Despite the huge amount of money allocated every year to sales promotions, brand managers still do not know how often and in what circumstances promotions are truly effective. This dissertation proposes an approach that allows managers to assess the impact of individual promotion events rather than the average effect of total promotional efforts. As such, more detailed information is gained on how promotions should be implemented.

Moreover, sales promotions are not only evaluated in a business-as-usual environment, but their role and effectiveness during retailer induced price wars is also critically examined. As retailer competition tends to degenerate more often into price wars, this research offers recommendations to brand managers on whether they should accommodate retailers’ wishes to lower regular, list prices rather than focusing on temporary promotions.

Finally, a brand manufacturer, when planning his promotional events for a retailer, should consider that a promotion can steal sales from rival supermarket chains. While these cross-chain effects are often negligible for the retailer, they are quite substantial for the manufacturer. Thus, to increase promotional effectiveness, a brand manager should carefully plan the promotional calendar across rival retailers.

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Not All Promotions are Made Equal:

From the effects of a price war to cross-chain cannibalization
Not All Promotions are Made Equal:
From the effects of a price war to cross-chain cannibalization

Niet alle promoties zijn gelijk: van prijzenoorlog tot kannibalisatie tussen supermarkketens

Thesis
to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
rector magnificus

Prof.dr. H.G. Schmidt
and in accordance with the decision of the Doctorate Board.

The public defense shall be held on
Wednesday, June 9, 2010 at 11.30 hours

by
Francesca Sotgiu
born in Pisa, Italy

ERASMUS UNIVERSITEIT ROTTERDAM
To My Family and Friends
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ACKNOWLEDGEMENTS

This work would not have been possible without the precious help and guidance of Marnik Dekimpe, Berend Wierenga, and Katrijn Gielens. Thanks for helping me in every step that led to the final result, even in times when you have been busy. You have taught me how to be straightforward and rigorous in my ideas. Without a doubt, your comments on various theoretical, empirical and textual issues have contributed to the quality of this dissertation. It was a great honor to have had the opportunity to work with you!

To my committee members, Josh Eliashberg, Inge Geyskens, Gilles Laurent, Koen Pauwels, and Gerrit van Bruggen, I would like to express my gratitude for their time and expert view. I had the great opportunity of getting to know them in the past few years and I am very pleased that they accepted to be part of my committee.

The very early stage of this dissertation has greatly benefited from the feedback of Tammo Bijmolt, Karen Gedenk, Els Gijsbrechts, V. Kumar, Peter Leeflang, Leigh McAlister and Harald van Heerde. Their passion for research and their fresh insights on the dissertation proposal, but also during conferences (in particular, during the EMAC doctoral colloquium and at the AMA Sheth Doctoral Consortium), inspired me and kept me motivated.

I want to express my appreciation to my colleagues and friends at the marketing management department of RSM Erasmus University. I would like to thank you all, Anja, Annette, Barbara, Baris, Bart, Berend, Berk, Daniel, Dirk, Erik, Ezgi, Frank, Fred, Gaby, Gerrit, Jan, Joëlle, Johan, Jolanda, Linda, Maarten, Maciej, Martijn, Mirjam, Niek, Patricia, Pinar, Peeter, Ralf, Stefanie, Stefano, Steven, Stijn, Willem, Yvonne, and all the others, for your help and cheerful chats during the past years. I will always look back with good memories on the time I spent with you.

I find myself very lucky to have found the same welcoming and friendly group at HEC Paris. Thanks to Anne, Barbara, Bige, Brigitte, Bruno, Dominique, Gilles, Jean-Marc, Jean-Michelle, Jean-Noël, Joe, Kristine, Frederic, Laurent, Marc, Nadine, Pascale, Patricia, Romain, Sandor, Selin, Stefan, Veronique, Vincent and Wolfgang, for the stimulating and dynamic environment, and for being so very helpful and supportive! It is a true pleasure working with you.
While a new “life” is starting, I look back and think of the reasons why I joined the Ph.D., and why in Rotterdam. To push me in this direction have been Fabio Ancarani and Venky Shankar. I want to thank them for their support and, in particular, for encouraging me and always showing appreciation for my work.

Finally, I would like to thank my family and all the friends who listened to all my never ending doubts. I dedicate this work to them. In particolare, alla mia famiglia, per esserci sempre, per il continuo supporto e per avermi insegnato a camminare sulle mie gambe, ad avere sempre coraggio e a non tirarmi mai indietro. Senza di voi, non sarei mai arrivata da nessuna parte. A special thank you goes out to Katrijn Gielens, for the stimulating discussions, her outstanding insights and guidance, and her incredible determination. Working all night has never been so nice! Our mid-night phone calls have cheered me up in many occasions! Berk Ataman, Patricia Heijndijk, Stefano Puntoni and Mirjam Tuk deserve a special medal for the unconditional support during the bad and the good times. Our millions of get-togethers over coffee, our lively dinners and drinks sparkled up these last years!

Un ringraziamento speciale va a Sarah (detta La Wanda!), Mascha, Denis, Cedric, Margreet, Laurens, Reinier, Sebastiaan, Jonathan, Thomas (thank you guys for all the nice drinks, dinners, parties, and the weekends together!!), Hans and Nicole (merci beaucoup!), Carlos, Jose, Lorenz, Maarten and Nuno. Thank you all guys!

As you all know, in a few months I will officially become part of the Bouwland clan. I say “officially” because Hetty, Gerrit, Annet, Marcel, Hester, Ruben, Marijn, Bert, and Ron made me always feel part of the family since the very beginning. Bedankt voor alles! Ik ben echt blij dat ik jullie ontmoet heb.

And finally, to Ron, thank you for your love and support, for making me smile every day, for listening and understanding when I make sense, and also when I do not, for coping with the stress related to this thesis, for not having hesitated in following me around Europe, for sharing your world, your dreams and love with me.

Ad maiora!

Francesca Sotgiu

Paris, April 2010
CHAPTER 1: INTRODUCTION

1.1. Motivation of the thesis

Consumers are continuously confronted with price promotions. Recent figures indicate that 24 percent of all Dutch supermarket purchases take place under some form of promotional support. In the US, purchases made under sales promotions comprise 38 percent of all purchases in supermarkets (Steenkamp et al. 2005). Therefore, it is not surprising that considerable attention has been devoted to study the performance implications of price promotions (for a recent review, see van Heerde and Neslin 2008).

These previous studies share a number of characteristics:

(1) So far, promotion studies tend to deal with average effects. Steenkamp et al. (2005: 42), for example, say that “the unit of analysis is not an individual price promotion... Instead, our elasticities estimate whether on average...”. Therefore, it is harder to obtain detailed insights into effectiveness differences across different promotional implementations and contexts (even though some first attempts have been made in that direction by Cooper et al. 1999 and Ailawadi et al. 2006).

(2) Most research investigated promotional effectiveness in fairly stable business conditions (Bass and Pilon 1980, Dekimpe and Hanssens 1999). While Nijs et al. (2001) considered evolutionary settings as well, they did not consider intervening effects of major structural changes in the market environment, such as price wars.

(3) While there has been considerable research on both the decomposition of the promotional sales bump (see e.g. Chiang 1991, Gupta 1988, van Heerde et al. 2003), and on the explanation of cross-brand and cross-category variability in promotional effectiveness (e.g. Nijs et al. 2001, Pauwels et al. 2002, Srinivasan et al. 2004), limited attempts have been made to investigate cross-store effects.

These observed commonalities in previous studies leave various areas for future research, to which we contribute in the following way:

(1) In Chapter 2, we no longer consider average effects, but rather assess the effectiveness of individual promotions which differ widely in terms of
executed and support. In a two-step approach, we first determine the total sales effectiveness of each individual promotion and, in a second step, we relate each of these effects to various promotional implementation and contextual characteristics.

(2) In Chapter 3, we relax the assumption of a "business-as-usual" scenario, and consider how a major disruption in the retailing landscape can affect the implementation and, most importantly, the effectiveness of price promotions. The major disruption we look at is the price war which started in the Netherlands in the Fall of 2003, and which lasted for more than two years.

(3) Finally, in Chapter 4, we quantify the impact of cross-chain effects, and check whether a promotion by the leading retailer is able to significantly attract customers of competing retailers. While doing so, we verify whether this effect is symmetric across different retailer formats.

To get empirical insights into the effectiveness of individual promotions, we study all promotional events of a multinational CPG manufacturer at four national retailers in the Dutch market, from the first week of 2001 to the end of 2005. The data cover promotions in eight different product categories, for forty different brands. The data we use are ACNielsen data combined with internal company data and Nielsen Media Research advertising data.

1.2. Outline

In the following pages, we briefly elaborate on each of the above-mentioned essays to provide an overview of the content of this thesis. The outline is illustrated in Figure 1.1.

Chapter 2. In Chapter 2, we propose a new “individual promotion” approach to analyze promotional effectiveness. Existing literature on price promotions has focused on average effects. Therefore, it is harder to obtain detailed insights into differences in the individual effectiveness across different promotion implementations and contexts.

This across-promotion variability is only partially reflected in prior academic research. Most studies focus on differences between brands and/or categories, while limited research explains differences within a given brand. In fact, any reference to
differences across promotion activity is generally absent, as in most aggregated time series approaches (e.g. Nijs et al. 2001), or limited to the moderation of the average effects of promotions by feature and/or display (e.g. van Heerde et al. 2000). An exception in this direction is the work of Ailawadi et al. (2006, 2007), which looks at the effectiveness of individual promotions from the point of view of the retailer, and which analyzes how the promotional effectiveness varies with promotional (e.g. discount depth, multi pack and feature) and/or contextual characteristics (e.g. market share, advertising, distribution, concentration, storability, size and type of the store, market demographics and competitive density).

While we also look at the effectiveness of individual promotions, we take the point of view of the manufacturer, whose interests are not necessarily aligned with those of the retailers (Srinivasan et al. 2004). For a retailer, a promotion is more successful when it expands the category sales (Raju 1992). For a manufacturer, in contrast, a promotion is more successful when it increases the product sales, possibly at the expense of competing brands, without cannibalizing its own sales at other retailers (Srinivasan et al. 2004). Moreover, we extend the set of promotional descriptors. For example, we also take into account retail and brand competition, filtering out the simultaneous occurrence of a competitive action, as well as the recency from the previous promotion. Indeed, the effect of the same nominal price cut may differ depending on whether competitive products are promoted in the same week or in the weeks before at that retailer, and/or whether the same product has recently been on promotion with other retailers.

In a two-step approach, we first determine the total sales effectiveness of each individual promotion using a multiple-break analysis. The model extends the intervention approach of Leone (1987) to multiple promotions, in line with the procedure developed by Ben-David and Papell (2000). With this approach, we calculate a net effect accounting also for factors such as deceleration and stockpiling. Moreover, unlike Ailawadi et al. (2006), we control for potentially intervening effects of advertising and/or competitive actions. In the second step, we subsequently relate the total sales effectiveness of each promotion estimated in the previous step to various promotion implementation (e.g. timing, framing. and communication) and contextual (e.g. retailer, brand and category characteristics) characteristics.

Chapter 3. In Chapter 3, we apply the method proposed in Chapter 2 to study the effectiveness of sales promotion during a price war, a business scenario largely ignored in the promotional literature. In fact, despite the increasing number of price wars, little is known about their consequences on marketing activities and marketing performance. The
extant literature has mainly provided a definition of the phenomenon (e.g. Heil and Helsen 2001) and the conditions leading to a price war (e.g. Fabra and Toro 2005, Busse 2002, Elzinga and Mills 1999, Levenstein 1997). However, "direct research on price wars in marketing is lacking" (Heil and Helsen 2001: 87). Up to now, the only empirical work in the field is the research of van Heerde et al. (2008) on the effects of a price war among grocery retailers on store choice and basket size. So far, no study has investigated the effects of price wars on promotional effectiveness. Also, the majority of the price war literature has focused on the consequences for the initiator of the price war and his competitors, ignoring the effects on a third party, i.e. the manufacturers.

In this essay, we relax the assumption of a "business-as-usual" scenario, and consider how a major disruption in the retailing landscape affects the effectiveness of price promotions. The major disruption we look at is the price war that started in the Netherlands in the fall of 2003 (van Heerde et al. 2008). Instead of looking at the impact on the retailers directly involved in the price war, we focus on what happens to the brands of the manufacturers.

Furthermore, we distinguish two settings: one where the price of the brand itself is not reduced during the price war (indirect price-war effect), and one where the brand is directly involved in the permanent price cuts (direct price-war effect). During these two regimes, price promotions may stimulate sales in different ways.

Indeed, a price war can have several potential implications for the effectiveness of price promotions. First, there have been many statements in the popular press that promotion frequency and depth tend to be reduced because of the price war (e.g. see De Financiële Telegraaf for reports on the Dutch price war, “Prijzenoorlog in de supermarkten” 2004, 2005, 2006). As promotion frequency and depth of the discount have been found to be key determinants of promotional effectiveness (e.g. Nijs et al. 2001, Mela et al. 1997), this already suggests that price wars may affect the usefulness of price promotions. Second, due to the high media coverage that typically accompanies a price war, customers are expected to pay increased attention to the price dimension (Sloot and van Aalst, 2005). Van Aalst et al. (2005) show that, during the price war, more consumers choose which brand to purchase on the basis of prices. As argued in Mela et al. (1997) and Nijs et al. (2001) this may again affect the effectiveness of price promotions, if only because customers make more explicit price comparisons between different offers. Given that the relative price image of brands not directly involved in the price war may have deteriorated (as they now have relatively higher prices), while it may be improved for brands directly involved, opposite effects can emerge. While the above discussion is not
yet exhaustive, it illustrates that there are various arguments to suspect that a price war may alter the promotional effectiveness.

In order to investigate how a price war among retailers changes consumer responses to price promotions, we proceed in two steps. In the first step, we identify the effects of each sales promotion activity before and during the price war using a multi-break event regression (e.g. Ben-David and Papell 2000). In the second step, we identify the drivers of promotion effectiveness by regressing the parameters obtained from the previous step against promotion-, product- and retailer characteristics, in a "business-as-usual" scenario versus, respectively, an indirect price-war and a direct price-war scenario.

We have detailed information on the promotional activities of 22 products in eight categories, between 2001 and 2005, across four leading Dutch national supermarket chains. Given that our dataset covers 147 weeks before the price war, and 114 weeks during the price war, we can investigate whether promotions’ effectiveness has changed because of the price war, while we can also identify the different impact of an indirect versus direct price war.

Chapter 4. Plenty of research decomposed the promotional sales bump into cross-brand, cross-period, and category-expansion effects (see e.g. Bell et al. 1999, van Heerde et al. 2004). However, sales promotions can transfer the demand not only across brands, period and categories, but also across competing chains (Gijsbrechts et al. 2008). These demand shifts across retailers may reduce the overall effect of manufacturers’ sales promotions. Yet, there is little empirical knowledge neither about the relative frequency and size of these cross-chain effects, nor about the impact of this phenomenon on the overall effectiveness of sales promotions for manufacturers. Therefore, the question becomes to what extent we can directly model and quantify the impact of cross-chain effects. In particular, we are interested in measuring: (1) How often do these cross-effects occur? (2) What is the effect size?, and (3) To what extent is the effect symmetric across stores?

The answers to these questions may be of interest to both retailers and the manufacturers. For retailers, it is relevant to get a better understanding of the competition, and to see clearly (i) who is “stealing” traffic, (ii) based on which type of promotions. For manufacturers, it may be even more important, as they need to have an unbiased picture of the true effectiveness of their promotion events. Indeed, their promotional sales may increase within the focal retailer, while cannibalizing non-promotional sales at competing chains.
Chapter 5. In Chapter 5, we conclude with a brief overview of the key take-away of the previous chapters, focusing on their conclusions and their managerial implications. We then provide a number of recommendations for further research.

Figure 1.1. Thesis outline
CHAPTER 2: NOT ALL PROMOTIONS ARE MADE EQUAL

2.1. Introduction

Every year, billions of euros and dollars are spent on price promotions. In 2005, US manufacturers and retailers spent $486 bn on sales promotions, corresponding to 4.5% of the US Gross Domestic Product (Promotion Marketing Association 2005). As such, it is not surprising that considerable attention has been devoted to studying the performance implications of price promotions (for a recent review, see van Heerde and Neslin 2008). Our study differs from this prior research along three key dimensions.

First, previous studies have typically dealt with the average effects of price promotions, either at the brand (e.g. van Heerde et al. 2000) or the primary-demand (e.g. Nijs et al. 2001) level. This implies that all promotions of the brand (or even all promotions occurring within a given category) are assumed to be equally effective. Therefore, it is harder (if not impossible) to obtain detailed insights into differences in the individual effectiveness across different promotion implementations and contexts. Still, managers are well aware of the fact that some of their promotions work better than others.

In this chapter, we introduce a new methodological approach that allows us to identify the effect of individual promotion events. In so doing, we follow the lead of Ailawadi et al. (2006), who quantified the effectiveness of individual promotions at the CVS drugstore chain in the United States. However, their approach required very detailed information, not only from point-of-sales scanner data, but also extensive internal company data (such as, for example, the panel data on CVS’s ExtraCare Loyalty Program), information that is often proprietary. Our approach, in contrast, uses conventional scanner data, which is more commonly available.

Second, as we are now able to pinpoint the effect of each individual promotion event, we can identify the drivers of promotional effectiveness in a much more detailed way, focusing on how the promotion is planned (timing, discount, duration), framed to the consumer (price cuts versus quantity discounts and/or involving other types of promotions like loyalty programs), and supported (with in-store and/or out-of-store communication).

Third, one domain where we show that an individual promotion analysis is particularly important is that of the promotional calendar. While studying the promotional calendar, researchers have often investigated the frequency of sales promotions (e.g.
Blattberg et al. 1995, Silva-Risso et al. 1999). However, two brands with the same “aggregate” frequency may still have a very different promotional schedule. For example, both brands in Figure 1 have four promotions in the considered time span. While they are uniformly spread for brand A, they are clustered in a limited time span for brand B (Figure 2.1), which may affect the effectiveness of a promotion at a given point \(X_o\). Although the average frequency of sales promotions is the same for brand A and brand B, in the case of brand B there is a large variation in the “time elapsed since the previous promotion”. For brand A, instead, this variable is constant.

Figure 2.1. Same frequency, different timing (\(X = \) promotion event)

<table>
<thead>
<tr>
<th>Example Brand A:</th>
<th>X</th>
<th>X</th>
<th>X</th>
<th>X</th>
<th>(X_o)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Example Brand B:</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>(X_o)</td>
</tr>
</tbody>
</table>

Moreover, prior research has focused almost exclusively on the frequency of the promotions within a given retailer. This was mainly due to the data available, often collected only at a single chain rather than across different chains (e.g. CVS for Ailawadi et al. 2006, Dominick’s Finer Foods for Srinivasan et al. 2004). Instead, we also consider the timing of promotions for the same brand with competing retailers, and show that this has an impact on the effectiveness of a new promotional event. As such, when planning their promotional activities, managers should take into account the promotional calendar not only with the focal chain, but also with competing chains.
2.2. Literature review

2.2.1. Individual versus average effects

The extant literature tends to estimate the average sales response to price promotions (e.g. Nijs et al. 2001, Steenkamp et al. 2005). This way, one cannot determine which promotion event was most successful, and why. Some attempts to capture cross-promotion variation have been made through the incorporation of moderating effects for folder and display communication (e.g. van Heerde et al. 2004) or through the use of varying parameter models (e.g. Foekens et al. 1999). As such, van Heerde et al. (2004) computed separate “average” effects for pure price cuts and price cuts supported by folder, display or folder and display, while Foekens et al. (1999) allowed the average promotional effectiveness to vary with the time and amount of previous promotions. On the one hand, these prior studies clearly indicate that promotional effectiveness (even for the same brand) is not constant across implementations. On the other hand, the number of interaction terms considered remained fairly limited.

The need to look at the effectiveness of individual promotions was recently emphasized by Ailawadi et al. (2006, 2007). Their research uses a cross-sectional method, based on internal company data, to compute how many incremental units each promotion was able to lift from the baseline sales. They find that promotions generate an average gross lift of 310% ($SD = 581\%$) and that only 45% of this lift is truly incremental (after controlling for cross-period, cross-store\(^1\) and cross-brand effects). Moreover, not all promotions were found to be effective. When profits were considered, in 17% of the cases in their dataset, the promotional margin was even negative. In the study of Ailawadi et al., very detailed company data were available/needed, which limits the general applicability of the method. In contrast, we propose a method to estimate econometrically the effectiveness of individual promotions from longitudinal data, using *commonly available retail scanner data*. To that extent, we use recently developed structural-break time-series techniques, which extend the intervention approach advocated by Leone (1987) to a setting where multiple promotions take place in the considered time span. In so doing, we explicitly account for deceleration and stockpiling effects, and control for a variety of other

\(^1\) In this context, the term “store” refers to another store of the same chain, CVS.
factors that may affect a brand’s baseline sales, such as advertising campaigns and competitive actions.

### 2.2.2. Drivers of promotional effectiveness

Prior research has investigated variations in promotional effectiveness mainly across brands and product categories. For example, Srinivasan et al. (2004) linked promotional effectiveness to *brand* characteristics (market share, private label vs. national brand, promotional frequency and depth)\(^2\) and *category* characteristics (market concentration, SKU proliferation, private-label share, ability to stockpile, impulse category). Such *brand* and *category* characteristics are of high strategic relevance to the retailers, as they are primarily interested in understanding which brand and/or category is most sensitive to the promotion. However, also within the same store and for the same brand, there is quite some variation across promotional activities, as promotion events can be planned, framed and supported differently. From a manufacturer’s point of view, contextual characteristics, such as brand and/or category characteristics, can hardly be varied. *Deal execution* characteristics (deal planning, framing and support), in contrast, can be managed more easily and more directly.

