</td>
<td>1.981</td>
</tr>
<tr>
<td>Event Soccer</td>
<td>3.38</td>
<td>3.42</td>
<td>2.900</td>
</tr>
<tr>
<td>Event Summer Olympics</td>
<td>3.05</td>
<td>2.68</td>
<td>2.547</td>
</tr>
<tr>
<td>Event Winter Olympics</td>
<td>3.67</td>
<td>5.44</td>
<td>1.981</td>
</tr>
<tr>
<td>Event Eurovision</td>
<td>3.40</td>
<td>3.11</td>
<td>2.900</td>
</tr>
</tbody>
</table>

Notes: Brand sales lift is determined as the average weekly brand sales during promotion weeks divided by average weekly brand sales in non-promotion weeks. For instance, a value of 3.45 means that brand sales are 3.45 times higher in a promotion week than in a week without a promotion. For non-event sales, we consider weeks during the same quarter of the event. Supporting advertising and promotion clutter represent means by brand (and retailer) per week (see Table 4).
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level 1</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S_{rt}$</td>
<td>Volume sales of brand $i$ at retailer $r$ in week $t$</td>
<td></td>
</tr>
<tr>
<td>$\text{Devent}_{t(n)}$</td>
<td>= 1 if week $t$ belongs to the time window around one of the events (around event $n$), 0 else (source: <a href="http://www.kijkonderzoek.nl">www.kijkonderzoek.nl</a>)</td>
<td>27.86%</td>
</tr>
<tr>
<td>$\text{PI}_{rt}$</td>
<td>Price index of brand $i$ at retailer $r$ in week $t$ expressed as actual price of brand $i$ divided by its regular price (source: Nielsen)</td>
<td>.969 (.060)</td>
</tr>
<tr>
<td>$\text{ADV}_{rt}$</td>
<td>Manufacturer (national) advertising expenditures for brand $i$ in week $t$ (in €1,000) (source: Nielsen)</td>
<td>2.611 (8.499)</td>
</tr>
<tr>
<td>$\text{CLUT}_{rt}$</td>
<td>In-store promotion clutter for brand $i$ at retailer $r$ in week $t$ expressed as a combination of the proportion of competing brands (including private labels) that promote and the (reverse scaled) average $\text{PI}_{rt}$ of all brands competing with brand $i$ at retailer $r$ that are promoted in the same week $t$</td>
<td>.075 (.001)</td>
</tr>
<tr>
<td>$\text{Preg}_{rt}$</td>
<td>Regular (or ‘baseline’) price of brand $i$ at retailer $r$ in week $t$ derived in a rolling window of the most recent four weeks</td>
<td>3.774 (14.467)</td>
</tr>
<tr>
<td>$\text{cPIrets}_{rt}$</td>
<td>Cross-store competitive price index for brand $i$ at retailer $r$ expressed as the average $\text{PI}$ of brand $i$ in week $t$ across retailers competing with retailer $r$</td>
<td>.915 (.212)</td>
</tr>
<tr>
<td>$\text{ASS}_{rt}$</td>
<td>Assortment breadth in the category of brand $i$ at retailer $r$ in week $t$ expressed as the ratio of the number of brands in the category available at the retailer to the total number of brands available in this category in the market (i.e., across the 4 retailers). A brand is assumed to be available at retailer $r$ in week $t$ if it has non-zero sales at retailer $r$ at least once in the most recent four weeks (week $t$, $t-1$, $t-2$, $t-3$)</td>
<td>.473 (.111)</td>
</tr>
<tr>
<td>$\text{Dxmas}_{t}$</td>
<td>= 1 if Christmas is in week $t$, 0 else</td>
<td>3.56%</td>
</tr>
<tr>
<td>$\text{Deaster}_{t}$</td>
<td>= 1 if Easter is in week $t$, and 0 else</td>
<td>3.62%</td>
</tr>
<tr>
<td>$\text{Trend}_{t}$</td>
<td>Trend variable for observations in week $t$ (with weeks consecutively numbered from 1 to 222)</td>
<td></td>
</tr>
<tr>
<td>$\text{Drec}_{t}$</td>
<td>= 1 if week $t$ is an official recession week, 0 else (source: OECD)</td>
<td>33.68%</td>
</tr>
<tr>
<td>$\text{Dquart}_{q,t}$</td>
<td>= 1 if week $t$ is in quarter $q$ (with $q = 2$, 3 or 4), 0 else</td>
<td>q2: 24.34%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>q3: 24.36%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>q4: 24.50%</td>
</tr>
<tr>
<td>$\text{Dret}_{r}$</td>
<td>= 1 if observation is from retailer $r$ (with $r = 1$, 2, 3), 0 else</td>
<td>r1: 31.07%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>r2: 25.54%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>r3: 21.74%</td>
</tr>
</tbody>
</table>
CopPRI_{rict}  Gaussian copula (control function term) for price variable \( c \) of brand \( i \) at retailer \( r \) in week \( t \) to control for potential endogeneity