**Deal planning.** When talking about deal planning, we refer to (1) the timing of the promotions (relative to previous promotions), (2) the depth of the promotions, and (3) the duration of the promotion event. So far, to capture deal planning, scholars have mainly used the aggregate frequency of sales promotions, instead of the time elapsed since the previous promotion event (Bell et al. 1999). They find conflicting evidence. While some of these studies find that fewer deals increase the saliency of price promotions, leading to more attractive deals (Bell et al. 1999, Raju 1992), others show that more frequent promotions are more effective (Neslin 2002). Moreover, prior research indicates that a higher discount level may improve consumers’ evaluation of the deal and trigger more purchases (Krishna 1991). A longer duration, in turn, may give consumers more opportunities to take advantage of the deal (Cooper et al. 1999), and to build more inventory at the promotion price, inducing greater post-promotion dips.

\(^2\) In this prior research, promotional frequency and depth were operationalized as brand characteristics. They captured variations across brands, and identified to what extent a given brand relied more or less on sales promotions to stimulate sales. In our study, in contrast, we will operationalize promotional frequency and depth at the individual promotion level. We will categorize them among promotional planning characteristics, as they explain variation across promotions and their individual implementation.
Deal framing. Consumers’ reactions to promotions may also be contingent on the way promotions are framed (Darke and Chung 2005, Krishna et al. 2002). As such, different reactions may be obtained depending on whether the discount is framed as a pure price cut, as a quantity discount (Macé and Neslin 2004, Wansink et al. 1998), as part of a loyalty program (Kivetz and Simonson 2002, Zhang and Wedel 2009) or as a non-monetary promotion (Chandon et al. 2000). For example, quantity discounts, loyalty programs and non-monetary promotions are often less effective than pure price cuts. However, as Chandon et al. (2000) point out, that may depend on the context, and in particular, on the product category.

Deal support. Promotional events can be supported by various forms of out-of-store communication. For example, retailers often employ features to communicate their promotional messages to potential customers, and to increase both store traffic and the sales of the promoted items (e.g. Bawa and Shoemaker 1987, Walters and MacKenzie 1988). Prior research has shown that folders are able to boost the sales lift within the focal retailer. Moreover, advertising support at the time of the promotion may lead to positive or negative synergies (Kaul and Wittink 1995, Mitra and Lynch 1995). For example, non-price advertisements that differentiate the brand’s image decrease price sensitivity, while price advertisements increase price and discount sensitivity.

Previous literature has also shown that the market share of the brand (e.g. Bolton 1989), the concentration level in the category (e.g. Pauwels et al. 2007) and the inventory turnover,3 which is closely related to the purchase frequency of a brand (e.g. Bell et al. 1999), can also influence the effectiveness of promotional activities. For example, brands with a higher market share (Bolton 1989), in less concentrated categories (Ailawadi et al. 2006), and with a higher purchase frequency (Bell et al. 1999) tend to have a lower promotional effectiveness than brands with a lower market share, in more concentrated categories, or with a lower purchase frequency.

2.3. Model

To investigate the effectiveness of individual price promotion events, we adopt a two-step approach. In a first step, we determine the total sales effectiveness of each individual promotion using a time-series structural-break model, developed by Ben-David

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3 Inventory turnover indicates how many times the brand’s inventory is sold and replaced over a period.
and Papell (2000). This extends the intervention approach of Leone (1987) to a setting involving multiple promotions. The occurrence of each price promotion is captured through a separate pulse dummy, which equals one in the week(s) of the promotion event and zero otherwise. This practice is conceptually very different from what is typically performed in the SCAN*PRO tradition (see e.g. van Heerde et al. 2008 for a review) where price promotions are captured by a single price index, defined as the ratio between the shelf price and the regular non-promoted price. However, as we mentioned before, this leads to the estimate of an average effect across all the promotion events implemented by that brand.

In the case of \( P \) promotions, we include a set of \( P \) pulse dummy variables \( PROMO_{i,c,j,p,t} \), which equal 1 in the week(s) \( t \) of promotion event \( p \) of product \( i \) (of category \( c \)) at retailer \( j \) and 0 otherwise. We account for possible post-promotion dips by adding lags of these dummy variables. For parsimony reasons, we consider two lags.\(^4\)

\[
(E1) \quad SALES_{i,c,j,t} = \ldots + \sum_{p=1}^{P} \sum_{l=0}^{2} \beta_{i,c,j,p,l} PROMO_{i,c,j,p,t-l} + \ldots ,
\]

where \( i \) indicates the product (\( i = 1, \ldots, I \)), \( c \) represents the category (\( c = 1, \ldots, C \)), \( j \) the chain (\( j = 1, \ldots, J \)), and \( t \) the week (\( t = 1, \ldots, T \)). \( SALES_{i,c,j,t} \) refers to the sales in volume, while \( \beta_{i,c,j,p,l} \) expresses the parameter for the impact of individual promotion event \( p \) (\( p = 1, \ldots, P \)) in week \( t - l \) (\( l = 0, 1, 2 \)) of product \( i \) of category \( c \) at retailer \( j \).

The total effect (\( TE \)) of a given promotional event is then given by:

\[
(E2) \quad TE_{i,c,j,p} = \sum_{l=0}^{2} \beta_{i,c,j,p,l} ,
\]

for which the standard errors can be derived through the Delta method (Greene 2003).

The model in Equation E1 is augmented in four ways to avoid confounding effects due to missing variables. First, to filter out the average effect of competitive promotions by the same brand at a competing retailer (\( CP_{i,c,j',t} \) (\( j' \neq j \)), three dummy variables are added to the model to capture, respectively, the instantaneous average effect and the two lagged effects of these events. To save degrees of freedom, we control for the average effect of these confounding events, rather than for their individual (promotion- and

\(^{4}\) We also considered the possibility of adding a third lag or one or more lead terms (to capture pre-promotional dips). However, the two-lag specification was preferred (based on the AIC fit criterion) for close to 95% of the brands.
Not all promotions are made equal

retail-specific) effects. Second, we control for the dynamic impact of brand advertising by adding the advertising goodwill of the focal brand (ADSTOCK\(_{i,c,t}\)) (Jedidi et al. 1999). The latter is operationalized using the conventional Adstock specification, in which we allow the decay parameter to be product-specific (we elaborate on this issue in the Data section). To capture the evolution of sales over time, a trend variable is included in the model (TREND\(_t\)). Finally, two trigonometric terms, sin \((2πt/52)\) and cos \((2πt/52)\), are added to account in a parsimonious way for seasonal fluctuations in the series (Hanssens et al. 2001: 46).

The final model is given in the equation below.

\[
\text{(E3)} \quad \text{SALES}_{i,c,j,t} = \alpha_{i,c,j} + \sum_{p=1}^{p} \sum_{l=0}^{2} \beta_{i,c,j,p,l} \text{PROMO}_{i,c,j,p,l,t-1} + \sum_{k=0}^{2} \gamma_{i,c,j,f,k} \text{CP}_{i,c,j,f,t-k} + \delta_{i,c,j} \text{ADSTOCK}_{i,c,t} + \eta_{i,c,j} \sin \left(\frac{2\pi t}{52}\right) + \eta'_{i,c,j} \cos \left(\frac{2\pi t}{52}\right) + \eta''_{i,c,j} \text{TREND}_t + \epsilon_{i,c,j,t}
\]

We estimate this equation for a given product \(i\) across all the retailers simultaneously. To allow for autocorrelation in the error terms, and to exploit cross-equation correlations, we adopt an iterative SUR-GLS procedure with Prais–Winsten correction, as in van Heerde et al. (2004), to obtain more efficient parameter estimates (Judge et al. 1985). The error is therefore distributed as:

\[
\epsilon_{i,c,j,t} = \rho_{i,c,j} \epsilon_{i,c,j,t-1} + \nu_{i,c,j,t}
\]

\[
\epsilon_{i,c,j',t} = \rho_{i,c,j'} \epsilon_{i,c,j',t-1} + \nu_{i,c,j',t}
\]

\[
\text{cov} [\nu_{i,c,j,t}, \nu_{i,c,j',t}] = \sigma_{i,c,j,j'}
\]

where \(\nu_{i,c,j,t} \sim N(0, \sigma^2_{\nu_{i,c,j}})\), and \(\nu_{i,c,j',t} \sim N(0, \sigma^2_{\nu_{i,c,j'}})\).

We then normalize the total effects of each promotion event by dividing them by the baseline sales (the baseline sales are measured as the average non-promotional sales of
each brand within the focal retailer).\

\[(E4) \quad TE^{*}_{i,c,j,p} = \frac{2}{\text{BASELINE_SALES}_{i,c}} \sum_{l=0}^{2} \beta_{i,c,j,p,l} / \text{BASELINE_SALES}_{i,c,j}\]

In a second step, we relate the normalized total effect of each promotion event \(p\) (from E4) to different promotional and contextual characteristics. To correct for a potential violation of the statistical independence assumption induced by the fact that several promotions were organized for the same brand, a random-effect correction at the brand level is used to allow within-brand correlation.\(^6\)

\[(E5) \quad TE^{*}_{i,c,j,p} = \mu_{j} + \sum_{j=2}^{J} \mu_{j} DR_{j} + \sum_{c=2}^{C} \mu_{c} DC_{c} + \\
\beta_{1} \log \text{TIMING}_{i,c,j,p} + \beta_{2} \log \text{TIMING\_COMP}_{i,c,j,p} + \\
\beta_{3} \text{SIMULTANEOUS}_{i,c,j,p} + \beta_{4} \log \text{DEPTH}_{i,c,j,p} + \\
\beta_{5} \log \text{DURATION}_{i,c,j,p} + \beta_{6} \text{QUANTITY}_{i,c,j,p} + \\
\beta_{7} \text{LOYALTY}_{i,c,j,p} + \beta_{8} \text{OTHER}_{i,c,j,p} + \beta_{9} \text{FEATURE}_{i,c,j,p} + \\
\beta_{10} \text{DISPLAY}_{i,c,j,p} + \beta_{11} \log \text{ADSTOCK}_{i,c,p} + \\
\beta_{12} \log \text{MKTSHARE}_{i,c,j} + \beta_{13} \log \text{CONCENTRATION}_{i,c,j} + \beta_{14} \log \text{INVENTORY}_{i,c} + u_{i} + \nu_{i,c,j,p}\]

where \(TE^{*}_{i,c,j,p}\) is the normalized total promotional effect, \(\mu_{j}\) is the intercept, and \(DR_{j}\) and \(DC_{c}\) are, respectively, retailer- and category-specific dummy variables. \(\text{TIMING}\) refers to the time elapsed since the previous promotion for the same brand implemented at, respectively, the same retailer (\(\text{TIMING}_{i,c,j,p}\)) and at a competing retailer (\(\text{TIMING\_COMP}_{i,c,j,p}\)). \(\text{SIMULTANEOUS}_{i,c,j,p}\) is a dummy variable capturing the effect of a concurrent promotion of the same brand at a competing retailer \(j^*\) (with \(j^* \neq j\)). \(\text{DEPTH}_{i,c,j,p}\)

\(^5\) In the computation of the average non-promotional sales, we do not include the promotional week, or the two weeks after the promotion event, in order to filter out any (post-) promotional effects from the baseline sales. Also, we checked if the sales series was trending.

\(^6\) One could use a one-stage approach instead of our two-stage approach. However, as shown by Bolton (1989: 159), as we have a large number of independent variables and brands, a one-stage approach becomes prohibitively complex. Moreover, we avoid possible bias in the standard errors of the second stage by weighting the estimated dependent variable \(TE^{*}\) by the inverse of its standard error (see Narasimhan et al. 1996, Nijs et al. 2001, Steenkamp et al. 2005 for a similar approach).
and $DURATION_{i,c,j,p}$ refer to the depth of the discount and the duration of the promotional event, respectively. $QUANTITY_{i,c,j,p}$ and $LOYALTY_{i,c,j,p}$ are dummy variables indicating, respectively, whether the promotion was framed as a quantity discount or tied to the retailer’s loyalty program. $OTHER_{i,c,j,p}$ captures non-monetary promotions, like free gifts, and is also a dummy variable. $FEATURE_{i,c,j,p}$ is a dummy variable indicating whether a feature communication supported the promotion event, while $DISPLAY_{i,c,j,p}$ is a dummy variable capturing the presence of an in-store display. $ADSTOCK_{i,c,p}$ represents the cumulative stock of past and current advertising expenditure at the time of promotion $p$.

To have more reliable estimates of the effects of the focal constructs, we also include the following control variables: the market share of the brand ($MKTSHARE_{i,c,j}$), the concentration level within the category ($CONCENTRATION_{i,c,j}$) and the inventory turnover of the brand ($INVENTORY_{i,c}$). To reduce the skewness of the data, a natural log transformation is applied to the continuous variables described above (e.g. Ruppert and Aldershof 1989). $u_i$ is the random effect of the $i$th brand, distributed with an expected value of 0 and variance $\sigma_u^2$. The error term $v_{i,c,j,p}$ is normally distributed with mean 0 and variance $\sigma_v^2$.

2.4. Data

2.4.1. Sample composition

The dataset covers a time span of 147 weeks, from January 2001 to mid October 2003. During these 3 years, we analyze a total of 519 promotional events. They represent all the national promotions for the 30 brands in the assortment of a leading multinational CPG manufacturer. The 30 brands belong to 8 different product categories, ranging from bread replacements to biscuits and snacks. The fact that these products are indulgence goods may have implications for our results, as “a sales promotion’s effectiveness is determined by the utilitarian or hedonic nature of the benefits it delivers and the congruence these benefits have with the promoted product” (Chandon et al. 2000: 65). For

7 $MKTSHARE$ and $CONCENTRATION$ vary over the years, depending on the timing of the promotional event. For reasons of simplicity, we do not include the year subscript. $INVENTORY$, instead, varies only across brands. This variable was not available at a more refined level.

8 For “national promotions”, we refer to promotions implemented at the national level, with a distribution coverage of no less than 80%.
example, non-monetary promotions (e.g. loyalty programs, free gifts) may work better for indulgence goods than pure price cuts, in contrast to more utilitarian products, like toilet paper or coffee, where pure price cuts outperform non-monetary promotions.

A first visual inspection of the data suggests a large variability in the effectiveness across promotion events of the same brand, even within the same retailer. Figure 2.2, for example, illustrates the sales of one of the brands in our sample over time. The different impacts of six promotion events of this brand (indicated by a vertical arrow) are evident from Figure 2.2. Some promotions generate only a modest sales lift (e.g. in weeks 11 and 51), while others appear to boost sales to a much greater extent (e.g. in weeks 73, 80, 125 and 129).

These promotions, however, were implemented in different ways: the first promotion (in week 11) had a 22% discount, lasted for two weeks, and was not supported by a folder or display; the last promotion (in week 129), in contrast, had a 30% discount, lasted for one week and was supported by both folder and display. On average, promotions for this brand seem to be quite effective.

However, as shown by the graph, some are considerably more effective than others.

Figure 2.2. Variation in promotion effectiveness within product.
Sales (in volume) over time (Product 13, Retailer 1)
The data are collected in the Netherlands at four leading national supermarket chains\(^9\) (these chains were also the key ones considered by van Heerde et al. 2008; while Retailer 1 was studied as well by Ailawadi et al. 2008). Together, these chains cover 70% of the Dutch FMCG market (Planet Retail 2006). They vary in terms of pricing, market share, service level and extent of promotional activities (see Figure 2.3 and Table 2.1) (GfK Report 2002).

Promotion and sales data were collected through ACNielsen, and augmented with internal company data on the way each promotion was framed to the consumer (for the second step). Finally, weekly advertising expenses for the brands in our dataset were obtained from Nielsen Media Research.

All the data used in the first step are commonly available, i.e. no proprietary company data are needed, which distinguishes our implementation from the approach of Ailawadi et al. (2006, 2007).

\(^9\) With 4 retailers and 8 product categories, there are 27 independent variables for our second step.
2.4.2. Measures

**Deal planning.** The TIMING since the previous promotion event was operationalized in terms of the number of weeks elapsed since the last promotion. We distinguish two timing variables, capturing the time elapsed since the previous promotion for the same brand implemented at, respectively, the same retailer ($TIMING_{i,c,j,p}$, $M = 5.07$, $SD = 13.46$) and at a competing retailer ($TIMING\_COMP_{i,c,j,p}$, $M = 6.83$, $SD = 10.16$) (see Table 2.1). The potential confounding effect generated by a SIMULTANEOUS promotion is measured by a dummy variable taking the value of 1 when there is a concurrent promotion event of the same brand at a competing retailer. This was the case in 68.6% of all instances. Deal DEPTH is defined as the percentage of the promotional discount (e.g. Nijs et al. 2001) ($M = 21.43$, $SD = 12.15$), while DURATION is operationalized as the number of promotional weeks (e.g. Cooper et al. 1999) ($M = 1.27$, $SD = .65$).

**Deal framing.** The framing of the promotion is operationalized by means of three dummy variables, (1) indicating the presence of a quantity discount involving the purchase of multiple packs of the product (e.g. “buy one, get one for free”-type of offer) (QUANTITY) ($frequency = 14.2\%$), (2) a loyalty program of the retailer (e.g. when a discount is offered only to holders of the retailer’s loyalty card) (LOYALTY) ($frequency = 12.4\%$), or (3) a non-monetary promotion (e.g. when a gift is included in the package, like a small toy/game for kids) (OTHER) ($frequency = 3.3\%$). As OTHER represents non-monetary promotions, DEPTH = 0, when OTHERS = 1. The reference group consists of pure price cuts.

**Deal communication.** Out-of-store communication is measured by a dummy variable, indicating whether the promotion is supported by feature communication (FEATURE) ($frequency = 42.2\%$), while in-store communication is captured by a dummy variable indicating whether the promotion is supported by an in-store display (DISPLAY) ($frequency = 4.7\%$). To quantify contemporaneous and delayed brand advertising effects, we use the log of the Adstock specification of the advertising expenditure of the brand, defined through the weighted average of past advertising expenditure, e.g. $log(ADSTOCK_{i,c,t}) = log\left(\sum_{w=0}^{\infty} \lambda^w Adv_{i,c,t-w}\right)$ (Jedidi et al. 1999), where the weight pattern evolves over time according to decay parameter $\lambda$. We use a fixed number of six lags, based on the average duration of six weeks identified by previous studies using weekly data (Leone...
1995: G143). The decay parameter $\lambda_i$ is estimated by means of a grid search procedure\(^{10}\) for each product $i$ conducted by running the model in E3 for each set of $\lambda$s (for $\lambda = .01$ to .99, in steps of .01). We chose the model with the $\lambda$ that minimizes the AIC criterion. The average $\lambda$ for the advertising expenditure of the brand is .56 ($SD = .19$), which is in line with the average decay parameter reported by Leone (1995: G144; $\lambda = .54$). For the second step, we use the value of this Adstock variable at the time of the promotion $p$, $ADSTOCK_i,c,p$ ($M = 62,475$, $SD = 14,1914$). This huge variability is due to the fact that the manufacturer did not invest in advertising for 37% of its brands. In those cases, this variable is equal to 0. Therefore, before taking the log, we add one to every observation of the Adstock variable.

**Control variables.** MKTSHARE is defined as the yearly sales (in volume) of brand $i$ at the focal retailer $j$ in the focal year, divided by the sales (in volume) of all the brands in the category at retailer $j$ ($M = 6.06$, $SD = 4.95$). CONCENTRATION refers to the sum of the yearly market shares of the top three brands in the category at the focal retailer, as in previous work in industrial organization (Bowman and Gatignon 1995) and marketing (Pauwels et al. 2007) ($M = 23.68$, $SD = 9.22$). INVENTORY is a ratio that indicates how many times the brand’s inventory is sold and replaced over a period (Bell et al. 1999) ($M = 9.51$, $SD = 6.15$). This variable is the inverse of a commonly-used metric for inter-purchase time.\(^{11}\)

To capture variation across the four retailers, we set Retailer 1 as the reference, and include in the model three dummy variables assuming the value of one for, respectively, Retailer 2, Retailer 3 and Retailer 4. Similarly, we use seven dummy variables to capture variation across the eight product categories in our sample.

All the marketing variables are available on a weekly basis and, unlike previous research, are specific to each individual promotion event, rather than averages computed over time and/or promotional events. In fact, we use averages only for the control variables.

\(^{10}\) The decay parameter (for a given brand) is assumed to be the same for every retailer. We assume that there is no variation across retailers. Nevertheless, we conducted a robustness check and we found little variation across retailers. Moreover, allowing the decay parameter to vary across products and retailers does not impact on the final results.

\(^{11}\) Given the differences among the retailers, certain brands may be more popular within a specific chain and less in a competing one, as the customers (their preferences and purchases) may differ across stores. For this reason, MKTSHARE and CONCENTRATION are retailer-specific. The variable INVENTORY was provided by ACNielsen, and was not available at the retailer level.
Table 2.1 summarizes the relevant descriptive statistics. It is worth noticing that there are significant differences across retailers. For example, overall, Retailer 3 implemented the smallest number of promotions (96), although in 38% of the cases, we find more promotions implemented at Retailer 3 than at Retailer 1 (suggesting more concentration of promotional support in a few categories). The promotions implemented at Retailer 4 and Retailer 2 are facing competition from a simultaneous promotion event offered at a competing retailer in 60% of the cases, in comparison with almost 80% of the cases for promotions implemented at Retailer 1 and Retailer 3. Also, there is great variation in the average discount depth offered: while Retailer 4 offers an average discount of 27%, at Retailer 3 (relatively less expensive and more service-oriented than Retailer 4, see Figure 2.3) the average discount depth is only 17%. Also features, another important driver of promotional effectiveness together with the depth of the discount (Blattberg et al. 1995), is differently implemented across retailers. At Retailer 3 only 5% of the promotions are supported by features, while Retailer 4 uses feature communication for 76% of its promotions. Instead, Retailer 1 uses more display communication than the other retailers, i.e. 11%. Displays are in fact implemented at Retailer 2 and Retailer 4 in only 1% of the cases, and in 4% of the cases at Retailer 3. We refer to Table 2.1 for more details.12

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12 For comparison purposes, we report some descriptive statistics of one of the most recent studies using data from the Dutch grocery stores, i.e. the work of Van Heerde et al. (2004) on peanut butter and shampoo. In their sample, promotions were implemented with an average discount of 17% (with a minimum discount of 6%), were supported by feature in 20% of the cases (with a minimum frequency of 12%), and by display in 18% of the cases (with a minimum frequency of 5%).
Table 2.1. Descriptive statistics ($M = \text{mean}, SD = \text{standard deviation}$)

<table>
<thead>
<tr>
<th></th>
<th>Retailer 1</th>
<th>Retailer 2</th>
<th>Retailer 3</th>
<th>Retailer 4</th>
<th>Overall</th>
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<tr>
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<td>$SD$</td>
<td>$M$</td>
<td>$SD$</td>
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<td>PLANNING</td>
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<td>TIMING (weeks)</td>
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<td>SIMULTANEOUS (frequency %)*</td>
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<td>2.73</td>
<td>4.1</td>
<td>3.6</td>
<td>2.56</td>
</tr>
</tbody>
</table>

*For the dummy variables, we report the frequency (%).
Chapter 2

2.5. Results

2.5.1. Are promotions effective?

We estimate the model specified in E2 for each product across all the retailers simultaneously, using iterative SUR-GLS with Prais–Winsten correction. The average $R^2$ across all the models (Judge et al. 1985, van Heerde et al. 2004) is .93. For each product–retailer combination, we compute the normalized total effect of every promotion event ($TE^*$), as described in E4. The respective standard errors are derived using the Delta method.

We find that $TE^*$ is significant (one-sided p-value <.05) and positive in 84% of the cases, indicating that the vast majority of the sales promotions were able to significantly increase sales (Table 2.2). This effect already incorporates dynamic effects like post-promotion dips (see E2).

Overall, these average results appear to be in line with the results reported by Srinivasan et al. (2004: 622) of 84% significant promotions. Although the overall picture is very positive, we notice quite some variability across retailers (Table 2.2). Whereas we find that up to 89% of all the promotions were effective at Retailer 2, at Retailer 4 only 77% of all the actions had a positive impact. The proportion test (Sheskin 2000) reveals that the percentage of effective promotions at Retailer 3 is significantly smaller than at Retailer 1 (two-proportion z-test = 1.67, $p < .10$) or at Retailer 2 (two-proportion z-test = 2.24, $p < .05$).

Even more variability exists across products. Figure 2.4 shows that, while all the promotional activities of some products systematically increase sales (in 100% of the cases for products 14, 19, 21, 27 and 30), for other products (e.g. products 7, 28 and 29) less than 40% of the promotions are able to lift sales significantly.

---

13 However, in Srinivasan et al. (2004), the unit of the analysis was not the effect of individual promotions, but the average effect of all the promotions for a given brand. That average effect was significant for 84% of all 63 brands considered.
Table 2.2. Percentage of significant promotion events (one-sided p-value < .05)

<table>
<thead>
<tr>
<th>Positive effects</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>84%</td>
</tr>
<tr>
<td>Retailer 1</td>
<td>86%</td>
</tr>
<tr>
<td>Retailer 2</td>
<td>89%</td>
</tr>
<tr>
<td>Retailer 3</td>
<td>77%</td>
</tr>
<tr>
<td>Retailer 4</td>
<td>84%</td>
</tr>
<tr>
<td>N (only positive effects)</td>
<td>436</td>
</tr>
<tr>
<td>Total N = 519</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2.4. Percentage of effective promotion events (t-value < 1.64) across products

The average (normalized) effect across all products and retailers is 5.9, suggesting that after accounting for stockpiling effects a promotion is able to lift sales by a factor of 6. This is in line with prior literature. For example, Narasimhan et al. (1996: 24) find that a promotion with a 20% discount may increase sales by, on average, a factor 8 (15 for displayed price cuts, 8 for featured price cuts and 2 for pure price cuts).

This effect varies substantially across products. More interestingly, our results also show great variation within products and retailers (see Figure 2.5 for details). For example, for product 5 at Retailer 3, the normalized effect varies across promotions from a maximum of 2.10 (p < .001) to a minimum of -.82 (n.s.), leading to a high coefficient of
variation (defined as the ratio of the standard deviation to the mean) of 4.89. Similarly, for product 8 at Retailer 3, the normalized effect fluctuates from a maximum of 4.64 ($p < .001$) to a minimum of -.37 (n.s.), with a coefficient of variation of 1.25.

**Figure 2.5. Coefficient of variation of promotional effectiveness**

![Coefficient of variation of promotional effectiveness](image)

**2.5.1.1. Model comparison**

We compared our results with those of a log-log model, where we define the promotion events by means of the log of the price index, in line with the SCAN*PRO model tradition (see e.g. van Heerde and Neslin 2008, Wittink et al. 1988), as well as with the results of a linear model, similar to Srinivasan et al. (2004). The main difference between the log-log model and our model is that, in the log-log model, we used the log of the sales as our dependent variable and the log of the price index (shelf price divided by regular non-promotional price) as our key independent variable, instead of the individual promotional indicator variables. In the linear model, we replaced the promotional indicator variables with the price index. Also, to allow a fair comparison, we re-estimated the ADSTOCK variable for each model separately, following the procedure explained above. Both models are estimated by iterative SUR-GLS, as we performed with E3.

The empirical comparisons demonstrate that, based on the AIC criteria, accommodating individual promotion heterogeneity does improve the accuracy of the promotional parameters relative to the log-log and linear model in 68% of the cases (see
Table 2.3). Also, in 96% of the cases our model and the log-log model outperform the linear model. Based on this, for simplicity of exposition, we drop the linear model from the comparison.

### Table 2.3. Model comparison: lowest AIC

<table>
<thead>
<tr>
<th></th>
<th>Individual promotion model</th>
<th>Average promotion model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Our model</td>
<td>Log-log model</td>
</tr>
<tr>
<td>Lowest AIC</td>
<td>68%</td>
<td>29%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3%</td>
</tr>
</tbody>
</table>

The results of the log-log model indicate that the promotions are effective (*one-sided p-value* < .05) for 91% of the brands (which account for 94% of the promotions), as shown in Table 2.4. Table 2.4 indicates that our findings, however, are much richer in the sense that they show that, for brands where the log-log model indicated a non-significant effect, more than one-third of the promotion events were actually effective (with one of them even having a lift of a factor 2.5). However, given that several promotions were not significant, these not significant effects dominate.

Alternatively, for brands for which promotions were significant in the log-log model, our approach reveals that as many as 13% of the events were not able to raise sales. In fact, Figure 2.4 has already shown that only for 17% of the brands were all the promotions significant. In all the other cases, at least one of the promotions was not able to lift sales significantly.

---

14 This corresponds to a total number of 27 brands with effective promotions. The number of promotions for those 27 brands is 488, i.e. 94% of the promotions in our sample (see Table 2.4).

15 To compare the individual effects of each promotion event, obtained from our individual promotion model, with the average effects estimated with the log-log model, we transform our results into elasticities. We achieve this by normalizing the incremental sales lift obtained in our model by the ratio of the sample mean of the brand’s weekly non-promotional sales to the sample mean of the brand’s weekly non-promotional price. Note that an increase of 250% is similar in magnitude to the results reported by previous research (see for example Ailawadi et al. 2006).

16 See products 7, 28 and 29 in Figure 2.4.

17 Figure 2.4 shows that all the promotions of product 10, 14, 19, 21, 27 and 30 were effective.
Table 2.4. Missed opportunities and spoiled arms

<table>
<thead>
<tr>
<th></th>
<th>Significant brands (%)</th>
<th>Not significant brands (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-log model</td>
<td>27 (91%)</td>
<td>3 (9%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Individual promotion model</th>
<th>Number of significant promotions (%)</th>
<th>MISSED OPPORTUNITIES</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>424 (87%)</td>
<td>12 (39%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Individual promotion model</th>
<th>Number of not significant promotions (%)</th>
<th>SPOILED ARMS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>64 (13%)</td>
<td>19 (61%)</td>
</tr>
</tbody>
</table>

| Total number of promotions (%) | 488 (100%) | 31 (100%) |

To summarize, two types of mistakes can be made:

**Missed opportunities.** When a brand shows overall *non-significant* promotions, managers may infer that *all* promotions are not effective and therefore may stop promoting that brand, missing important opportunities to increase sales. They should instead look at the impact of each individual promotion. This way, they would realize that some individual promotions might still work.

**Spoiled arms.** When a brand shows overall *significant* promotions, managers may infer that *all* promotions for that brand lift up sales, not realizing that some individual ones do not work, and therefore can be considered “spoiled arms” (Leeflang and Wittink 1996, Steenkamp et al. 2005).

---

18 The terms “missed opportunities” and “spoiled arms” were previously adopted in the literature by Leeflang and Wittink (1996: 106) and Steenkamp et al. (2005: 48).
2.5.2. Drivers of promotional effectiveness

To investigate the drivers of those more effective promotions, we relate the *normalized total effect* of each promotion to the way the promotion was implemented (as shown in E5). Such knowledge is important, as for 83% of the brands, less than 100% of their promotions were effective. Even when they were all effective, we find considerable variation among them. If this variation is systematic, managers may exploit it to achieve higher overall effectiveness of their promotional events. Table 2.5 shows the estimated impact of promotion characteristics and other correlates. Due to space limitation, we do not report the category-specific effects (but they are available in Appendix 1).

The Pseudo R² is .50. The Chi-square tests ($\chi^2 = 243.8, p < .0001$) show that the model described in E5 significantly outperforms a model where only retailer and category effects are considered. VIF statistics indicate that multicollinearity is not a serious concern (VIF < 2).

**Deal planning. Timing.** Previous research has worked mainly with the frequency of sales promotions. Although frequency and timing are two different constructs, they are highly related to each other. Based on these previous studies, we would expect that when more time elapses since the previous promotion event (for less frequent promotions) implemented at the same retailer, the impact of the focal promotion event may be higher (Bell et al. 1999). We would also expect this effect when we consider the timing since the previous promotion implemented at a competing retailer, as previous research showed that more than 80% of consumers shop for bargains across competing retailers (Fox and Hoch 2005). This suggests a great amount of cherry-picking and store-switching behavior induced by promotion activities (Gijsbrechts et al. 2008). Our results confirm both assumptions. We find promotions to be more effective when more time elapses between two consecutive events, not only when implemented at the same retailer ($\beta_1 = .44, p = .07$), but also at competing retailers ($\beta_2 = .51, p = .01$). Moreover, we also find evidence that the simultaneous occurrence of a promotion at a competing retailer (during the same week) decreases significantly the effectiveness of the focal promotion event ($\beta_3 = -1.26, p = .01$).¹⁹

¹⁹ We also controlled for the timing since the promotion event of competing brands, as well as for the simultaneous events of competing brands. Both effects were insignificant ($p > .15$).
Table 2.5. Moderator analysis

<table>
<thead>
<tr>
<th>Dependent variable: TE*</th>
<th>Parameter estimate</th>
<th>t-value</th>
<th>Two-sided p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_1 ) INTERCEPT</td>
<td>11.831</td>
<td>2.170</td>
<td>.042</td>
</tr>
<tr>
<td>( \mu_2 ) DR2</td>
<td>.900</td>
<td>1.440</td>
<td>.152</td>
</tr>
<tr>
<td>( \mu_3 ) DR3</td>
<td>-2.443</td>
<td>-3.600</td>
<td>.000</td>
</tr>
<tr>
<td>( \mu_4 ) DR4</td>
<td>-1.427</td>
<td>-1.900</td>
<td>.058</td>
</tr>
</tbody>
</table>

**PLANNING**

| \( \beta_1 \) Log TIMING | .440               | 1.800   | .073            |
| \( \beta_2 \) Log TIMING_COMP | .510          | 2.480   | .014            |
| \( \beta_3 \) SIMULTANEOUS | -1.264          | -2.590  | .010            |
| \( \beta_4 \) Log DEPTH  | .932              | 1.850   | .065            |
| \( \beta_5 \) Log DURATION | -1.770          | -3.000  | .003            |

**FRAMING (vs. pure price cut)**

| \( \beta_6 \) QUANTITY  | -.056             | -.080   | .935            |
| \( \beta_7 \) LOYALTY    | -1.653             | -1.010  | .312            |
| \( \beta_8 \) OTHER      | 4.261              | 1.870   | .062            |

**COMMUNICATION (vs. in-store shelf tag)**

| \( \beta_9 \) FEATURE   | 1.496              | 2.950   | .003            |
| \( \beta_{10} \) DISPLAY | 2.365              | 2.210   | .027            |
| \( \beta_{11} \) Log ADSTOCK | -.001             | -.030   | .978            |

**CONTROL VARIABLE**

| \( \beta_{12} \) Log MKTSHARE | -.900              | -2.280  | .023            |
| \( \beta_{13} \) Log CONCENTRATION | 5.032            | 2.420   | .016            |
| \( \beta_{14} \) Log INVENTORY  | -1.392             | -1.480  | .140            |

N = 519
Pseudo R² = .50
Not all promotions are made equal

Depth. Another important driver of price promotion effectiveness is the depth of the discount. In line with previous research, we find that higher discounts work better than smaller discounts (e.g. Blattberg et al. 1995) ($\beta_4 = .93$, $p = .07$). We checked for the presence of threshold effects, but did not find any evidence to support their presence.

Duration. Longer promotion events perform worse than shorter ones ($\beta_5 = -1.77$, $p < .01$). This result differs from that of Cooper et al. (1995). Cooper and colleagues show that a longer duration of a promotion generates a higher level of sales, as consumers have more opportunities to take advantage of the deal. However, consumers may also be able to build more inventory at the promotion price and will induce them to purchase less when the price goes up again. The study of Cooper et al. does not account for the negative effects induced by these implicit inventory build-ups. One could expect that, when these effects are incorporated, longer promotion events may induce a lower level of sales than promotion events lasting only one week, as their post-promotion dips can be greater.

Deal framing. When we look at the way the promotion is framed to the final consumers, we compare pure price cuts with other promotional formats like quantity discounts, loyalty programs and non-monetary promotions. We find no significant difference among pure price cuts, quantity discounts and loyalty programs. The use of a non-monetary promotional format (OTHER), however, outperforms pure price cuts ($\beta_8 = 4.26$, $p = .07$). This result is not surprising given the fact that, for indulgence goods like those in our sample (hedonic products), non-monetary promotions are found in the literature to work better than monetary promotions (Chandon et al. 2000).

Deal communication. Out-of-store feature communication ($\beta_9 = 1.50$, $p < .01$) as well as in-store displays ($\beta_{10} = 2.37$, $p < .05$) increase sales, confirming the findings of the extant literature (e.g. van Heerde et al. 2004). The difference between the effects of features and displays is significant ($p < .01$). Although the majority of previous research has shown a higher effectiveness for features than for displays, there are also studies which find the opposite effect (e.g. Albuquerque and Bronnenberg 2009, Narasimhan et al. 1996). Moreover, we can explain our result based on the nature of our product categories. The

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20 To check the presence of diminishing returns or threshold effects, we used different specifications. We replaced the log of the depth of the discount in E5, log DEPTH, by the depth and its quadratic term, DEPTH and DEPTH². Alternatively, we substituted log DEPTH by three new dummy variables, capturing small, medium, and large discounts. In so doing, we used different cut-off values, based on previous literature (e.g. Fok et al. 2007), and based on the distribution of our data (i.e. by using as cut-off values the 33rd and the 66th percentile of DEPTH).

21 We also excluded from the analysis all the non-monetary promotions to limit the investigation to promotions for which the consumers could perceive a clear monetary discount (pure price cuts, quantity discounts, loyalty programs), and we found no significant change in the results (see Table A.1 in the Appendix).
sales promotion response to hedonic products (like the indulgence goods in our sample) may differ from product categories like tuna, ketchup or coffee, often studied by previous studies. The recent work of Stilley at al. (2009) shows that, for hedonic products, purchases are driven more by unplanned in-store decisions. As in-store displays stimulate unplanned in-store decisions, it is not surprising to find a higher effectiveness for in-store displays than for features.

The cumulative effects of advertising expenditure do not significantly influence price promotion effectiveness ($p > .10$).

**Control variables.** In line with previous research, we find that promotions of brands with a high market share are less effective ($\beta_{12} = -.90$, $p < .05$) (e.g. see Blattberg et al. 1995), and that a higher concentration in the product category leads to higher effectiveness of sales promotions ($\beta_{13} = 5.03$, $p < .05$) (e.g. Bell et al. 1999). Also consistent with prior literature, we find a negative impact for the inventory turnover, even though this effect fails to reach statistical significance ($\beta_{14} = -1.39$, $p > .10$) (Ailawadi et al. 2006, Bell et al. 1999).

### 2.6. Conclusions

The extant literature has investigated in detail sales promotion variation across products and retailers. Brand managers could therefore infer which brand sells more on promotion, and at which retailer. Yet, for a specific brand, they still cannot identify how many promotions are truly able to lift up sales, as they cannot pinpoint which ones are more effective and which ones are just wasted money. This is the focus of this study.

Indeed, every promotion stimulates sales in a unique way, as clearly visible when we look at the different heights of the deal spikes (Figure 2.2). Nevertheless, research on cross-promotion variation is still limited. We propose an “individual promotion” approach that allows us to capture in a more flexible way the effectiveness of promotion events and their drivers. This way, we obtain a much richer picture of how many promotions are truly effective, in comparison with models based on an average promotional parameter. In an “average” approach, like a SCAN*PRO model, the researcher computes one average parameter across several promotion events. A (not) significant parameter may lead managers to (under-) over-estimate the actual number of effective promotions. With our approach, we show that such conclusions may be misleading, and result in spoiled arms or missed opportunities. For example, while an average approach shows that the promotional
activities of a focal brand are not able to stimulate sales, we may find that almost 40% of those promotions are actually effective. They would result in a missed opportunity if the manufacturers decide to abandon them. In contrast, 13% of the promotion events of brands for which the average model indicates a significant promotional effectiveness, are in reality spoiled arms, as an individual-promotion analysis indicates that they are not significantly able to increase sales. Furthermore, our approach highlights that only for 17% of the brands, all promotions are truly able to boost sales. This type of more detailed information is not possible with an average model.

In the second step of the analysis, our approach allows us to use promotion-specific (dependent and independent) variables, rather than averages computed across different promotions. In other words, we can utilize the exact number of weeks between two promotion events, the exact discount, etc., and not average frequencies, average discounts, etc. This is particularly important when dealing with variables directly controlled by manufacturers in the negotiations with retailers. For example, the promotional calendar is typically measured at the aggregate brand level (as frequency). However, as mentioned above, the same deal frequency can correspond to very different promotional calendars (Figure 2.1), with promotions equally spread over time or concentrated in a limited time spam. With an average measure it becomes difficult, if not impossible, to capture the diverse consequences for the effectiveness of promotional activities of distinct promotional calendars. Similarly, the same average discount could correspond to different implementations. Three promotions with an average price cut of 20% could have been implemented with individual discounts of 20% each, or with a discount of 5%, 20% and 35%, leading to individual differences in their deal spikes, again not fully captured by an average model. Therefore, we highlight the importance of looking at a more refined measure, identified at the individual promotion level.

Moreover, we take into account the promotional calendar of competing chains, not considered by previous studies (e.g. Srinivasan et al. 2005). The fact that previous studies have long ignored the promotional calendar of competing stores may be due to a lack of data of competing chains, as the majority of work in the sales promotion domain tends to rely on data of a single retail chain (e.g. CVS for Ailawadi et al. 2006, Dominick’s Finer Foods for Srinivasan et al. 2004). An additional reason why this aspect may have been ignored so far could be that managers tend to ignore competing promotion events, and do not react to them (Steenkamp et al. 2004). We find that this practice may not be optimal. In particular, we show that promotion events at a competing retailer (for the same product) reduce significantly the effectiveness of sales promotions at the focal chain, not
only when they occur simultaneously (in the same week) but also when little time has elapsed between these competing events. Manufacturers, selling through competing retailers, should take this into account when planning their sales promotions.

These results provide some first evidence to support the existence of cross-chain effects. In fact, so far limited attempts have been made to capture the impact of cross-chain effects. While some studies report no signs of cross-chain effects (Bucklin and Lattin 1992, Vlccassim and Chintagunta 1992), others show that more than 80% of the households cherry-pick (Fox and Hoch 2005), suggesting that cross-chain effects may be significant. In this chapter, we capture the existence of cross-chain effects by means of the competitive promotional calendar (without explicitly modeling these effects; for a more formal approach see Chapter 4). In so doing, we provide some first empirical evidence that shows that cross-chain effects may reduce significantly the effectiveness of sales promotions, and therefore should no longer be ignored.
CHAPTER 3: SALES PROMOTION EFFECTIVENESS DURING A PRICE WAR

3.1. Introduction

Over the years, price competition has tended to increasingly degenerate into price wars (Rao et al. 2000), especially during economic recessions (Green and Porter 1984, Staiger and Wolak 1992), or when the industry faces a new entrant (Elzinga and Mills 1999, Milgrom and Roberts 1982). Despite the growing number of price wars, little systematic research has assessed how price wars alter the effectiveness of brand manufacturers’ price and promotional strategies. More specifically, while the sales implications have been investigated, the impact on promotional sensitivity remains unclear. Are temporary price discounts more (or less) effective in a scenario characterized by frequent announcements of permanent price cuts on various players in the market?