| Level 2 | 
|----------------|--------------------------------------------------|
| D.EVENT\( _n \)  | = 1 if observation is from the time window around event \( n \), 0 else |
| EVTFIT\( _{in} \) | Fit of event \( n \) with the category of brand \( i \), derived from 2 items (source: consumer survey): |
| | - To what extent does the event (XX) fit the category (YY)? (1 = does not fit at all, 7 = fits very well) |
| | - How similar is the event (XX) to the category (YY)? (1 = not similar at all, 7 = very similar) |
| Cronbach’s alpha = .96; | 
| | 2.653 (.685) |
| D.EVTSPON\( _{in} \) | = 1 if brand \( i \) is an official (individual or corporate) sponsor of event \( n \), 0 else (source: event, company, and brand websites) |
| | 3.25% |
| D.LEADER\( _i \) | = 1 if brand \( i \) has the highest volume share across the four retailers in the category over the data period, 0 else |
| | 12.51% |
| PRIPREM\( _i \) | Price premium of brand \( i \) over the private label price (PI of brand \( i \) divided by the PI of the private labels in the category; cfr. Ailawadi, Lehmann, and Neslin 2003) |
| | 1.076 (.868) |
| D.NFOOD\( _i \) | = 1 if brand \( i \) is from a non-food category, 0 else |
| | 49.79% |

Notes: Unless the source is explicitly mentioned, all measures are derived from the GfK consumer panel data. Descriptive statistics for level 1 variables are at the brand-week-retailer level (N = 120,692), and for level 2 variables at the brand-event level (N = 1,198). Reported means and standard deviations (SD) are before ln-transformation and mean-centering. For dummy variables, we report the percentage of observations having a value of one instead of the mean and SD. More details on the construction of the price variables are provided in Web Appendix W2.
## Table 5