Price wars can be initiated by both retailers and manufacturers. While the extant literature concentrates on the initiators of the price war and their competitors, we study how price wars initiated by retailers impact the sales and price-promotion effectiveness of the manufacturers. The latter have to sell and sustain their brands in a price war environment. Even though the decrease in the overall price level may have a favorable effect on the national brand’s sales, it is unclear how a price war alters the effectiveness of the brand manufacturer’s marketing activities. In particular, the impact of one of the manufacturer’s main pricing tools, price promotions, may change as retailers decrease regular prices. Basically, national brand manufacturers may face one of the two following scenarios:

(1) an indirect price-war scenario: the retailer does not permanently reduce the price of the focal brand, but reduces the price of a competing brand in the category. Given that the focal brand’s price is not reduced, its relative price increases.

22 In this chapter, when talking about the indirect effects, we focus on a scenario where the prices of competing brands are reduced during the price war. One could also identify another type of indirect effect, where the prices of other brands in the category are as well not affected. In our dataset, only four promotion events fall in this additional scenario. For this reason, this setting is not considered and these four observations are removed from the analysis.
(2) a *direct* price-war scenario: the retailer reduces the price of the focal brand, and thus involves it *directly* in the price war. Depending on what happens with other brands in the category, the focal brand’s relative price may increase or decrease.

Figure 3.1 illustrates these two scenarios. At time $t$ the price war starts. As long as the focal brand is not included in the retailer’s round of regular price reductions, it only experiences the price war *indirectly*. At time $t'$ the retailer decides to decrease the regular price of the focal brand. From that point onwards, the focal brand experiences the price war *directly*. In the second panel of Figure 3.1, some potential implications of the indirect and direct price wars for both sales and sales promotions are illustrated. As the effects may depend on the relative price of the focal brand, the graph illustrates different scenarios:

**Figure 3.1. Example of the effects of indirect and direct price wars on a focal brand $j$**

![Graph illustrating the effects of indirect and direct price wars on a focal brand.](image)
Sales promotions during a price war

(1) a decrease in sales, if the relative price deteriorates (solid line), (2) an increase in sales, if the relative price improves (dashed line), or (3) no impact, if the relative price does not change (dotted line). Similarly, these changes may affect also sales promotion effectiveness. As the regular (relative) price changes during price wars, a similar percentage price cut may generate a different sales lift (for a closer look at the implications of the price war, we refer to paragraph 3.3).

Based on previous research, it is difficult to assess ex ante the impact of an indirect and direct price war on sales and promotional effectiveness. For example, Rao et al. (2000) advise managers to avoid price wars, as they will train consumers to focus on lower prices exclusively, rather than on other differentiating elements based on quality. As such, they believe price wars may degenerate the profitability of the focal company and of the entire industry. Although managers recognize the importance of this message, they may be afraid that an unfavorable relative price position (in case they do not lower their prices) will inevitably lead to lower sales (and therefore a severe loss in terms of market share). Still, no study has empirically tested the impact of these two scenarios on sales and promotional effectiveness.23

So far, little systematic research has assessed the marketing consequences of price wars. In 2001, after a comprehensive review, Heil and Helsen (2001: 87) pointed out that “direct research on price wars in marketing is lacking, as such research is predominantly situated in the area of non-cooperative game theory.” This situation has not changed much since then. The existing literature has mainly provided a definition of the phenomenon (e.g. Heil and Helsen 2001), and insights into the conditions leading to a price war (e.g. Griffith and Rust 1997, Heil and Helsen 2001, Leeflang and Wittink 1996, Ramaswamy et al. 1994). To the best of our knowledge, the only empirical work on the topic is the recent work of van Heerde et al. (2008) on the effects of price wars among grocery retailers on two major components of retailer performance, store choice and spending per shopper (for more details, see paragraph 3.2). They find that, during a price war, as price sensitivity increases, consumers tend to base their store choice on the overall price image of the store. These insights raise further questions regarding the impact of the price war on the effectiveness of manufacturers’ pricing and promotional policies. For example, since a price war trains consumers to decide where to shop based on price (van Heerde et al.

23 The work of van Heerde et al. (2008) has empirically tested the impact of a price war on regular sales. In so doing, the authors did not distinguish between an indirect price-war phase and a direct price-war phase.
will it also make consumers more sensitive to price promotions once inside the store? Will consumers pay disproportional attention to the promotions of products whose price are reduced during the price war?

In this paper, we address these questions by investigating the Dutch price war that started in October 2003 among Dutch grocery retailers. We intend to contribute to previous literature along four dimensions. First, we build on the research developed by van Heerde et al. (2008) on the marketing consequences of price wars by investigating the effectiveness of sales promotions during price wars. While van Heerde et al. (2008) study the effects of the price war on store choice and basket size, we assess the extent to which the price war changes consumers’ responsiveness to price promotions.

Second, the price war literature has mainly looked at the price wars’ consequences for the initiators, e.g. the retailers (see Heil and Helsen 2001 for a review). As a result, the consequences for third parties, e.g. individual brands in the assortment of a retailer, remain under-investigated. In this essay, we focus on this aspect from the perspective of the manufacturer. The latter’s objectives may not be aligned with those of the retailers (Srinivasan et al. 2004). A price war among supermarket chains (such as the one we study) is initiated by retailers to attract customers to their stores (i.e. to increase store traffic), by improving their price image and to prevent consumers from switching to competitors. These objectives do not necessarily match manufacturers’ interest in maximizing their brands’ sales and market shares. For example, the lower in-store price level may amplify consumers’ attention to prices rather than quality, modifying consumers’ purchases in favor of cheaper alternatives. If the relative price of the manufacturer’s goods deteriorates due to the in-store price reductions, the manufacturer may experience a decrease in sales.

Third, we extend the price war literature by looking at two different scenarios within the price war: (1) an indirect price-war scenario, where the regular prices of competing brands are reduced while the regular price of the focal brand remains unaffected (see Figure 3.1), and (2) a direct price-war scenario where the regular prices of both the competing brands and the focal brand itself are reduced. During these two scenarios, the relative price position of the brand may change differently. Consequently, consumers’ responses to sales promotions may not be the same under the two regimes.

Fourth, the effect of the price war may change over time. On the one hand, Helson’s adaptation-level theory (1964) suggests that price sensitivity decreases as consumers become used to the lower price level. On the other hand, van Heerde et al. (2008) find an increase in price sensitivity (see also paragraph 3.2.2). Therefore, it is
unclear how this will affect sales volumes as well as price-promotion effectiveness. We therefore investigate whether sales promotion effectiveness decreases or increases over time for brands indirectly and directly involved in the price reductions.

Table 3.1 summarizes the key contribution of this paper vis-à-vis the extant literature on price wars, based on the four points discussed above. The remainder of this chapter is organized as follows. In the next section, we provide an overview of the price war literature. Then we present the implications of the price war for sales and sales promotions. Next, we introduce the model, the data and the results. Finally, we discuss the key findings and suggest directions for future research.

### Table 3.1. Selection of empirical studies on price wars

<table>
<thead>
<tr>
<th>Impact of the price war on:</th>
<th>Perspective:</th>
<th>When:</th>
<th>Evolution over time of the effect on:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>Promotion effectiveness</td>
<td>Initiators and competitors</td>
<td>Third parties</td>
</tr>
<tr>
<td><strong>Industrial organization papers</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fabra and Toro (2004)</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elzinga and Mills (1999)</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scherer and Ross (1990)</td>
<td>√</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Marketing papers</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>van Heerde et al. (2008)</td>
<td>√</td>
<td>√</td>
<td></td>
</tr>
<tr>
<td><em>This paper</em></td>
<td>√</td>
<td>√</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.2. Literature review

The term price war has typically been used to refer to periods of excessive rivalry among firms whereby price is used as the main weapon in the competitive interaction (e.g. Rao et al. 2000). Based on an extensive review of previous literature, Heil and Helsen (2001) provide a comprehensive definition of price wars. They define a price war as when one or more of the following criteria are met: (1) the direction of the pricing is

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24 The study of Heil and Helsen (2001) is not empirical, but theoretical, and as such it is not included in Table 3.1.
“downward,” (2) the pricing interaction among the actors occurs at a much faster rate than normal, (3) the actions and reactions focus mainly on the competitors, rather than on the customers, (4) the competitive interaction violates industry norms, (5) the pricing interaction as a whole is undesirable to the competitors, (6) the competitors neither intended nor expected to ignite the price war through their preceding competitive behavior, and (7) this pricing interplay is believed to be unsustainable (Heil and Helsen 2001: 89).

Price wars occur in every kind of industry, from airline or energy businesses to food grocers (Table 3.2) (for an extensive review, see Heil and Helsen 2001). In the remainder, we focus exclusively on price wars initiated by and between grocery retailers. For example, in November 2008, due to the economic downturn, the leading British retailers, Asda, Marks and Spencer, Sainsbury and Tesco lowered their prices in order to increase their market share, triggering a new price war (after the price wars started in 1998 and 2004 by Asda) (Time 2008). We find a similar scenario in the US with the price wars initiated by Kroger in 2001, by Rainbow and Cub Food in 2002 and by Giant Eagle in 2003, causing retailers’ margins to shrink and several smaller grocery stores to close (Progressive Grocer 2003). In a similar vein, Albert Heijn, the Dutch grocery market leader, wanted to improve their price image and regain the market share lost to hard discounters (Sloot 2004). On October 20, 2003, Albert Heijn announced a permanent price reduction for more than 1000 products, involving mainly A-brands. The competitors reacted within the same week, matching or even exceeding the price reductions (see van Heerde et al. 2008 for more details). This price war lasted for more than two years, squeezing grocery prices and impacting heavily on retailers’ and suppliers’ profitability (Sloot 2005).

In sum, price wars between grocery retailers occur frequently and in different geographical markets. Before elaborating on how these price wars affect sales and price promotion effectiveness, we briefly discuss what typically triggers them (3.2.1) and the scope of their consequences (3.2.2).
### Table 3.2. Examples of price wars (adapted from Heil and Helsen 2001)

<table>
<thead>
<tr>
<th>Business*</th>
<th>Location</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus rides (Greyhound, Peter Pan Trailways)</td>
<td>New York, Washington</td>
<td>1992</td>
</tr>
<tr>
<td>Car rentals (Avis, Budget, Hertz, National)</td>
<td>US</td>
<td>1992</td>
</tr>
<tr>
<td>Tires (Goodyear, Michelin, Pirelli)</td>
<td>Europe</td>
<td>1992</td>
</tr>
<tr>
<td>PC software (Borland, Lotus, Microsoft)</td>
<td>US</td>
<td>1993</td>
</tr>
<tr>
<td>Laser printers (Apple, HP)</td>
<td>US</td>
<td>1994</td>
</tr>
<tr>
<td>Minivans (Chrysler, GM)</td>
<td>US</td>
<td>1995</td>
</tr>
<tr>
<td>Salty snacks (Eagle Snack, Frito Lay)</td>
<td>US</td>
<td>1996</td>
</tr>
<tr>
<td>Beers (Coors, Miller)</td>
<td>US</td>
<td>1998</td>
</tr>
<tr>
<td>Contact lenses (Bausch and Lomb, Cooper Vision)</td>
<td>US</td>
<td>1998</td>
</tr>
<tr>
<td>Hamburgers (McDonald’s)</td>
<td>Japan, US</td>
<td>1998</td>
</tr>
<tr>
<td>Pizza chains (Little Caesar’s, Pizza Hut)</td>
<td>US</td>
<td>1998</td>
</tr>
<tr>
<td>Video games (Nintendo)</td>
<td>US</td>
<td>1998, 2002</td>
</tr>
<tr>
<td>Mutual funds (Fidelity)</td>
<td>US</td>
<td>1998, 2008</td>
</tr>
<tr>
<td>Greeting cards (American Greetings, Hallmark)</td>
<td>US</td>
<td>1999</td>
</tr>
<tr>
<td>Notebooks (Compaq, Sony)</td>
<td>US</td>
<td>2007</td>
</tr>
<tr>
<td>HD DVD players (Toshiba)</td>
<td>Worldwide</td>
<td>2008</td>
</tr>
<tr>
<td>Health insurance (Aetna, Humana)</td>
<td>US</td>
<td>2009</td>
</tr>
<tr>
<td>Grocery (Food Lion, HFB)</td>
<td>Houston</td>
<td>1997</td>
</tr>
<tr>
<td>Grocery (Asda, Tesco)</td>
<td>UK</td>
<td>1998, 2004</td>
</tr>
<tr>
<td>Grocery (Kroger)</td>
<td>US</td>
<td>2001</td>
</tr>
<tr>
<td>Grocery (Food Lion, Kash n’ Karry)</td>
<td>US</td>
<td>2002</td>
</tr>
<tr>
<td>Grocery (Cub Food, Rainbow)</td>
<td>US</td>
<td>2002</td>
</tr>
<tr>
<td>Grocery (Albert Heijn)</td>
<td>The Netherlands</td>
<td>2003</td>
</tr>
<tr>
<td>Grocery (Giant Eagle)</td>
<td>US</td>
<td>2003</td>
</tr>
<tr>
<td>Grocery (Asda, Sainsbury, Tesco)</td>
<td>UK</td>
<td>2008</td>
</tr>
</tbody>
</table>

*Table 3.2 reports the initiators of the price war, or the main actors involved in the initial price reductions.*
3.2.1. Antecedents of price wars

The extant price-war literature has mainly provided insights into the antecedents of the price war. This stream of literature is mostly characterized by analytical work. Three groups can be distinguished, based on the events that are thought to have triggered the price war: (1) demand fluctuations, (2) firms’ reputation, and (3) financial conditions. Specifically,

(1) The triggering event lies within demand fluctuations. Depending on the assumptions made, price wars can occur (a) during economic downturns (e.g. Green and Porter 1984, Staiger and Wolak 1992), or (b) during boom times (e.g. Rotemberg and Saloner 1986).

(a) During economic downturns, price wars can occur because of (i) a firm’s cost structures, (ii) unobservable prices, or (iii) a misunderstanding of the competitive interaction. Specifically,

(i) When the demand is low, firms’ cost structures can generate a price war, in particular when a firm has high fixed costs to cover (Scherer and Ross 1990, Staiger and Wolak 1992). For example, when part of a firm’s capacity is not used and produces no returns, the overcapacity can create an incentive for the firm to adopt a volume-oriented pricing strategy by undercutting its competitors’ prices (Scherer and Ross 1990). These competitors may over-react with retaliatory price cuts, instigating a price war (e.g. Busse 2000, Schunk 1999).

(ii) Price wars can occur when a firm cannot observe the prices of its competitors. Therefore, a fall in the demand of its own output can be interpreted as a sign that the competitor has offered a “secret” price cut (Green and Porter 1984). This may lead to retaliatory price cuts, triggering a price war.

(iii) Price wars can also emerge without a real predatory strategy, as the outcome of a misunderstanding of the competitive interactions that causes competitors to over-react (Schunk 1999).

(b) During a booming economy, price wars can occur because the benefit from undercutting can result in larger immediate revenues than during recessions, damaging the competitive interplay (e.g. Rotemberg and
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Saloner 1986). Deleersnyder et al. (2004), for example, find that during economic contractions companies tend to increase prices, while they tend to cut them during economic expansion.

(2) The triggering event of the price war is related to the reputation of the firm (e.g. Kreps and Wilson 1982, Milgrom and Roberts 1982). This reputation may come to play in case of a competitive entry. When the incumbent tries to push the entrant out of the market, or when the entrant tries to gain an immediate market share at the expense of the incumbent, price wars are likely to erupt. In fact, the new entry induces the incumbent to take actions to create a reputation of toughness and to discourage future entries (e.g. Elzinga and Mills 1999, Milgrom and Roberts 1982, Organski 1969). The studies of Klemperer (1989) and Elzinga and Mills (1999) illustrate that price wars are especially triggered by actual entry in markets where the customers of new entrants incur switching costs. In fact, to attract new customers who will incur switching costs (as a result of switching from the incumbent to the new entrant), the entrant needs to offer (temporary) lower prices. The incumbent reacts by lowering the prices as well, starting a price war. Once the entrant has established a clientele, the price war stops, and the firms (can) raise their prices again. This theory finds empirical evidence in the wholesale distribution of generic cigarettes in 1984–1985, analyzed by Elzinga and Mills (1999).

(3) Firms’ financial conditions are also identified as one of the causes of price wars (e.g. Bhattacharya 1997, Busse 2002). A firm that initiates a price war gains higher current profits at the expense of lower future profits. This is valued more by a financially distressed company. For example, if a firm is on the verge of bankruptcy, it is more likely to “borrow” returns from future periods by initiating a price war (Busse 2002). Busse (2002) offers empirical support to this thesis using data on the airline industry between 1985 and 1992. Not only firms risking bankruptcy but also firms facing reductions in their revenues and market share to the advantage of a competitor might ignite a price war, as shown by the work of Fabra and Toro (2005) on the Spanish electricity market. Van Heerde et al. (2008), Griffith and Rust (1997) and Leeftang and Wittink (1996) argue that price wars often start when managers are focused on minimizing the difference in market shares and profits relative to the competition. To pursue this competitive-oriented
objective, they are willing to sacrifice absolute profits for relative standing in market shares and profits versus other firms (Griffith and Rust 1997: 115). The grocery Dutch price war studied by van Heerde et al. (2008) offers a clear example of this scenario, as the war among retailers was initiated by the market leader in an attempt to regain customers lost to hard discounters.

3.2.2. Consequences of price wars

Overall, price wars may affect four performance measures: (1) sales, (2) margins and profits, (3) choice sets, and (4) firms’ reputations.

(1) The initiator of the price war sets lower prices that attract higher sales (e.g. Elzinga and Mills 1999, Fabra and Toro 2005, Scherer and Ross 1990). Van Heerde et al. (2008) show empirically that this sales effect is only temporary. During a price war among Dutch grocery retailers, consumers’ basket size increases (in value) in the short run, but it tends to shrink to the old level as the price war evolves. The heavily advertised permanent price decreases create a “psychological income”: the price war’s sudden promise of huge savings induces consumers to increase their spending disproportionally in the short run. In the long run, consumers’ spending decreases, while their price sensitivity increases with every new wave of price reductions (van Heerde et al. 2008).

(2) As the competitor reacts, the whole market faces lower profits (e.g. Griffith and Rust 1997), eventually leading to a reduction in the number of competitors because of the bankruptcy and/or market exit of some of the competing firms (e.g. Busse 2002, Milgrom and Roberts 1982).

(3) As consumers tend to base their choices on price (van Heerde et al. 2008), firms have an additional incentive to continue an undercutting pricing strategy. This competitive interaction can force firms to modify their cost structures (or to exit from the market), undermining consumer welfare by reducing the set of choices and/or the overall quality of the products (Guiltinan and Gundlach 1996).
(4) Finally, the price war can create a credible reputation for the firms involved, and can help prevent future market instability by discouraging new entries or predatory pricing (e.g. Levenstein 1997).

To summarize, the price war literature has mainly focused its attention on the causes leading to a price war, only partially covering its consequences. Moreover, all the price-war effects tend to be discussed from the point of view of the initiator and its competitors, e.g. the retailers. However, little is known about the consequences for third parties, e.g. the brands of the manufacturers in the assortment of a retailer, that may suffer (or benefit) from the situation as a result.

### 3.3. Impact of price wars on sales and sales promotions

Three key factors may be altered during the indirect and direct price war, potentially modifying sales and sales promotions: (1) price sensitivity, (2) consumers’ income, and (3) the way promotions are implemented.

1. **Price sensitivity.** During the price war, the lower level of the prices increases the attention to the price dimension (van Heerde et al. 2008, van Aalst et al. 2005). As such, consumers may use prices more than quality signs to compare different alternatives. This way, they may be drawn to cheaper offers.

2. **Income effect.** The reduced in-store prices may also generate an income effect. Consumers may directly observe an increase in their real disposable income (which depends on whether the brands they usually purchase become cheaper). Moreover, the numerous bargains announced inside and outside the stores by the retailers may bias consumers’ perceptions, creating also a “psychological income” effect (Heilman et al. 2002, van Heerde et al. 2008).²⁵

3. **Promotion implementation.** As price wars force firms to reduce their prices, ceteris paribus, fewer resources are left to support their products and price

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²⁵ An illustration of the “psychological income” effect on sales can be found in Heilman et al. (2002): consumers receiving a monetary reward before entering a store, spend more in the store, far above the monetary reward.
promotion events. Therefore, the implementation of price promotions may have to be altered (see paragraph 3.4).26

The resulting effects of these three factors on sales and promotional effectiveness may differ for brands not engaged in the price reductions (indirect price war), from those directly involved (direct price war), as discussed below and summarized in Table 3.3.

3.3.1. Indirect price war

As the overall retailers’ price levels decrease (including the price of competing brands), the actual and perceived relative price of a focal brand increases. Given the high price sensitivity characterizing the price war (van Heerde et al. 2008), we can expect lower sales for the focal brand. As for the promotional effectiveness, previous research has shown that higher relative prices are associated with higher promotional effectiveness (Bell et al. 1999, Narasimhan et al. 1996).

At the same time, due to the lower store prices, more money may be left over that can be spent by consumers on a given manufacturer’s product not involved in the price cuts. This may be due to the fact that the savings allow them to afford superior, high-quality brands and enjoy the feeling of getting a great deal (Chandon et al. 2000). While this increase of the disposable income (even if only “psychological”) may positively affect baseline sales, it may negatively influence promotional effectiveness, as higher-income consumers tend to be less sensitive to price promotions (Ailawadi et al. 2006).

The price war may also impact the way promotions are implemented, modifying sales promotion effectiveness. On the one hand, retailers may become more demanding, and ask higher promotional support from the manufacturers, or reduce the pass-through for all brands. At the same time, manufacturers may be willing to provide retailers with better deals (e.g. steeper discounts and more frequent promotions) to help their brands to remain competitive. As for features and displays, we may observe a decrease, since they are relatively less used to communicate price promotions, and retailers will mainly employ them to announce to consumers their permanent price cuts to gain store traffic, market

26 Although the lower margin may be compensated by an increase in volumes sold, retailers’ and manufacturers’ profits tend to shrink during price wars (Busse 2002, Milgrom and Roberts 1982). This is due to the competitive interactions that further reduce margins at every new price war round. Industry reports and the popular press confirm that this occurred in the Netherlands, UK and USA, where the profitability of both retailers and manufacturers was hit by retailers’ price wars (Time 2008, van Aalst et al. 2005).
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share and sales. Given that features and displays are linked with higher promotional effectiveness (e.g. van Heerde et al. 2005), a reduction in their use may modify the effectiveness of a discount. This effect may differ depending on the relative price of the focal brand. For example, Lemon and Nowlis (2002) find that the combination of feature advertising and price promotions, or of display and price promotions, is less effective for brands with a higher relative price, like those facing an indirect price war.

3.3.2. Direct price war

If a focal brand is part of a direct price-war regime, its *relative price* may have improved or may have deteriorated (depending on the price of the competing brands). If the relative price is improved, this could result in switching in favor of the focal brand. Also, consumers may find an additional incentive to take advantage of the brand when on promotion (as the savings from the temporary discount are added to the savings from the lower permanent price). This would lead to higher baseline sales and promotional effectiveness.

If the relative price deteriorates instead, then we can expect lower regular sales. The high price sensitivity may induce consumers to purchase a cheaper alternative (van Heerde et al. 2008), or to buy the brand only when on promotion, leading to higher promotional effectiveness (Bell et al. 1999, Narasimhan et al. 1996).

Other factors may be at play. For example, the income effect may increase baseline sales, while decreasing promotional effectiveness. We could expect this to happen even in case of a deterioration of the relative price of the focal brand, due to the “psychological income” effect discussed above for the indirect price-war scenario.

Finally, promotion implementation may change, modifying its effectiveness. The lower regular price of the focal brand reduces the margin of the retailer (Busse 2002), leaving fewer resources available to implement price promotion activities with the same *depth* and *frequency* as before. While a lower depth of the discount may decrease the effectiveness of sales promotions, a longer inter-promotional time may increase it (e.g. Blattberg et al. 1995), making it hard to predict the resulting effect. Also, as retailers now need to advertise both their permanent and temporary price cuts, the proportion of *features* and *displays* dedicated to temporary price reductions may decrease. Hence, the augmented number of price cues outside and inside the store may reduce the effectiveness of these
instruments (Anderson and Simester 2003), therefore impacting on consumers’ response to sales promotions.

3.3.3. Evolution over time

The novelty of the price war and the intensity of price cues may diminish over time. Given that these factors are positively linked to price sensitivity (Taylor and Thompson 1982, Wathieu et al. 2004), one could expect a decrease in price sensitivity (Helson 1964). Still, as price wars are characterized by several waves of price reductions, price sensitivity may instead increase when more brands are involved over time (van Heerde et al. 2008). This may harm the sales of brands facing an indirect price war, as they may be the only brands not yet reduced in price. Which of these two effects will prevail remains to be tested empirically.

Moreover, as time progresses, consumers update their reference price to a lower level (e.g. Briesch et al. 1997, Monroe 1990). As such, their perception of “huge savings” may be reduced (Fiske and Taylor 1991, Lichtenstein et al. 1991), decreasing regular sales. At the same time, as consumers use the updated (lower) reference price to evaluate sales promotions, the depth of the discount may be reduced, thereby decreasing the effectiveness of sales promotions.

To conclude, because of the opposing forces described above, we cannot make directional hypotheses on the price war’s effects. Therefore, we investigate the indirect and direct impacts of the price war in an exploratory way.

Table 3.3. Summary of the effects

<table>
<thead>
<tr>
<th></th>
<th>Indirect price war</th>
<th>Direct price war</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>-</td>
<td>-/+</td>
</tr>
<tr>
<td>Promotion effect</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Income effect</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Promotion</td>
<td>-/+</td>
<td>-/+</td>
</tr>
</tbody>
</table>
3.4. Impact on sales promotion implementation

Indirect and direct price wars can also change the effectiveness of the sales promotion implementation tools: i.e. the timing of the discount, the deal depth, features and displays.

**Timing.** Generally speaking, the literature on the timing of the discount is controversial. On the one hand, deals with longer inter-promotion time increase the saliency of each individual promotion, leading to more attractive deals (Bell et al. 1999). On the other hand, previous research has found that more frequent deals work better (Neslin 2002). During a price war, this second argument may hold given the high level of price sensitivity. Promotions implemented after a shorter inter-promotion time may be needed to keep the brand competitive. This may be especially relevant when the relative price of the brand deteriorates (e.g. during an indirect price-war scenario).

**Deal depth.** Retailers and manufacturers may also have to rethink the impact of the depth of the discount. Brands facing an indirect price war may need deeper discounts to compensate for their higher relative prices and, thus, to stimulate sales. For brands involved in the price reductions, instead, less steep discounts may already be very effective, as consumers may confuse the permanent price reductions and the temporary price discounts. Nevertheless, during a direct price war, the same percentage of the discount represents a lower absolute price cut that may not exceed the “just noticeable difference,” i.e. the minimum discount threshold that could have an incentive value (Campbell and Diamond 1990, Monroe 1971). In this case, a deeper percentage of the discount may be needed to match the pre-price war discount in absolute terms.

**Features and displays.** During price wars, consumers’ store choice is based on the overall price image of the store (van Heerde et al. 2008). Consequently, features may become more important, as they attract consumers to the stores. Once inside the stores, (given the high price sensitivity) consumers may select also what to buy on the basis of price. Displays may then be more effective. However, as retailers now communicate their permanent and temporary lower prices, this overload of signs with price cues could decrease the effectiveness of both features and displays (Anderson and Simester 2003).
3.5. Method

To investigate promotional effectiveness before versus during the price war, we proceed in two steps. In the first step, we use the individual promotion approach discussed at length in Chapter 2 (see paragraph 2.3). We therefore express the sales of each brand (at a focal retailer) as a function of all the promotions implemented at that focal retailer and other covariates. This way, we obtain not an average sales response to sales promotions, but individual parameters for each promotion event.

We further extend the model described in E3 to account for a shift in sales due to the price war by means of two step dummy variables, capturing the instantaneous effect of the indirect price war (INDIRECT_PW) and of (the incremental impact of) the direct price war (DIRECT_PW), respectively (see paragraph 3.3). The dummy variable INDIRECT_PWt assumes the value of 1 during the entire length of the price war, and 0 otherwise, while the dummy variable DIRECT_PWt equals 1 when the price of product i at retailer j is permanently reduced because of the price war (see Figure 3.1). To capture the evolution of sales during the indirect and direct price war, we add two trend variables (TREND_INDIRECT_PW = 1, …, T’ and TREND_DIRECT_PW = 1, …, T’’) that start counting at 1 one week after the beginning of the indirect and direct price war, respectively.

As the promotional dummy variables PROMO capture individual events p over time, we do not need to add an interaction with the price war. Knowing when each promotion event p has been implemented, i.e. before or during the price war, allows us

---

27 Additionally, one could add two continuous variables capturing the number of competitive brands involved in the price war within the same category, and/or in other categories. A similar approach has been used by van Heerde et al. (2008), whereby they considered all the items involved in the price war, with no distinction across categories. Moreover, one could further extend the model with another variable capturing the relative price of the focal product, as it plays an important role in this context. These additions to the model may provide important insights into the competitive dynamics and the evolution of the price war over time. Unfortunately, we cannot incorporate these extensions, as we have only fragmented information related to the competing brands.

28 For both INDIRECT_PW and TREND_INDIRECT_PW, we need only a subscript t, as we assume the price war to start in the same week t for all brands and retailers. This is the case in the price war studied in this chapter and in most of the examples reported in Table 3.2. In other examples of price wars (e.g. car rentals, contact lenses, health insurances, pizza chains, video games), the competitors reacted to the lower prices of the initiator of the price war with some delay, entering the price war at different stages. In those instances, one should allow both INDIRECT_PW and TREND_INDIRECT_PW to vary across brands and retailers.

29 If the brand is directly involved in the price reductions from the first week of the price war, the parameters related to INDIRECT_PW and TREND_INDIRECT_PW are set to zero. This happens for two of the products in our dataset. (Our conclusions remain substantively the same even when these two products are excluded from the analysis.)
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easily to test for differences in the parameters before versus during the price war in the second step of the analysis.

We checked the necessity of adding other interactions of the price war with variables such as the competing promotion events (CP) or advertising (ADSTOCK). In both cases, these interactions were not significant in 82% and 93% of the cases, respectively ($p > .05$). When significant, these interactions were added to the model.

The final model for the first step is:

(E6) \[ \text{SALES}_{i,c,j,t} = \alpha_{0,i,c,j} + \alpha_{1,i,c,j} \text{INDIRECT}_P W_{t} + \alpha_{2,i,c,j} \text{DIRECT}_P W_{i,c,j,t} + \]

\[ \alpha_{3,i,c,j} \text{TREND}_\text{INDIRECT}_P W_{t} + \]

\[ \alpha_{4,i,c,j} \text{TREND}_\text{DIRECT}_P W_{i,c,j,t} + \]

\[ \sum_{p=1}^{P} \sum_{l=0}^{2} \beta_{i,c,j,p,l} \text{PROMO}_{i,c,j,p,t-1} + \sum_{k=0}^{2} \gamma_{i,c,j,k} \text{CP}_{i,c,j',t-k} + \]

\[ \delta_{i,c,j} \text{ADSTOCK}_{i,c,j} + \eta_{i,c,j} \sin \left( \frac{2\pi t}{52} \right) + \eta'_{i,c,j} \cos \left( \frac{2\pi t}{52} \right) + \]

\[ \eta''_{i,c,j} \text{TREND}_{t} + \epsilon_{i,c,j,t} \]

where $i$ indicates the $i$th product ($i = 1, \ldots, I$), $c$ represents the category ($c = 1, \ldots, C$), $j$ the chain ($j = 1, \ldots, J$), and $t$ the week ($t = 1, \ldots, T$). $\text{SALES}_{i,c,j,t}$ refers to the sales in volume, while $\beta_{i,c,j,p,l}$ expresses the parameter for the impact of individual promotion event $p$ ($p = 1, \ldots, P$) in week $t - l$ ($l = 0, 1, 2$) of product $i$ of category $c$ at retailer $j$. $\text{CP}_{i,c,j,t}$ depicts the competitive promotions by the same product $i$ at a competing retailer $j'$, and $\text{ADSTOCK}_{i,c,t}$ corresponds to the advertising goodwill of product $i$ in week $t$. $\sin \left( \frac{2\pi t}{52} \right)$ and $\cos \left( \frac{2\pi t}{52} \right)$ allow to correct for seasonal fluctuations in the series.

The model is estimated for all retailers simultaneously, by means of iterative SUR-GLS with Prais–Winsten correction (van Heerde et al. 2004). The error is therefore distributed as in Chapter 2:

\[ \epsilon_{i,c,j,t} = \rho_{i,c,j} \epsilon_{i,c,j,t-1} + \nu_{i,c,j,t} \]

\[ \epsilon_{i,c,j',t} = \rho_{i,c,j'} \epsilon_{i,c,j',t-1} + \nu_{i,c,j',t} \]
Chapter 3

$$\text{cov} [\nu_{i,c,j,t}, \nu_{i,c,j',t}] = \sigma_{i,c,j,j'}$$

where $$\nu_{i,c,j,t} \sim \text{N}(0, \sigma_{\nu_{i,c,j}}^2)$$ and $$\nu_{i,c,j',t} \sim \text{N}(0, \sigma_{\nu_{i,c,j'}}^2)$$. To be able to compare promotional effectiveness across different products (with different baseline sales), we compute the normalized total effect of each promotion event ($$TE^*$$) as:

(E7) $$TE^*_{i,c,j,p} = \sum_{l=0}^{2} \beta_{i,c,j,p,l}/\text{BASELINE_SALES}_{i,c,j,z(p)}$$

where the baseline sales are expressed differently depending on the price war scenario, $$z(p)$$, that the brand is facing at the time of promotion event $$p$$: $$z(p)$$ equals 1 if the promotion event $$p$$ is implemented before the price war, it equals 2 during the indirect price war, and 3 during the direct price war. Therefore, the baseline sales are equal to the average non-promotional sales of product $$i$$ at retailer $$j$$ computed during each period $$z$$. The standard errors of $$TE^*$$ are derived through the Delta method (Greene 2003).

In the second step, we use $$TE^*$$ as the dependent variable and the inverse of the standard errors as weights in the regression model (Judge et al. 1985). We then relate the normalized total effect ($$TE^*$$) to the indirect ($$\text{INDIRECT_PW}$$) and the direct price war ($$\text{DIRECT_PW}$$). Moreover, we test whether the price-war effects decrease over time, by adding two trend variables to the model that start counting one week after the beginning of the indirect and direct price war ($$\text{TIME_LAG_INDIRECT_PW}$$ and $$\text{TIME_LAG_DIRECT_PW}$$).

The model is further augmented to include the impact of the most important drivers found in Chapter 2, i.e. the timing since previous promotion events at the same retailer, $$\text{TIMING}$$, or at competing retailers ($$\text{TIMING_COMP}$$ and $$\text{SIMULTANEOUS}$$), the depth of the discount ($$\text{DEPTH}$$), the duration ($$\text{DURATION}$$) as well as features ($$\text{FEATURE}$$) and displays ($$\text{DISPLAY}$$). As discussed in Chapter 2, we also include additional covariates that may influence promotional effectiveness, such as advertising ($$\text{ADSTOCK}$$), market share ($$\text{MKTSHARE}$$) and category concentration ($$\text{CONCENTRATION}$$). We refer to Chapter 2 for the operationalization of these variables (paragraph 2.4.2).

To account for variation across the retailer and categories, we use a fixed-effect correction for the retailer ($$DR_j$$) and categories ($$DC_c$$). To capture within-brand correlations, we use a random effect correction for the brands ($$u_i$$). The error term $$\nu_{i,c,j,p}$$ is assumed to follow a normal distribution with mean 0 and variance $$\sigma_{\nu}^2$$. 
The model is as follows:\(^{30}\)

\[
TE_{i,c,j,p} = \mu_1 + \sum_{j=2}^{J} \mu_j DR_j + \sum_{c=2}^{C} \mu'_c DC_c + \\
\gamma_1 \text{INDIRECT}_P W_{P} + \gamma_2 \text{DIRECT}_P W_{i,c,j,p} + \\
\gamma_3 \text{TIME\_LAG\_INDIRECT}_P W_{P} + \\
\gamma_4 \text{TIME\_LAG\_DIRECT}_P W_{i,c,j,p} + \\
\xi_1 \log\text{(TIMING)}_{i,c,j,p} + \xi_2 \log\text{(TIMING\_COMP)}_{i,c,j,p} + \\
\xi_3 \text{SIMULTANEOUS}_{i,c,j,p} + \xi_4 \log\text{(DEPTH)}_{i,c,j,p} + \\
\xi_5 \log\text{(DURATION)}_{i,c,j,p} + \xi_6 \text{FEATURE}_{i,c,j,p} + \\
\xi_7 \text{DISPLAY}_{i,c,j,p} + \xi_8 \log\text{(ADSTOCK)}_{i,c,p} + \\
\xi_9 \log\text{(MKTSHARE)}_{i,c,j} + \xi_{10} \log\text{(CONCENTRATION)}_{i,c,j} + \\
u_i + \nu_{i,c,j,p}
\]

3.6. Data

3.6.1. Sample composition

The dataset extends the sample described in Chapter 2, as it includes the promotions for 2001-2005. The data are collected in the Netherlands, at four leading national supermarket chains, Retailer 1, Retailer 2, Retailer 3 and Retailer 4 (for more information see paragraph 2.4). As mentioned above, these supermarket chains entered a price war (triggered by Retailer 1) on October 20, 2003.\(^{31}\) Consequently, their price and service image changed during the price war (see Figure 3.2) (van Heerde et al. 2008). Figure 3.2 shows how the positioning map of the Dutch supermarkets differs across the

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\(^{30}\)For reasons of parsimony, we do not show the subscript for the annual variation in the control variables.

\(^{31}\)The time window of the sample used in Chapter 2 ended on October 20, 2003.
years 2002–2004, with a repositioning of the price image of supermarket chains previously considered expensive, like Retailer 1 (GfK 2005).

Figure 3.2. Relative position of the Dutch supermarkets (source: GfK 2005)

The dataset covers 147 weeks before the price war, from January 2001 to October 20, 2003, and 114 weeks during the price war (until the end of 2005). We observe a total of 687 promotions, 374 implemented before the price war and 313 during the price war, from 22 brands of a leading multinational PCG manufacturer, in eight product categories.

In the second step we excluded ten promotions. Four of them were removed because they were the only ones implemented in a scenario where the prices of the entire category (and therefore also the prices of competing brands) were not reduced by the price war (which we may refer to as a category indirect price-war effect). We deleted the remaining six because the price of the focal brand increased during the price war. Nevertheless, as a robustness check, we conducted the analysis including these ten promotions.

32 Of the sample used in Chapter 2, eight products were discontinued between 2003 and early 2004, impeding the comparison of their promotional effectiveness before versus during the price war. We therefore excluded them from the analysis. This explains why we now have 374 sales promotions instead of the 519 analysed in Chapter 2.
promotions in the dataset, with the addition of two dummy variables, one capturing the category indirect effect (i.e. assuming the value of 1 when the prices of competing brands were not reduced by the price war) and one capturing the price increase. The results were similar to those reported below.

3.6.2. Some first descriptive statistics

The Dutch price war started on October 20, 2003 and lasted until the end of 2005. Within the first week, all the main competitors reacted to the price cuts of the leading retailer. After that, prices were lowered in a series of waves, involving different product categories and brands in every new round (Table 3.4).

Table 3.4. Price war rounds (adapted from van Heerde et al. 2008)

<table>
<thead>
<tr>
<th>Date</th>
<th>Initiator</th>
<th>Number of products</th>
<th>Emphasis on</th>
</tr>
</thead>
<tbody>
<tr>
<td>October 20, 2003</td>
<td>Retailer 1</td>
<td>1000</td>
<td>National brands</td>
</tr>
<tr>
<td>October 27, 2003</td>
<td>Retailer 1</td>
<td>550</td>
<td>National brands</td>
</tr>
<tr>
<td>November 10, 2003</td>
<td>Retailer 1</td>
<td>300</td>
<td>National brands and dairy</td>
</tr>
<tr>
<td>January 19, 2004</td>
<td>Retailer 1</td>
<td>500</td>
<td>National brands and produce</td>
</tr>
<tr>
<td>March 8, 2004</td>
<td>Retailer 1</td>
<td>100</td>
<td>Meat</td>
</tr>
<tr>
<td>May 10, 2004</td>
<td>Retailer 1</td>
<td>100</td>
<td>Cheese</td>
</tr>
<tr>
<td>September 20, 2004</td>
<td>Retailer 1</td>
<td>1000</td>
<td>Private labels</td>
</tr>
<tr>
<td>November 13, 2004</td>
<td>Retailer 1</td>
<td>2000</td>
<td>National brands</td>
</tr>
<tr>
<td>January 30, 2005</td>
<td>Retailer 1</td>
<td>1000</td>
<td>National brands, cleaning and personal care</td>
</tr>
<tr>
<td>February 21, 2005</td>
<td>Retailer 1</td>
<td>100</td>
<td>Meat and cheese</td>
</tr>
<tr>
<td>March 7, 2005</td>
<td>Retailer 2</td>
<td>250</td>
<td>National brands and private labels</td>
</tr>
<tr>
<td>April 4, 2005</td>
<td>Retailer 2</td>
<td>250</td>
<td>National brands and private labels</td>
</tr>
<tr>
<td>August 23, 2005</td>
<td>Retailer 4</td>
<td>600</td>
<td>National brands</td>
</tr>
<tr>
<td>September 12, 2005</td>
<td>Retailer 1</td>
<td>100</td>
<td>Cleaning and personal care</td>
</tr>
<tr>
<td>October 31, 2005</td>
<td>Retailer 1</td>
<td>1000</td>
<td>National brands</td>
</tr>
</tbody>
</table>

The business press highlighted several changes caused by the price war in the retailing landscape. First, the overall level of prices for national grocery brands was reduced, on average, by 11% (van Heerde et al. 2008). Every new wave of price reductions increased consumers’ attention to the price dimension (Sloot and van Aalst 2005, van Heerde et al. 2008). Van Heerde et al. (2008) show that during the price war, there was a significant decrease in the percentage of consumers choosing which brand to purchase on the basis of brand/product characteristics other than price.
Because of the fierce price competition, the price level changed over time. For example, during the first week of the price war Retailer 1 reduced the price of a 1.5 liter bottle of Coca Cola by 9% (from a starting price of €1.23 to €1.12), and by another 9% during the following week (to €1.02)(van Heerde et al. 2008) (Figure 3.3).

Prices did not only vary over time, but also across retailers (see Figure 3.3), impacting the retailers’ relative price positioning (as shown in Figure 3.2 and discussed above). Especially at the beginning of the price war, retailers were investing more money...
Sales promotions during a price war

in media advertisements and, in particular, on newspapers, to communicate their lower offers (“Newspapers earn millions thanks to the supermarket war,”33 De Financiële Telegraaf 2004). A selection of these announcements is exhibited in Figure 3.4.