**Model Results**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equation 1 (level 1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Devent1 (skating) ((\ln(\beta_{1.1})))</td>
<td>-.031***</td>
<td>-3.970</td>
</tr>
<tr>
<td>Devent2 (soccer) ((\ln(\beta_{1.2})))</td>
<td>-.012</td>
<td>-1.153</td>
</tr>
<tr>
<td>Devent3 (Summer Olympics) ((\ln(\beta_{1.3})))</td>
<td>-.002</td>
<td>-.131</td>
</tr>
<tr>
<td>Devent4 (Winter Olympics) ((\ln(\beta_{1.4})))</td>
<td>-.061***</td>
<td>-4.054</td>
</tr>
<tr>
<td>Devent5 (Eurovision) ((\ln(\beta_{1.5})))</td>
<td>.007</td>
<td>.653</td>
</tr>
<tr>
<td>PI × ADV ((\beta_{3}))</td>
<td>.055</td>
<td>1.349</td>
</tr>
<tr>
<td>PI × CLUT ((\beta_{4}))</td>
<td>.094***</td>
<td>-5.95</td>
</tr>
<tr>
<td>PI × Devent × ADV ((\beta_{6}))</td>
<td>-.137**</td>
<td>-1.756</td>
</tr>
<tr>
<td>PI × Devent × CLUT ((\beta_{7}))</td>
<td>.064**</td>
<td>2.215</td>
</tr>
<tr>
<td>ADV ((\beta_{8}))</td>
<td>.020***</td>
<td>8.566</td>
</tr>
<tr>
<td>CLUT ((\beta_{9}))</td>
<td>-.007***</td>
<td>-6.943</td>
</tr>
<tr>
<td>Preg ((\beta_{10}))</td>
<td>-.987***</td>
<td>-78.919</td>
</tr>
<tr>
<td>cPIrets ((\beta_{11}))</td>
<td>.037***</td>
<td>6.084</td>
</tr>
<tr>
<td>ASS ((\beta_{12}))</td>
<td>-.173***</td>
<td>-5.302</td>
</tr>
<tr>
<td>PI(lag=1) ((\beta_{13.1}))</td>
<td>.268***</td>
<td>8.203</td>
</tr>
<tr>
<td>PI(lag=2) ((\beta_{13.2}))</td>
<td>.259***</td>
<td>7.840</td>
</tr>
<tr>
<td>PI(lag=3) ((\beta_{13.3}))</td>
<td>.044</td>
<td>1.32</td>
</tr>
<tr>
<td>PI(lag=4) ((\beta_{13.4}))</td>
<td>.103***</td>
<td>3.218</td>
</tr>
<tr>
<td>Dxmns ((\ln(\beta_{14})))</td>
<td>-.059***</td>
<td>-4.844</td>
</tr>
<tr>
<td>Deaster ((\ln(\beta_{15})))</td>
<td>-.033***</td>
<td>-2.49</td>
</tr>
<tr>
<td>Trend ((\beta_{16}))</td>
<td>-.035**</td>
<td>-9.79</td>
</tr>
<tr>
<td>Drec ((\ln(\beta_{17})))</td>
<td>.003</td>
<td>-6.94</td>
</tr>
<tr>
<td>Dquart2 ((\ln(\beta_{18.2})))</td>
<td>.033***</td>
<td>4.154</td>
</tr>
<tr>
<td>Dquart3 ((\ln(\beta_{18.3})))</td>
<td>.006</td>
<td>.847</td>
</tr>
<tr>
<td>Dquart4 ((\ln(\beta_{18.4})))</td>
<td>-.012*</td>
<td>-1.713</td>
</tr>
<tr>
<td>Dret1 ((\ln(\beta_{19.2})))</td>
<td>.335***</td>
<td>49.237</td>
</tr>
<tr>
<td>Dret2 ((\ln(\beta_{19.2})))</td>
<td>.731***</td>
<td>96.746</td>
</tr>
<tr>
<td>Dret3 ((\ln(\beta_{19.2})))</td>
<td>-.297***</td>
<td>-43.934</td>
</tr>
<tr>
<td>Dret1 ((\ln(\beta_{19.2})))</td>
<td>.335***</td>
<td>49.237</td>
</tr>
<tr>
<td>Drt2 ((\ln(\beta_{19.2})))</td>
<td>.731***</td>
<td>96.746</td>
</tr>
<tr>
<td>Drt3 ((\ln(\beta_{19.2})))</td>
<td>-.297***</td>
<td>-43.934</td>
</tr>
<tr>
<td>Copula correction term for PI ((\beta_{20}))</td>
<td>-.275***</td>
<td>-68.807</td>
</tr>
<tr>
<td>Equation 2a (level 2: intercept (\beta_{0i}))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept ((\gamma_{00}))</td>
<td>7.617***</td>
<td>61.864</td>
</tr>
<tr>
<td>Equation 2b (level 2: price promotion response (\beta_{2i}))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PI ((\gamma_{20}))</td>
<td>-1.226***</td>
<td>-12.25</td>
</tr>
<tr>
<td>PI × D.LEADER ((\gamma_{21}))</td>
<td>-2.343***</td>
<td>-21.414</td>
</tr>
<tr>
<td>PI × PRIPREM ((\gamma_{22}))</td>
<td>.164***</td>
<td>3.443</td>
</tr>
<tr>
<td>PI × D.NFOOD ((\gamma_{23}))</td>
<td>.487***</td>
<td>6.839</td>
</tr>
<tr>
<td>Equation 2c (level 2: interaction price promotion x events (\beta_{5,io}))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PI × Devent1 (skating) ((\gamma_{50.1}))</td>
<td>-2.297***</td>
<td>-3.236</td>
</tr>
<tr>
<td>PI × Devent2 (soccer) ((\gamma_{50.2}))</td>
<td>-1.530**</td>
<td>-2.224</td>
</tr>
<tr>
<td>PI × Devent3 (Summer Olympics) ((\gamma_{50.3}))</td>
<td>-1.060</td>
<td>-1.533</td>
</tr>
<tr>
<td>PI × Devent4 (Winter Olympics) ((\gamma_{50.4}))</td>
<td>-2.192***</td>
<td>-3.028</td>
</tr>
<tr>
<td>PI × Devent5 (Eurovision) ((\gamma_{50.5}))</td>
<td>-1.403**</td>
<td>-2.01</td>
</tr>
<tr>
<td>PI × Devent × EVTFIT ((\gamma_{51.1}))</td>
<td>1.221***</td>
<td>3.53</td>
</tr>
<tr>
<td>PI × Devent × EVTFIT^2 ((\gamma_{51.2}))</td>
<td>-.215**</td>
<td>-2.897</td>
</tr>
<tr>
<td>PI × Devent × D.EVTSPON ((\gamma_{52}))</td>
<td>-1.488***</td>
<td>-5.097</td>
</tr>
<tr>
<td>PI × Devent × D.LEADER ((\gamma_{53}))</td>
<td>-.145</td>
<td>-.714</td>
</tr>
<tr>
<td>PI × Devent × PRIPREM ((\gamma_{54}))</td>
<td>-.511***</td>
<td>-5.285</td>
</tr>
<tr>
<td>PI × Devent × D.NFOOD ((\gamma_{55}))</td>
<td>.359**</td>
<td>2.548</td>
</tr>
</tbody>
</table>

N = 112,327  
Brands = 242  

Notes: Estimates are unstandardized coefficients.  
* \(p < .10\); ** \(p < .05\); *** \(p < .01\) (two-sided tests).