In all these announcements, the retailers emphasize the new rounds of permanently reduced prices of several products. They communicate own actions (for example, “Permanently reduced in price. Next round,”34 “The prices go even further down,”35 “Retailer 1 is again scattering around price reductions”36 etc.), as well as the competitors’ reactions (e.g. “Retailer 2 will keep being the cheapest, whatever Retailer 1 tries,”37 “Nobody can stop us. Again hundreds of articles permanently reduced in price,”38 etc.).

As a result of this massive communication, lower prices service supermarkets, like Retailer 1 and Retailer 4, attracted more customers than other etailers, thereby increasing their sales by 5% (see the article “Service supermarkets are the winners of the price war”39 in the online report of RTL Z on the Dutch price war, 2003–200640).

The popular press also highlighted that promotion frequency and promotion depth were reduced because of the price war (see the financial reports in RTL Z, “Price war in supermarkets”41 2003–2006), as manufacturers provided less promotional support to retailers (Sloot 2004).

However, not every retailer reduced the frequency and the depth of the discounts. Retailer 4, for example, not only lowered its prices, but it accompanied its permanent price reductions with an aggressive special offer program in which buy one, get one for free program (BOGOF) played a major role (see Planet Retail, “Casino report,” pp. 7–8).

In the next section, more descriptive information about the effects of the price war will be given.

33 “Dagbladen verdienen miljoenen aan supersupermarktoorlog.”
34 “Blijvend in prijs verlaagd. Volgende ronde.”
35 “De prijzen gaan nog verder naar beneden.”
36 “Retailer 1 strooit weer met prijsverlagingen.”
37 “Retailer 2 blijft veel goedkoper, wat Retailer 1 ook probeert.”
38 “We zijn niet te stoppen! Alweer honderden artikelen blijvend in prijs verlaagd.”
39 “Service-supermarkten winnaars prijsoorlog.”
41 “Prijzenvooroorlog in de supermarkten.”
3.6.3. Brief overview of the impact of the price war in the data

We present a set of descriptive statistics with respect to changes in the regular price and promotion implementation. For example, the price war altered the price of 71%
of the brands in the dataset, showing an overall price reduction of 5%\textsuperscript{42} and great variability across retailers (see Figure 3.5).

Moreover, the timing of the permanent price reductions differed across brands and retailers. Figure 3.6 shows the different length of the indirect price-war scenario (in weeks) across brands (reporting on the y-axis how many brands (in %) face the indirect price-war scenario for a given number of weeks). The figure illustrates that the price of some products was reduced immediately during the first week of the price war (week 1 in the figure), while the price of others was cut only 99 weeks after the start of the price war. In some instances (for 6 brands), the price was not reduced at all (week 114 in the figure). Therefore, the duration of the indirect and direct effect varies considerably across brands.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure3_5.png}
\caption{Average price decrease during the price war (%), computed across all brands involved in the price war}
\end{figure}

\textsuperscript{42} The overall price reduction of 5% is the average of all the price reductions across all the brands directly involved in the price war computed as: \((\text{regular price during the direct price war}_{i,c,j} - \text{regular price before the price war}_{i,c,j}) / \text{regular price before the price war}_{i,c,j}\).
The price war not only influenced the overall price level, but also the implementation of sales promotions, as illustrated in Table 3.5.\textsuperscript{43} We observe an overall decrease in the frequency of sales promotions and in the implementation of simultaneous promotions at competing retailers. Promotions also last longer, and are more often supported by means of features and displays than before the price war. For example, we observe a significant increase in the number of promotions implemented at Retailer 3 (66 promotions in 147 weeks vs. 85 promotions in 114 weeks) \textit{(two-proportion z-test = 4.74, two-sided p-value < .01)}\textsuperscript{44} and Retailer 4 (92 promotions in 147 weeks vs. 91 promotions in 114 weeks) \textit{(two-proportion z-test = 3.03, p < .01)}, but a significant decrease at Retailer 1 (119 promotions in 147 weeks vs. 70 promotions in 114 weeks)\textit{(two-proportion z-test = 3.10, p < .01)} and Retailer 2 (97 promotions in 147 weeks vs. 57 promotions in 114 weeks)\textit{(two-proportion z-test = 2.16, p < .01)}. Also, the depth of price promotions has been significantly reduced from 27\% to 16\% at Retailer 2, and from 20\% to 14\% at Retailer 4. During the price war, Retailer 1, the price war initiator, remained the retailer with the highest discounts (in percentages), offering on average a price cut of 23\%, while retailers like Retailer 2 and Retailer 4 reduced the percentage of the discount, respectively, from

\textsuperscript{43} From the time series of the prices of the focal brands in our dataset, provided by ACNielsen, we identified temporary and permanent price cuts. Moreover, we double checked if we correctly coded the temporary promotions and the permanent price reductions through internal company data.

\textsuperscript{44} In the reminder of the text, unless differently specified, all the \textit{p-values} refer to \textit{two-sided p-values}. 

58
Table 3.5. Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Retailer 1 Before M (SD)</th>
<th>Retailer 1 During M (SD)</th>
<th>Retailer 2 Before M (SD)</th>
<th>Retailer 2 During M (SD)</th>
<th>Retailer 3 Before M (SD)</th>
<th>Retailer 3 During M (SD)</th>
<th>Retailer 4 Before M (SD)</th>
<th>Retailer 4 During M (SD)</th>
<th>Overall Before M (SD)</th>
<th>Overall During M (SD)</th>
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<tbody>
<tr>
<td><strong>PLANNING</strong></td>
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<tr>
<td>TIMING (weeks)</td>
<td>5.50 (14.21)</td>
<td>9.80 (11.03)</td>
<td>4.34 (11.06)</td>
<td>8.84 (14.06)</td>
<td>6.75 (12.56)</td>
<td>6.58 (9.09)</td>
<td>3.05 (8.40)</td>
<td>4.16 (6.93)</td>
<td>4.82 (11.37)</td>
<td>7.03 (9.26)</td>
</tr>
<tr>
<td>TIMING_COMP (weeks)</td>
<td>6.83 (8.29)</td>
<td>7.91 (7.98)</td>
<td>7.58 (16.49)</td>
<td>6.27 (5.59)</td>
<td>5.83 (12.76)</td>
<td>7.18 (8.48)</td>
<td>6.30 (8.12)</td>
<td>6.64 (7.07)</td>
<td>6.43 (10.28)</td>
<td>7.21 (7.40)</td>
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<tr>
<td>SIMULTANEOUS (frequency %)*</td>
<td>69.66 (11.27)</td>
<td>48.45 (13.56)</td>
<td>74.24 (8.29)</td>
<td>28.24 (7.98)</td>
<td>19.94 (9.18)</td>
<td>13.53 (10.35)</td>
<td>21.61 (10.48)</td>
<td>16.33 (9.41)</td>
<td></td>
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</tr>
<tr>
<td>DEPTH (%)</td>
<td>21.02 (11.08)</td>
<td>22.55 (7.02)</td>
<td>27.21 (15.32)</td>
<td>15.87 (12.98)</td>
<td>16.66 (5.35)</td>
<td>16.34 (7.87)</td>
<td>19.94 (9.18)</td>
<td>13.53 (10.35)</td>
<td>21.61 (10.48)</td>
<td>16.33 (9.41)</td>
</tr>
<tr>
<td>DURATION (weeks)</td>
<td>1.50 (0.96)</td>
<td>2.16 (0.46)</td>
<td>1.74 (1.09)</td>
<td>2.23 (0.75)</td>
<td>1.16 (0.67)</td>
<td>2.09 (0.29)</td>
<td>1.51 (1.05)</td>
<td>1.96 (0.43)</td>
<td>1.49 (0.75)</td>
<td>2.21 (0.56)</td>
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<td><strong>COMMUNICATION</strong></td>
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<tr>
<td>FEATURE (frequency %)*</td>
<td>43.91 (94.37)</td>
<td>73.11 (94.92)</td>
<td>6.97 (18.24)</td>
<td>38.91 (74.57)</td>
<td>43.73 (67.17)</td>
<td>4.43 (8.13)</td>
<td>24.12 (25.02)</td>
<td>25.02 (20.06)</td>
<td>24.12 (25.02)</td>
<td>25.02 (20.06)</td>
</tr>
<tr>
<td>DISPLAY (frequency %)*</td>
<td>9.52 (14.08)</td>
<td>.89 (9.78)</td>
<td>4.23 (6.62)</td>
<td>2.11 (16.09)</td>
<td>4.53 (26.76)</td>
<td>2.11 (16.09)</td>
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<td>2.11 (16.09)</td>
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<td>ADSTOCK (in 100,000 euro)</td>
<td>47.54 (112.45)</td>
<td>52.78 (84.66)</td>
<td>52.82 (83.48)</td>
<td>52.82 (132.02)</td>
<td>52.82 (205.74)</td>
<td>52.82 (132.02)</td>
<td>52.82 (132.02)</td>
<td>52.82 (205.74)</td>
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<td><strong>OTHER CONTROL VARIABLES</strong></td>
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<tr>
<td>MKTSHARE (%)</td>
<td>5.72 (4.43)</td>
<td>7.03 (4.60)</td>
<td>6.13 (4.23)</td>
<td>6.62 (4.27)</td>
<td>5.99 (4.49)</td>
<td>5.25 (4.67)</td>
<td>5.72 (4.27)</td>
<td>6.25 (4.63)</td>
<td>5.90 (4.41)</td>
<td>6.75 (4.59)</td>
</tr>
<tr>
<td>CONCENTRATION(C3 %)</td>
<td>24.12 (8.13)</td>
<td>25.02 (10.65)</td>
<td>24.76 (9.31)</td>
<td>18.64 (9.83)</td>
<td>23.72 (8.86)</td>
<td>24.58 (10.16)</td>
<td>22.53 (8.24)</td>
<td>21.01 (10.22)</td>
<td>23.75 (8.64)</td>
<td>24.21 (10.09)</td>
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<td><strong>SAMPLE CHARACTERISTICS</strong></td>
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<tr>
<td>Number of promotions</td>
<td>119 (70)</td>
<td>97 (57)</td>
<td>66 (85)</td>
<td>92 (91)</td>
<td>374 (283)</td>
<td>283 (283)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
</tr>
<tr>
<td>Number of weeks</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
<td>147 (114)</td>
</tr>
<tr>
<td>Average number of promotions per week</td>
<td>.81 (.61)</td>
<td>.66 (.50)</td>
<td>.45 (.74)</td>
<td>.63 (.80)</td>
<td>2.54 (1.98)</td>
<td>67.50 (9.26)</td>
<td>24.21 (10.09)</td>
<td>24.21 (10.09)</td>
<td>24.21 (10.09)</td>
<td>24.21 (10.09)</td>
</tr>
</tbody>
</table>

*For the dummy variables, we report the frequency (%).
27% to 16% \((p < .01)\) and from 20% to 14% \((p < .01)\), and Retailer 3 kept the discount depth around 16%. These preliminary descriptive statistics are in line with what was highlighted by the public press during the price war, and by managerial reports, as mentioned above (see also van Heerde et al. 2008).

Moreover, we notice a significant change in how the promotions are communicated to consumers, increasing the usage of both features and display (see Table 3.5 for details on the descriptive statistics).

3.7. Results

In the next paragraph, we first discuss the results of the effect of the price war on sales, and then describe the impact on promotional effectiveness and its drivers.

3.7.1. Does a price war increase sales?

To assess whether a price war increases sales, for each brand and retailer, we consider a set of parameters from E6 capturing the indirect and direct effects of the price war on sales at the beginning of the permanent price cuts, i.e. \(\alpha_{1, i, c, j}\) and \((\alpha_{1, i, c, j} + \alpha_{2, i, c, j})\), and over time, i.e. \((\alpha_{1, i, c, j} + \alpha_{3, i, c, j} \times \text{TREND\_INDIRECT\_PW}_t)\) and \((\alpha_{1, i, c, j} + \alpha_{2, i, c, j} + \alpha_{3, i, c, j} \times \text{TREND\_INDIRECT\_PW}_i + \alpha_{4, i, c, j} \times \text{TREND\_DIRECT\_PW}_{i, c, j, t})\). Their standard errors are derived through the Delta method. Tables 3.6 and 3.7 report the percentage of the positive (negative) signs of the instantaneous indirect and direct price-war effects across our sample, together with their weighted average value. Table 3.8 and Figure 3.7 (panel A and B) present the evolution of these effects over time (Figure 3.7 includes also the results for the effectiveness of price promotions, to be discussed later on).

To check if the effects are significant, we follow the Stouffer’s meta-analytic test of “adding zs” by Mousteller and Bush (see Rosenthal 1991 for technical details). This method consists of pooling significance levels by using a standard normal table to convert the one-tailed \(p\)-value of each individual effect \(n\) (e.g. related to \(\alpha_{1, i, c, j}\) and \((\alpha_{1, i, c, j} + \alpha_{2, i, c, j})\)) to a standard normal \(z\). The meta \(z\) is computed as follows:

\[
\text{meta } z = \sqrt{\frac{\sum_{s=1}^{N} \chi_s^2}{N}}.
\]
where \( z_n \) is the standard normal \( z \) of each effect \( n \). This way, we obtain a new \( z \)-value that is then converted back into a one-tailed \( p \)-value, which tests whether sales, on average, increased significantly.\(^{45}\) Each \( z \) and \( p \) obtained by this procedure is displayed in Tables 3.6, 3.7 and 3.8 as \( \text{meta } z \) and \( \text{meta } p \).

We observe a total of 86 effects for the indirect price war (22 brands times 4 retailers, minus two cases where the brand’s price was directly reduced during the first week of the price war), and 64 effects for the direct price war (17 brands were involved in the direct price war at Retailer 1, 16 at Retailer 2 and 4, 14 at Retailer 3).

Table 3.6 shows a higher percentage of brands experiencing a sales decrease than a sales increase at the beginning of the indirect price war (32% positive effects versus 46% negative effects). The weighted average (using as weights the reciprocal of the standard errors) of the normalized indirect price-war effects (which reflects the percentage sales change) is -.17.\(^{46}\) We also notice that, at the beginning of the indirect price war, while at Retailer 1, Retailer 2 and Retailer 4 there is a negative impact of the indirect price war on sales, at Retailer 3 there is a positive effect.

**Table 3.6. Percentage of significant effects of the beginning of the indirect price war on sales (two-sided \( p \)-value < .05) and weighted average normalized effects**

<table>
<thead>
<tr>
<th>(Initial) Indirect Effect (( \alpha_{i,c,j} ))</th>
<th>Positive</th>
<th>Negative</th>
<th>Not Significant</th>
<th>Weighted Average Normalized Effect</th>
<th>Meta ( z )</th>
<th>Meta ( p^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total</strong></td>
<td>32%</td>
<td>46%</td>
<td>24%</td>
<td>-0.17</td>
<td>-1.45</td>
<td>0.07</td>
</tr>
<tr>
<td>Retailer 1</td>
<td>28%</td>
<td>42%</td>
<td>29%</td>
<td>-0.19</td>
<td>-3.22</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Retailer 2</td>
<td>36%</td>
<td>52%</td>
<td>12%</td>
<td>-0.18</td>
<td>-2.85</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Retailer 3</td>
<td>44%</td>
<td>33%</td>
<td>23%</td>
<td>0.02</td>
<td>1.79</td>
<td>0.04</td>
</tr>
<tr>
<td>Retailer 4</td>
<td>14%</td>
<td>57%</td>
<td>29%</td>
<td>-0.12</td>
<td>-1.53</td>
<td>0.06</td>
</tr>
<tr>
<td><strong>N = 86</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* For the meta-analysis, we report one-tailed \( p \)-values.

\(^{45}\) Following van Heerde et al. (2008), we look at sales increase rather than decrease.

\(^{46}\) To compare the indirect price-war effects across different products and retailers, we normalized them by dividing each effect by the baseline sales of the focal product during the indirect price war.
Table 3.7 illustrates that, at the beginning of the direct price war, when the price of a product has been reduced, sales tend to rise (for a total of 57% positive effects versus 29% negative effects) and this pattern is consistent across all retailers. The weighted average of the normalized (initial) impact of the direct price war is 0.48.

Table 3.7. Percentage of significant effects of the beginning of the direct price war on sales \( (two-sided \ p < .05) \) and weighted average normalized effects

<table>
<thead>
<tr>
<th>(Initial) Direct Effect ( (\alpha_{1,i,c,j} + \alpha_{2,i,c,j}) )</th>
<th>Positive</th>
<th>Negative</th>
<th>Not Significant</th>
<th>Weighted Average Normalized Effect</th>
<th>Meta ( z )</th>
<th>Meta ( p^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>57%</td>
<td>29%</td>
<td>14%</td>
<td>0.48</td>
<td>3.13</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Retailer 1</td>
<td>52%</td>
<td>39%</td>
<td>9%</td>
<td>0.58</td>
<td>2.45</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Retailer 2</td>
<td>57%</td>
<td>40%</td>
<td>3%</td>
<td>0.49</td>
<td>4.12</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Retailer 3</td>
<td>64%</td>
<td>14%</td>
<td>22%</td>
<td>0.23</td>
<td>2.99</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Retailer 4</td>
<td>59%</td>
<td>23%</td>
<td>18%</td>
<td>0.47</td>
<td>3.35</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>N = 64</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* For the meta-analysis, we report one-tailed \( p \)-values.

Over time, sales tend to decrease even further when the focal brand is not involved in the price reductions \( (\alpha_{1,i,c,j} + \alpha_{3,i,c,j} \ TRENDS_{INDIRECT\_PWt}) \). The weighted average size of this decay (computed after normalizing \( \alpha_{1,i,c,j} + \alpha_{3,i,c,j} \ TRENDS_{INDIRECT\_PWt} \) and using the reciprocal of the standard errors as weights) is -0.40 after one quarter (when \( TRENDS_{INDIRECT\_PWt} = 13 \)), and -1.05 after one year from the start of the price war (when \( TRENDS_{INDIRECT\_PWt} = 52 \)). Instead, the weighted average of the normalized impact of the direct price war \( (\alpha_{1,i,c,j} + \alpha_{2,i,c,j} + \alpha_{3,i,c,j} \ TRENDS_{INDIRECT\_PWt} + \alpha_{4,i,c,j} \ TRENDS_{DIRECT\_PWt_{i,c,j,t}}) \) is 0.09 after 13 weeks since the beginning of the direct price war (when \( TRENDS_{DIRECT\_PWt_{i,c,j,t}} = 13 \)), and is not significantly different from zero after one year of the direct price war.\(^{47}\)

\(^{47}\) We assume that the focal brand was included in the direct price war after 20 weeks since the first wave of price reductions (20 weeks represent the median for brands that did not enter the price war immediately, see also Figure 3.6).
Table 3.8. Average effect of the indirect and direct price war on sales

<table>
<thead>
<tr>
<th>Total indirect effect over time</th>
<th>Weighted Average Effect</th>
<th>Meta z</th>
<th>Meta p*</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_{1,i,c,j}^{+} ) + ( \alpha_{2,i,c,j}^{+} \times \text{TEND_INDIRECT_PW}_{i,j} )</td>
<td>TEND_INDIRECT_PW_{i} = 13</td>
<td>-0.40</td>
<td>-3.96</td>
</tr>
<tr>
<td>( \alpha_{3,i,c,j} \times \text{TEND_INDIRECT_PW}_{i,j} )</td>
<td>TEND_INDIRECT_PW_{i} = 52</td>
<td>-1.05</td>
<td>-10.17</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total direct effect over time</th>
<th>Weighted Average Effect</th>
<th>Meta z</th>
<th>Meta p*</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_{1,i,c,j} + \alpha_{2,i,c,j}^{+} \times \text{TEND_DIRECT_PW}<em>{i,c,j} ) + ( \alpha</em>{3,i,c,j} \times \text{TEND_DIRECT_PW}_{i,c,j} )</td>
<td>TEND_DIRECT_PW_{i,c,j} = 13</td>
<td>0.09</td>
<td>1.31</td>
</tr>
<tr>
<td>( \alpha_{3,i,c,j} \times \text{TEND_DIRECT_PW}_{i,c,j} )</td>
<td>TEND_DIRECT_PW_{i,c,j} = 52</td>
<td>-0.01</td>
<td>-0.09</td>
</tr>
</tbody>
</table>

Note: \( \alpha_{1,i,c,j} + \alpha_{2,i,c,j}^{+} \times \text{TEND\_INDIRECT\_PW}_{i,j} \) and \( \alpha_{1,i,c,j} + \alpha_{2,i,c,j}^{+} + \alpha_{3,i,c,j} \times \text{TEND\_INDIRECT\_PW}_{i,j} \) refer to the normalized effects of \( \alpha_{1,i,c,j} + \alpha_{3,i,c,j} \times \text{TEND\_INDIRECT\_PW}_{i,j} \) and \( \alpha_{1,i,c,j} + \alpha_{2,i,c,j}^{+} + \alpha_{3,i,c,j} \times \text{TEND\_INDIRECT\_PW}_{i,c,j} \) + \( \alpha_{3,i,c,j} \times \text{TEND\_DIRECT\_PW}_{i,c,j} \), respectively.

Panel A of Figure 3.7 illustrates the evolution of the indirect price-war effect on sales (in %), while the resulting total direct price-war effect is shown in panel B of the same figure. In panel B of Figure 3.7, we assume that the focal brand was directly included in the price war after 20 weeks (in week 167). The total direct effect becomes insignificant in week 181 \((p > .10)\), so the positive effect generated by the direct price war disappears after 14 weeks.48 (Note that almost 30% of the brands in our dataset did not enter the price war at all. In those cases, the evolution of the price war on baseline sales is represented by the solid line in Panel A of Figure 3.7.)

These results offer some first implications for manufacturers. First of all, the high number of negative indirect effects (see Table 3.6, column “Negative”), suggest that avoiding permanent price reductions during a price war does harm sales.

Second, during a direct price-war scenario national brands seem to benefit from permanent price reductions. However, for 29% of the brands directly involved in the price war, we observe a reduction in sales. This may happen because when the price of a brand is reduced, its relative price changes, but it does not necessarily improve, as this depends on the prices of the competing brands in the category and on the fact that consumers may get used to the lower price level.

48 If we use a more conservative test \((p < .01)\), the effect disappears, after nine weeks from the beginning of the direct price war (in week 29).
Third, both manufacturers and retailers should take into account that lowering the price of a focal brand leads to higher sales, but only for few months. As consumers update their reference price at the lower level (Helson 1964), sales return to the pre-price war level in 3 months.

Fourth, it is interesting to notice that retailers that are perceived as cheaper, like Retailer 3 (see Figure 3.2), experience both strong positive indirect and direct effects. Already aware of the store’s lower prices, consumers increase purchases, even for those products whose prices have not been reduced.

### 3.7.2. Are promotions more or less often effective during a price war?

To look at the impact of the price war on sales promotions, we first observe the sign of the normalized total effects \( TE^*_{i,c,j,p} \), obtained from E7, with particular attention to the three scenarios the brand can face, either (1) a business-as-usual scenario (before the price war), (2) an indirect price-war scenario, or (3) a direct price-war scenario. To these three, we add a general “overall” price-war scenario, obtained by analyzing all the \( TE^*_{i,c,j,p} \) of promotions implemented during the price war, with no difference between indirect or direct price wars. Table 3.9 reports the percentage of the positive \( TE^*_{i,c,j,p} \) in these different environments, while Table 3.10 shows whether the percentages displayed in Table 3.9 are significantly different across the four scenarios, based on proportion tests. We find a similar percentage of significant promotion events \( (p < .05) \) before the price war (80%) as well as during the price war (84%) (Table 3.9). The proportion test reported in Table 3.10 confirms that there is no difference between these percentages. Moreover, during the price war, when the price of the focal brand has not been directly reduced (indirect price war), 89% of the promotions are significant. Similarly, when the price is reduced (direct price war), we find that 82% of the promotion events are significantly able to lift up sales. Again, the proportion test indicates no difference between the percentage of the positive direct effects and the positive indirect effects (two-proportion z-test: \( z-value = -1.21, p = .23 \)).

---

49 Remember that each \( TE^*_{i,c,j,p} \) corresponds to an individual promotion event \( p \). Therefore, we can easily identify when the promotion was implemented, as specified in E7.
Table 3.9. Percentage of significant positive promotion events ($p < .05$)

<table>
<thead>
<tr>
<th>Positive effects</th>
<th>Before the price war</th>
<th>During the price war</th>
<th>Indirect price war</th>
<th>Direct price war</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>80%</td>
<td>84%</td>
<td>89%</td>
<td>82%</td>
</tr>
<tr>
<td>Retailer 1</td>
<td>82% (N = 119)</td>
<td>93% (N = 70)</td>
<td>100% (N = 13)</td>
<td>96% (N = 57)</td>
</tr>
<tr>
<td>Retailer 2</td>
<td>95% (N = 97)</td>
<td>83% (N = 57)</td>
<td>72% (N = 17)</td>
<td>88% (N = 40)</td>
</tr>
<tr>
<td>Retailer 3</td>
<td>71% (N = 66)</td>
<td>74% (N = 85)</td>
<td>88% (N = 19)</td>
<td>73% (N = 66)</td>
</tr>
<tr>
<td>Retailer 4</td>
<td>82% (N = 92)</td>
<td>81% (N = 91)</td>
<td>95% (N = 22)</td>
<td>73% (N = 69)</td>
</tr>
<tr>
<td>N</td>
<td>374</td>
<td>303</td>
<td>71</td>
<td>232</td>
</tr>
</tbody>
</table>

Table 3.10. Proportion test of significant positive promotion events

<table>
<thead>
<tr>
<th>Positive effects</th>
<th>Before vs. during</th>
<th>Before vs. indirect</th>
<th>Before vs. direct</th>
<th>Indirect vs. direct</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δ%</td>
<td>z-value</td>
<td>Δ%</td>
<td>z-value</td>
</tr>
<tr>
<td>Total</td>
<td>-3.55%</td>
<td>-.90</td>
<td>-8.75%</td>
<td>-1.22</td>
</tr>
<tr>
<td>Retailer 1</td>
<td>-11.25%</td>
<td>-1.90**</td>
<td>-18.26%</td>
<td>-1.35</td>
</tr>
<tr>
<td>Retailer 2</td>
<td>12.08%</td>
<td>2.17*</td>
<td>23.42%</td>
<td>2.75*</td>
</tr>
<tr>
<td>Retailer 3</td>
<td>-3.02%</td>
<td>-.11</td>
<td>-16.66%</td>
<td>-1.11</td>
</tr>
<tr>
<td>Retailer 4</td>
<td>1.09%</td>
<td>.16</td>
<td>-12.95%</td>
<td>-1.08</td>
</tr>
</tbody>
</table>

* two-sided $p$-value < .05, ** two-sided $p$-value < .10

Greater variability exists across retailers. For example, while at Retailer 1 we observe more often effective promotions during the price war than before the price war started (two-proportion $z$-test: $z$-value = 1.90, $p = .057$), at Retailer 2 we notice a decrease in the percentage of effective promotions (two-proportion $z$-test: $z$-value = -2.17, $p < .05$). In contrast, the price war did not affect the number of effective promotions implemented at Retailer 3 and Retailer 4.

These findings indicate that, overall, the price war did not increase or decrease the number of effective promotions.
3.7.3. What is the size of the effect of a price war on sales promotions?

Table 3.11 reports the results of the model described in equation E8. At first sight, these results may appear to contradict those described above. However, in the previous paragraph we focused on the number of effective promotions, making an abstraction of the magnitude of the effects, and we did not filter out important factors that could be at play. Here, instead, we look at the size of those effects, estimated in E8. Of central interest here are the gamma parameters, \( \gamma_1 \) and \((\gamma_1 + \gamma_2)\), representing, respectively, the instantaneous effects of the indirect and direct price wars on sales promotion effectiveness, followed by their evolution over time, \((\gamma_1 + \gamma_3 \text{TIME}_\text{LAG INDIRECT_PW}_p)\) and \((\gamma_1 + \gamma_2 + \gamma_3 \text{TIME}_\text{LAG INDIRECT_PW}_p + \gamma_4 \text{TIME}_\text{LAG DIRECT_PW}_{i,c,j,p})\). The Pseudo R² is .42. The model does not present serious multicollinearity (all VIFs < 5).

Although there are no differences before versus during the price war in terms of the number of effective promotions, the results of the regression analysis in E8 suggest that promotions are more effective at the beginning of the indirect price war than before \((\gamma_1 = 1.14, p < .01)\), but that their effectiveness decreases as the price war continues \((\gamma_3 = -.03, p < .01)\); after 13 weeks, \(\gamma_1 + \gamma_3 = .70, p < .05\); after one year, \(\gamma_1 + \gamma_3 = -.63, p = .06\). Then, when the product’s price has been reduced, sales promotions are even more effective than during the indirect price war \((\gamma_2 = .15, p < .05)\) and/or before the price war \((\gamma_1 + \gamma_2 = 1.29, p < .01)\). However, this positive direct effect is only temporary and decreases over time \((\gamma_4 = .02, p < .0001)\); for \(\text{TIME}_\text{LAG INDIRECT_PW}_p = 20\), when \(\text{TIME}_\text{LAG DIRECT_PW}_{i,c,j,p} = 13\), \(\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 = .37, p < .05\); when \(\text{TIME}_\text{LAG DIRECT_PW}_{i,c,j,p} = 52\), \(\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 = -.32, p > .10\), as also illustrated in Figure 3.7, panel C and D.\(^{50}\) Panel C of Figure 3.7 shows the evolution of the effect of the indirect price war, while Panel D of Figure 3.10 displays the total price-war impact on promotional effectiveness over time, assuming a duration of the indirect price war of 20 weeks (based on the median of our sample). During both the indirect and direct price war, the promotional effectiveness first increases (immediate effect) and then decreases over time. The positive effects generated by the price war vanish after a few

\(^{50}\) As mentioned above, one could instead capture the evolution of the price war over time by means of the number of items involved in the price war, as in van Heerde et al. (2008). Not having the necessary information at hand, we use two linear trends instead. We also tested non-linear alternatives (1) by adding a quadratic term \((\gamma_5 \text{TIME}_\text{LAG INDIRECT_PW}_p^2; \gamma_6 \text{TIME}_\text{LAG DIRECT_PW}_{i,c,j,p}^2)\), and (2) by using two inverted trends (instead of the trends) \((\gamma_3' = 1/\text{TIME}_\text{LAG INDIRECT_PW}_p; \gamma_4' = 1/\text{TIME}_\text{LAG DIRECT_PW}_{i,c,j,p})\). The resulting parameters are not significant.
months for both the indirect and direct price-war scenario, as promotional effectiveness drop below the business-as-usual scenario level.

Further variation in the effectiveness of sales promotions is captured by a set of control variables related to the way each promotion was implemented (deal planning and deal communication) and other covariates. The results are displayed in Table 3.10 and discussed below.

**Deal planning. Timing.** In line with our previous findings (see Chapter 2), our results indicate that promotions are more effective when more time elapses between two consecutive events, not only when implemented at the same retailer but also at competing retailers ($\xi_1 = 1.21, p < .0001, \xi_2 = .83, p < .005$). The simultaneous occurrence of a promotion at a competing retailer (during the same week) is not significant, although the negative sign is in line with our previous findings.

**Depth.** Another important driver of price promotion effectiveness is the depth of the discount. In line with the extant literature, we find that larger discounts work better than smaller discounts (e.g. Blattberg et al. 1995) ($\xi_4 = .94, p = .01$).

**Duration.** Consistent with our prior findings (see Chapter 2), shorter promotion events work better than longer ones ($\xi_5 = -1.22, p < .05$).

**Deal communication.** Out-of-store feature communication ($\xi_6 = 1.20, p < .0001$) as well as in-store displays ($\xi_7 = 1.44, p = .001$) increase sales, in line with the results discussed in Chapter 2 and the literature on sales promotion (e.g. van Heerde et al. 2004). The cumulative effects of advertising expenditure do not significantly influence price promotion effectiveness.

**Other control variables.** In line with previous research, we find that a higher concentration in the product category leads to higher effectiveness of sales promotions ($\xi_{10} = 2.72, p < .10$) (e.g. Bell et al. 1999). We report no differences across categories, but strong variation across retailers, with less effective promotions implemented at Retailer 2, Retailer 3 and Retailer 4 than at Retailer 1.

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51 The full results, including the category fixed-effects, can be found in Appendix A2.
Figure 3.7. Evolution of the indirect and direct price war (assuming that the indirect price-war scenario starts in week 147 – panel A, B, C, D – and lasts for 20 weeks – panel B, C –)
Table 3.11. Moderator analysis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>t-value</th>
<th>Two-sided p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\mu_1) INTERCEPT</td>
<td>4.218</td>
<td>1.42</td>
<td>0.156</td>
</tr>
<tr>
<td>(\mu_2) DR2</td>
<td>-2.073</td>
<td>-2.45</td>
<td>0.015</td>
</tr>
<tr>
<td>(\mu_3) DR3</td>
<td>-2.012</td>
<td>-2.24</td>
<td>0.025</td>
</tr>
<tr>
<td>(\mu_4) DR4</td>
<td>-1.741</td>
<td>-1.85</td>
<td>0.065</td>
</tr>
</tbody>
</table>

**PRICE WAR**

| \(\gamma_1\) INDIRECT_PW | 1.142 | 3.11 | 0.002 |
| \(\gamma_2\) DIRECT_PW | 0.153 | 1.93 | 0.054 |
| \(\gamma_3\) TIME_LAG INDIRECT_PW | -0.034 | -2.25 | 0.001 |
| \(\gamma_4\) TIME_LAG DIRECT_PW | 0.015 | 3.73 | <.0001 |

**CONTROL VARIABLES**

**PLANNING**

| \(\xi_1\) Log TIMING | 1.213 | 3.98 | <.0001 |
| \(\xi_2\) Log TIMING_COMP | 0.832 | 2.99 | 0.002 |
| \(\xi_3\) SIMULTANEOUS | -0.783 | -1.27 | 0.204 |
| \(\xi_4\) Log DEPTH | 0.945 | 2.54 | 0.011 |
| \(\xi_5\) Log DURATION | -1.219 | -1.99 | 0.047 |

**COMMUNICATION** (vs. in-store shelf tag)

| \(\xi_6\) FEATURE | 1.195 | 4.77 | <.0001 |
| \(\xi_7\) DISPLAY | 1.436 | 3.18 | 0.001 |
| \(\xi_8\) Log ADSTOCK | -0.071 | -0.82 | 0.412 |

**OTHER CONTROL VARIABLES**

| \(\xi_9\) Log MKTSHARE | 0.671 | 0.44 | 0.660 |
| \(\xi_{10}\) Log CONCENTRATION | 2.719 | 1.97 | 0.049 |

N = 657
Pseudo R² = .42
3.7.3.1. Impact on the drivers of sales promotions

Additionally, we check whether there was a change in the effectiveness of each promotion implementation variable (i.e. TIMING, TIMING\_COMP, SIMULTANEOUS, DEPTH, FEATURE and DISPLAY) during the price war. To do so, we extend equation E8 with the interactions of these variables with the indirect and direct price wars. For example, with regard to the timing, the model is augmented in the following way: $\xi_{1}^{\text{INDIRECT}} \times TIMING_{i,c,j,p} \times \text{INDIRECT\_PW}_{p} + \xi_{1}^{\text{DIRECT}} \times TIMING_{i,c,j,p} \times \text{DIRECT\_PW}_{i,c,j,p}$. As a result, below we focus the attention on the parameter related to the indirect effects, i.e. $\xi_{1}^{\text{INDIRECT}}$, and the direct effects, i.e. ($\xi_{1}^{\text{INDIRECT}} + \xi_{1}^{\text{DIRECT}}$). In order to avoid high multicollinearity, we do not test all the variables simultaneously, but we add the four interactions for one variable at a time.

We find evidence of a significant change in some of these drivers during the price war. More specifically, promotions implemented after a longer interval of time at the focal retailer ($\xi_{1}^{\text{INDIRECT}} =-.97, p < .01; \xi_{1}^{\text{INDIRECT}} + \xi_{1}^{\text{DIRECT}} =.15, p = .11$) and at a competing retailer ($\xi_{2}^{\text{INDIRECT}} =-.58, p < .01; \xi_{2}^{\text{INDIRECT}} + \xi_{2}^{\text{DIRECT}} =.33, p = .18$) are less effective than before the price war. We find this effect during the indirect price war, suggesting that when the manufacturer’s brand has a higher relative price, more frequent promotions than those implemented during a business-as-usual scenario are needed to keep the brand competitive.

A greater depth of discount works better during the indirect price war ($\xi_{4}^{\text{INDIRECT}} =.38, p < .01$), suggesting once again that manufacturers’ brands facing an indirect price war need more resources (in this case, steeper discounts) to remain attractive. Instead, brands with a reduced price (facing a direct price war) are able to stimulate the same level of sales as they did before the price war.

Feature communication is more effective during both the direct and indirect price wars ($\xi_{6}^{\text{INDIRECT}} =.41, p < .01; \xi_{6}^{\text{INDIRECT}} + \xi_{6}^{\text{DIRECT}} =.52, p < .01$). Indeed, as we said above, features become an essential tool for retailers to communicate their competitive offers and for consumers to decide where and what to buy.

The increased usage of displays inside the store, for both price discounts and permanent price reductions, creates a saturation effect and lowers the effectiveness of display communication. We find evidence of this during the direct price war ($\xi_{7}^{\text{INDIRECT}} =.97, p = .23; \xi_{7}^{\text{INDIRECT}} + \xi_{7}^{\text{DIRECT}} =-1.24, p < .001$).
3.8. Conclusions

Price wars are often described as a sequence of battles to win the customer using permanent lower prices as the key weapon. When a price war is initiated, both retailers and manufacturers have two main options: lower their prices or not. Even when lowering his/her prices, a retailer may decide not to involve all the products in a given category and a manufacturer’s brand may end up in an indirect price war. Although Rao et al. (2000) suggest managers to avoid direct price wars and the use of price reductions during price wars, to the best of our knowledge, this advice has not yet been empirically tested. It is in fact difficult for managers to follow this type of recommendation, as they are afraid of losing sales if they do not reduce the prices when their competitors do so. Indeed, we find that avoiding permanent price reductions might be counterproductive, since sales tend to immediately decrease by 17%, on average (Table 3.6). A relative price deterioration thus harms sales, and brand managers should be advised to join the direct price war as quickly as possible.

In fact, when the brand’s price is reduced, sales increase by 48% (in comparison with their level before the price war) (Table 3.7). Managers should view this information with caution for two reasons. First of all, this positive effect is only temporary and wears off after a couple of months. Second, they should also notice that, for 29% of the brands involved directly in the price waves, there is a drop in sales. In fact, reducing the absolute price may not be enough if there is no significant improvement in the relative attractiveness of the focal brand’s price (i.e. in the relative price of the brand vis-à-vis its competitors).

Before manufacturers decide to (or not to) try to convince retailers to permanently reduce the price of their products (e.g. by means of lower trade prices and trade promotions), they must also consider the impact of the price war on their promotional activities. During an indirect price war, sales promotions increase their effectiveness for the first seven months. In this scenario, manufacturers need to offer more sales promotions (i.e. by reducing the inter-promotion timing), with steeper discounts and with feature communication support. Instead, if the manufacturer decides to reduce the product’s price, he/she will observe more effective promotions, although also this effect wears off after five months since the price of the product has been lowered. In this environment, manufacturers can keep the same timing and depth of the discount they used to implement before the price war, as their effectiveness does not change. They should communicate promotions even more by means of features, as consumers select where and what to buy.
based on the store flyers. Finally, they must keep in mind that displays are less effective than before the price war (due to the cluttered in-store environment now displaying also permanent price reductions).

### Table 3.12. Summary of the results

<table>
<thead>
<tr>
<th>Indirect price war</th>
<th>Direct price war</th>
</tr>
</thead>
<tbody>
<tr>
<td>If the brand’s price has not been reduced</td>
<td>If the brand’s price has been reduced</td>
</tr>
<tr>
<td>Brand sales</td>
<td>Lower sales</td>
</tr>
<tr>
<td>Brand’s promotional effectiveness</td>
<td>≤ 7 months: Higher promotional effectiveness</td>
</tr>
<tr>
<td>Drivers of promotional effectiveness</td>
<td>Decreased effectiveness of timing</td>
</tr>
<tr>
<td></td>
<td>Increased effectiveness of discount depth</td>
</tr>
<tr>
<td></td>
<td>Increased effectiveness of features</td>
</tr>
</tbody>
</table>

Note: This table is based on the results discussed on page 84-85, 88-94.

Future research could investigate in more detail the impact of the decisions of the competitors to decrease their prices on the sales of the focal manufacturer. For example, manufacturers’ sales and promotion activities may be affected to a different degree if only one of the competitors reduces the price, or if several big players lower their prices within the category. This could be captured by adding to both the first and the second step of the analysis an interaction between the indirect price war dummy variable and the cumulative number of SKUs of the competing brands involved in the price reductions. Alternatively, to capture the attraction power of these brands, instead of the cumulative number of competing SKUs, one could use the sum of the market shares of the competing brands involved.

We also want to point out that we consider the effects on sales and not on profit. This is not uncommon in the promotional literature, as margin data are very rarely available. We could expect a different (if not opposite) picture when margins are considered. For example, will the incremental lift in sales be able to compensate for the lower margin? Future research could address this question and focus on the impact of the price war on the profitability of sales promotions.
To conclude, despite the limitations of this study, our chapter makes an important step in documenting the impact of price wars on sales promotion. Every year, manufacturers spend billions on price promotions and yet, despite the increasing number of price wars, no study so far has investigated the consequences of price wars for promotional effectiveness. We hope this study will stimulate further research in this direction.
CHAPTER 4: CROSS-RETAILER EFFECTS

4.1. Introduction

While there has been considerable research on the decomposition of the promotional sales bump into cross-brand effects, cross-period effects, and category-expansion effects (see e.g. Bell et al. 1999, van Heerde et al. 2004), limited attempts have been made to investigate cross-store effects. However, sales promotions can also transfer demand across competing chains (Gijsbrechts et al. 2008). For instance, Ailawadi et al. (2006: 531) suggest that a large part of the gross lift generated by sales promotions at CVS may be due to store switching behavior. They state that “45% of the gross lift is incremental, coming either from other stores or from increased consumption. Because the latter is likely to be small for most of these mature product categories, store switching must be a significant phenomenon, and it deserves further investigation.”

Because manufacturers sell their goods through competing retailers, these demand shifts across chains may reduce the overall effect of manufacturers’ sales promotions. Yet, there is little empirical knowledge neither about the size of these cross-chain effects, nor about their impact on the overall effectiveness of sales promotions for manufacturers.

Previous research has often focused on the effect of promotions in a single store/chain. For example, several studies have used the Dominick’s data (see e.g. Srinivasan et al. 2004), while Ailawadi et al. (2006) focused on the effectiveness of price promotions at CVS. However, there is increasing evidence that many customers are multiple-store shoppers (Gijsbrechts et al. 2008). This is also emphasized in the literature on cherry-picking behavior, describing the characteristics of shoppers who shop around for the best deals across several stores. Fox and Hoch (2005), for example, find that more than 80% of the households in their sample cherry-picked. First attempts to measure cross-chain effects have been done by van Heerde et al. (2004). The authors argue that the cross-store effect may account for most of the category-expansion effect. Unfortunately, these results were significant in only 25% of the cases, and for a dataset limited to four brands of tuna.

A manufacturer, in order to identify possible solutions, should also know if these cross-store effects are homogeneous across competing stores, or if some retailers are less (or more) affected. Previous studies find greater rivalry within store formats than between store formats (Cleeren et al. 2010, González-Benito et al. 2005), suggesting higher
cannibalization among chains sharing similar characteristics. Identifying who suffers more will help the manufacturer to develop strategies to contain the problem and avoid channel conflict.

In Chapter 2, we found preliminary evidence for the existence of these cross-store effects, where we show that the timing since the last promotion with a competing retailer, as well as the simultaneous promotions of competing retailers, diminish the effectiveness of the current promotion event at the focal retailer.

In this chapter, we directly model and quantify the impact of cross-chain effects. In particular, we are interested answering the following questions: (1) How often do these cross-effects occur?, (2) What is the effect size?, and (3) To what extent is the effect homogeneous across stores?

4.2. Model

To investigate the effectiveness of individual price-promotion events across competing retailers, we expand the model specification presented in E3 in the following way. We explain the sales of each product $i$ at retailer $j$ (with $j = 1$ to $J$) as a function of its own promotions $p$, and the promotion events $p'$ of the market leader $ml$ (with $ml \neq j$). In particular, we are interested in measuring the individual effects of the promotions ($\text{PROMOML}$) of the market leader $ml$, on the sales of the competing retailers $j$. Moreover, we control for the average effect of other competing promotions ($CP$) at retailers $j'$ (with $j \neq j'$, $ml \neq j'$). The model is:

\begin{equation}
\text{SALES}_{i,\epsilon,j,t} = \alpha_{i,\epsilon,j} + \sum_{p=1}^{P} \sum_{t=0}^{2} \beta_{i,\epsilon,j,p,d} \text{PROMO}_{i,\epsilon,j,p,d-t} + \\
\sum_{p'=1}^{P'} \sum_{t=0}^{2} \gamma_{i,\epsilon,j,p',d} \text{PROMOML}_{i,\epsilon,ml,p',d-t} + \\
\delta_{i,\epsilon,j,j'} \text{CP}_{i,\epsilon,j',d} + \delta_{i,\epsilon,j} \text{ADSTOCK}_{i,\epsilon,d} + \\
\eta_{i,\epsilon,j} \sin \left( \frac{2\pi t}{52} \right) + \eta'_{i,\epsilon,j} \cos \left( \frac{2\pi t}{52} \right) + \\
\eta''_{i,\epsilon,j} \text{TREND}_{t} + \epsilon_{i,\epsilon,j,t}
\end{equation}
The equation E9 is estimated for each product $i$ across all retailers $j$ simultaneously using iterative SUR-GLS with Prais–Winsten correction to obtain more efficient parameter estimates (Judge et al. 1985). The error term has the following distribution:

$$
e_{i,c,j,t} = \rho_{i,c,j} e_{i,c,j,t-1} + \nu_{i,c,j,t}$$

$$
e_{i,c,j',t} = \rho_{i,c,j'} e_{i,c,j',t-1} + \nu_{i,c,j',t}$$

$$\text{cov} [\nu_{i,c,j,t}, \nu_{i,c,j',t}] = \sigma_{i,c,j,j'}$$

where $\nu_{i,c,j,t} \sim N(0, \sigma_{\nu_{i,c,j}}^2)$ and $\nu_{i,c,j',t} \sim N(0, \sigma_{\nu_{i,c,j'}}^2)$.

The cross-retailer effect ($CE$) of each promotion $p'$ implemented by retailer $ml$, the market leader, on the sales of retailer $j$ for brand $i$ is therefore:

(E10) $CE_{i,c,j,p'} = \sum_{l=0}^{2} \gamma_{i,c,p'}$

Next, we test whether the focal retailer is stealing more customers away from retailers with a similar format, or whether this effect is the same across all competing retailers. To do this, we regress the normalized cross-store effect, $CE^*$, on the dummy variables for the different retailers (in our case, Retailer 3, Retailer 4, using Retailer 2 as reference group) in a WLS model, using as weight the inverse of the standard error of $CE^*$.

(E11) $CE^*_{i,c,j,p'} = \beta_1 + \beta_2 \text{Retailer 3} + \beta_3 \text{Retailer 4} + e_{i,c,j,p'}$

$CE^*_{i,c,j,p'}$ was computed by normalizing $CE_{i,c,j,p'}$ by dividing it by the baseline sales of brand $i$ (of category $c$) at retailer $j$ (the baseline sales are measured as the average non-promotional sales of each brand within rival retailer $j$; when computing the average, we excluded the weeks when either the market leader $ml$ or retailer $j$ carried a promotion of brand $i$, and the two weeks following the event, to account for post-promotion effects).

Finally, the total sales shift generated by each promotion $p'$ of retailer $ml$ across all the competing retailers is captured by the normalized total cross-retailer effect ($TCE^*$) as follows:

Cross-retailer effects
Chapter 4

\[ TCE^{*}_{i,c,p} = \frac{\sum_{j=1}^{I} CE_{i,c,j,p}}{\sum_{j=1}^{J} BASLINE_{i,c,j} - SALES_{i,c,j}} \text{ with } j \neq j' \]

whereby for a given promotion of a focal product \( i \), we divide the sum of each \( CE \) generated across all the retailers \( j \), by the sum of the baselines of those retailers \( j \). The standard errors of \( CE^{*} \) and \( TCE^{*} \) are derived through the Delta method (Greene 2003).

4.3. Data

We use a subset of the database used in Chapter 2. We select products with a limited numbers of promotion events (\( \leq 4 \)), to allow us to identify the own- and cross-store effect of each individual promotion, together with its lags. The final dataset covers a time span of 147 weeks, with a total of 32 promotions of Retailer 1 for 12 brands of a leading multinational CPG manufacturer, across four product categories. In particular, we focus on the effects of the promotions of the market leader, Retailer 1, on the sales of three retailers, Retailers 2, 3 and 4. We measure a total of 96 effects (i.e. the effects of 32 promotions of the market leader at three retailers).

These promotions varied greatly in terms of the timing since the previous one implemented at Retailer 1 (\( M = 45.51, SD = 42.94 \)) and at Retailer 2, 3 and 4 (\( M_{\text{Retailer 2}} = 8.25, SD_{\text{Retailer 2}} = 3.77; M_{\text{Retailer 3}} = 18.25, SD_{\text{Retailer 3}} = 16.46; M_{\text{Retailer 4}} = 40.75, SD_{\text{Retailer 4}} = 16.78 \)).\(^{52}\) There were no simultaneous promotions of Retailer 2, Retailer 3 and Retailer 4 taking place. Moreover, all the deals lasted for only one week, with an average percentage of the discount of 19% (\( M = 19.21, SD = 6.49 \)). Most of the promotions implemented at Retailer 1 were supported by feature communication (in 82% of the cases), and only very few were accompanied by an in-store display (in 12% of the cases) (Table 4.1). Table 4.1 provides an overview of the main descriptive statistics of the promotions implemented at Retailer 1.

\(^{52}\) These means refer to the average number of weeks between a promotion implemented at Retailer 1 and the previous promotion implemented at, respectively, Retailer 1 (TIMING), Retailer 2 (TIMING_ RETAILER2), Retailer 3 (TIMING_ RETAILER3), and Retailer 4 (TIMING_ RETAILER4).
4.4. Results

To analyze the cross-store effects, we look at the sign of the cross-store effects, \( CE \), estimated in E10. A negative sign would confirm the existence of cross-store cannibalization effects. Figure 4.1 illustrates the percentage of the signs of these effects. We find that 86% of the promotion events of the market leader, Retailer 1, reduces the sales of its competing retailers, although in only 24% of the cases this reduction is significant (two-sided \( p \)-value < .05)\(^{53} \) (see Figure 4.1).

<table>
<thead>
<tr>
<th>Table 4.1. Descriptive statistics of the promotions implemented at Retailer 1</th>
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<tbody>
<tr>
<td><strong>PLANNING</strong></td>
</tr>
<tr>
<td>TIMING RETAILER1 (weeks)</td>
</tr>
<tr>
<td>TIMING RETAILER2 (weeks)</td>
</tr>
<tr>
<td>TIMING RETAILER3 (weeks)</td>
</tr>
<tr>
<td>TIMING RETAILER4 (weeks)</td>
</tr>
<tr>
<td>SIMULTANEOUS (frequency %)*</td>
</tr>
<tr>
<td>DEPTH (%)</td>
</tr>
<tr>
<td>DURATION (weeks)</td>
</tr>
<tr>
<td><strong>COMMUNICATION</strong></td>
</tr>
<tr>
<td>FEATURE (frequency %)*</td>
</tr>
<tr>
<td>DISPLAY (frequency %)*</td>
</tr>
<tr>
<td><strong>SAMPLE CHARACTERISTICS</strong></td>
</tr>
<tr>
<td>Number of promotions</td>
</tr>
<tr>
<td>Number of weeks</td>
</tr>
</tbody>
</table>

*For the dummy variables, we report the frequency (%).

Subsequently, we test whether Retailer 1 is stealing more customers away from a similar retailers’ format, like Retailer 4, or whether this effect is the same across all three retailers. The results of the WLS regression (E11) suggest that there is a main effect of the retailer format on the normalized cross-store effects \( CE^* \). When promoting at Retailer 1, the manufacturer is cannibalizing his/her own sales at Retailer 3 (\( \beta_1 + \beta_2 = -.19, p < .01 \))

\(^{53} \) The percentage of significant cross-effects increases to 31% when we consider a two-sided \( p \)-value < .10, and to 39% when we consider a one-sided \( p \)-value < .10.
and Retailer 4 ($\beta_1 + \beta_3 = -.22, p < .01$), but not at Retailer 2 ($\beta_1 = .05, p = .19$).

Looking at the perceptual map of Figure 2.3, we notice that in the mind of the consumers Retailers 2 is far from Retailer 1 in terms of prices and service quality. Retailer 3 and 4, instead, are characterized a medium level of prices and service quality, and are positioned between Retailer 1 and Retailer 2. Our findings suggest that chains like Retailer 2, with a different store format from the focal retailer (“low price, low service” vs. “high price, high service”), face lower direct competition than retailers with a less dissimilar store profile.

Finally, from the results of E10 (Figure 4.1) we notice that the individual impact of the promotion of Retailer 1 on the sales of the focal brand in each of the competing retailers ($CE$) tends to be weak (two-sided $p$-value > .20 in 62% of the cases) but in the same direction (negative). This highlights that a case-by-case test may be misleading, and unable to detect any significant cannibalization effect to worry about (Deleersnyder et al. 2002). Instead, the collective evidence could reveal a highly significant cannibalization effect that manufacturers should monitor. Therefore, we conduct a meta-analysis to test for cross-store cannibalization using the Stouffer’s meta-analytic test of “adding $zs$” (see Rosenthal 1991: 97 for technical details, or Gijsbrechts et al. 2003 and Deleersnyder et al. 2002 for some marketing applications). As discussed by Deleersnyder et al. (2002), this offers a stronger test for the presence of cannibalization than the significance of the individual estimates. The results of the meta-analysis confirm that the overall effect is negative and significant ($meta-analytic\ \text{effect size} = -.12, p < .01$).

Moreover, if we look at the (normalized) sum of these effects, $TCE^*$ (obtained in E12), we notice that a single promotion event is shifting a significant amount of traffic toward the focal chain. In fact, as displayed in Figure 4.3, the sum of the cross-store effects is negative for 93% of the promotions (and significant in 77% of the cases). This relevant effect may go unnoticed when the manufacturer collects the sales information from each retailer separately.

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54 We report no difference between $\beta_2$ and $\beta_3$ ($p > .10$).
Figure 4.1. Percentage of (not) significant CE (cross effects of the sales promotions implemented at Retailer 1 on competing retailers) (two-sided p-value < .05)

![Bar chart showing percentage of significant and not significant CE](chart1.png)

Figure 4.2. Percentage of (not) significant $TCE^*$ (normalized total cross effects of promotions implemented at Retailer 1 on competing retailers)

![Bar chart showing percentage of significant and not significant $TCE^*$](chart2.png)
4.5. Conclusions

When dealing with sales promotion effectiveness, cross-chain effects have largely been ignored in previous research. However, more and more scholars have pointed out that these effects could be substantial (Ailawadi et al. 2006). Our results shed some light in this direction.

We find that a sales promotion event at a focal retailer shifts a small amount of customers away from another competing chain. If the point of view of the analysis is that of the retailer, then this effect may not be noticed. In fact, we find that a retailer does not observe a significant decrease in sales due to a competing promotion event in 74% of the cases.

However, if the point of view is that of the manufacturer selling through competing retailers, the picture is changing dramatically. In fact, the sum of these shifts in sales across the competing retailers is significant for almost 80% of the promotions, suggesting that the manufacturer is mainly shifting traffic toward the focal retailer. This cannibalization effect is not visible when manufacturers look at the sales of each individual chain. To monitor it, the manufacturer should analyze the results of his/her sales promotions across all competing chains.

Moreover, our result suggests that the promotions of the manufacturer’s brand at a “high-price, high-service” retailer, do not induce consumers of a different format (“low-price, low-service”) to switch stores. The promotional literature (Blattberg and Wisniewski 1989, Bronnenberg and Wathieu 1996) indicates that when a high quality national brand promotes, it steals away more customers from the lower quality brands than vice versa. Here we find the opposite effect between stores. Our result is in line with previous studies showing lower rivalry between different store formats (González-Benito et al. 2005). This may be due to the type of consumers that the different store formats attract. Lower price retailers are preferred by large basket shoppers (Bell and Lattin 1998). These consumers may not be easily lured to switch store because of a single promotion event (as they search for the lower prices of a set of products).

Our study has several limitations, as we look at the promotion events of the leading retailer, for products of only one manufacturer. Also, the analysis is confined to FMCG, and for goods of a unitary value of less than 10 euro. We can expect that a lower unitary value may induce lower store switching. Instead, a higher unitary price could also induce shoppers of a “low-price, low-service” retailer to switch. For example, the effect
may be even stronger for durable goods. It would be thus interesting to verify these findings across different manufacturers, retailers and industries. Additionally, future research should identify the drivers of these cross-store effects, and provide guidelines for manufacturers on how to limit (if not avoid) these effects. Moreover, in this study, we focus on brands with limited promotional activity. As we found in Chapter 2 that less frequent promotions are the most effective, this may lead to a sample selection bias.
CHAPTER 5: CONCLUSIONS

5.1. What have we learned?

Every year manufacturers and retailers alike spend a substantial amount of their marketing budget on sales promotions. As such, it is not surprising that many scholars have focused on the topic. Managing national brands’ promotions across competing retailers is a complex task in today’s competitive market. A brand manager must decide which type of promotion to implement and when, accounting for the effects generated by each promotion event (1) during stable business-as-usual scenarios as well as (2) during price wars, not only at the focal retailer, but also (3) at competing retailers.

Previous research has mainly focused on the first aspect, investigating sales promotion variation across products and retailers, providing brand managers with a clear understanding of which brand sells more on promotion, and at which retailer. However, for a specific brand, they still cannot identify how many promotions are truly able to lift up sales. Still, managers are well aware of the fact that some of their promotions work better than others.

Therefore, we built on the extant literature, and we extended it in three directions. In Chapter 2, we introduced a new methodological approach based on Leone’s (1987) intervention analysis. This method allowed us to identify in a flexible way the effect of individual promotion events, finally understanding how many promotions are truly effective. This was not possible with models based on an average promotional parameter. In an “average” approach, as with the SCAN*PRO model, the researcher computes one average coefficient across several promotion events, not allowing the scholar to identify the number of effective promotions.

Also, our approach allowed us to use promotion event-specific (dependent and independent) variables, rather than averages computed across different promotion implementations. For example, we did not use an average frequency computed across different promotions of the same brand, but the individual timing since the previous promotion event. This more refined approach provides detailed insights into what works and what does not.

In Chapter 3, using the method discussed in Chapter 2, we compared the effectiveness of sales promotions in a business-as-usual scenario versus a price war
environment. The price war studied in this dissertation is the one initiated in the Netherlands in 2003 by the leading supermarket chain. We added to both the promotional literature and the price war literature by focusing not on the consequences of the initiator of the price war, nor of the main actors involved directly in the price interactions (as commonly done so far), but of a third party. In our setting, this third party is the brand manufacturer, who has to sell his/her products through a channel involved in a price war. In particular, we showed what happens to the regular and promotional sales of a national manufacturer’s brands. In so doing, we looked at two different scenarios within the price war: an indirect and a direct price war. If the manufacturer’s brand is (not) directly involved in the price reductions characterizing the price war, then the brand faces a (in)direct price war. The consequences for its regular and promotional sales are different. This can be attributed to the differential changes in the brand’s relative price.

Finally, in Chapter 4, we focused on the effects of sales promotions not only within the focal retailer but also at competing chains, largely understudied by the promotional literature. In fact, although the cherry-picking literature had established that a segment in the consumer market only buys items on promotions, and thus bases its store choice on the occurrence of price promotions, limited research has investigated the impact of promotions on competing store chains. From the perspective of the manufacturer, for a promotion to be successful, a promotion must be able to lift up total sales, even after accounting for potential reductions in competing stores. In Chapter 4, we tried to capture these potential cannibalization effects.

5.2. Summary of the main findings

Overall, we systematically analyzed the effects of a total of 832 promotions in eight different product categories, using a maximum of five years of weekly data and a wide set of marketing mix variables. We found that:

1. From the perspective of the manufacturer, around 80% of the promotions are truly able to lift the brand sales significantly within the focal chain.
2. In comparison with an “average-effect” model, like a log-log model, we gain a more detailed overview of what really works and what does not. For instance:
Conclusions

(a) A non significant parameter of the log-log model indicates that the promotional activities of that brand are not able to lift sales. With our approach, instead, we are able to identify that almost 40% of those promotions are actually effective, and may result in a missed opportunity if the manufacturers decide to abandon them.

(b) Instead, 13% of the promotional events of brands for which the log-log model indicates significant promotions are spoiled arms, as they are not able to significantly increase sales.

(c) Only for 17% of the brands are all promotions able to boost sales.

(3) When disentangling the total price war effect into an indirect price-war and a direct price-war effect, we observed that:

(a) During an indirect price war, sales decrease. Manufacturers may be better off reducing their prices immediately. (Of course, more research is needed to assess the profitability implications).

(b) When the focal brand is involved in the direct price war, sales increase. However, before taking action, brand managers should consider the following findings as well:

(i) This positive effect is only temporary, as it returns to a business-as-usual scenario level after few months.

(ii) For almost 30% of the brands facing a direct price war, sales are lower than the business-as-usual scenario. Indeed, a lower price may not guarantee a significant improvement in the relative attractiveness of the focal brand vis-à-vis its competitors.

(4) We could identify how many promotions are effective during a business-as-usual scenario versus a price war environment. We found that:

(a) The proportion of promotions able to lift up sales is not different during a price war.

(b) The magnitude of the effects is higher during both the indirect and direct price war. These effects decline over time, disappearing after few months.
(c) More detailed data at the promotion level, instead of at the brand or category level, help us understand whether the implementations of sales promotions (deal timing within the focal chain, deal timing at competing chains, deal depth, features and displays) and their effectiveness change during different competitive settings.

(d) Two understudied variables related to the promotional calendar of the focal chain and of the competing retailers are found to be important drivers of promotional effectiveness. In particular, we find that promotions implemented long after previous events within the focal retailer and/or at a competing chain are more effective.

(e) During the price war, we see a clear change in the implementations of these drivers, with an overall decrease in the frequency of sales promotions and in the implementation of simultaneous promotions at competing retailers. Promotions also last longer, and are more often supported by means of features and displays than before the price war.

(f) The price war changes the effectiveness of sales promotion implementation tools. When the price of the focal brand is not reduced, the brand manager should avoid leaving several weeks between two consecutive promotions (as suggested by the results obtained during the business-as-usual scenario) and instead implement more frequent promotions, with deeper discounts and supported by feature communications. In fact, given the disadvantageous relative price image, the brand needs more support to generate the same level of sales on promotion.

(g) When the brand’s price has been directly reduced during the direct price war, displays become less effective while features increase their importance in stimulating sales. During a price war, consumers in fact tend to decide what to buy based on price, and a feature ad facilitates their selection. Although for this reason one could expect an increase also in the importance of display communication, the over-usage of in-store displays for both permanent and temporary price reductions seems to dilute their effectiveness. As the price war continues and more competing brands are also reduced in price, steeper discounts are then needed.
For each promotion we were able to estimate the impact on sales not only within the focal retailer but also at the competing retailers. We found significant evidence of cross-chain effects. We investigated the potential cannibalization of the promotion events of a brand implemented within the leading retailer on the sales of the main rival chains. Our results suggested that:

(a) While for brand manufacturers these effects may go unnoticed when looking at each individual chain, they become significant when looking at the total impact across rival chains.

(b) The competing retailers with a similar store format are negatively affected by the promotion events organized by the manufacturer at a rival store. For example, the market leader, characterized by high prices and high service, is stealing more customers away from a competing chain also characterized by a high price and service level.

(c) Signs of potential cannibalization were evident when looking at the drivers of sales promotions during a stable business environment, as well as during a price war. In both settings, the timing since a promotion implemented at a competing store, and the presence of simultaneous promotions have a significant impact on the effectiveness of the focal event.

(i) During a business-as-usual scenario and during a direct price war, it is important for the manufacturer not to promote the brand simultaneously across rival stores, or shortly after the temporary discount implemented at a competing retailer.

(ii) During an indirect price war, instead, promotions are more effective if they are implemented more frequently, shortly after the promotion at a competing chain.

5.3. Limitations and directions for future research

The following paragraphs outline possible research opportunities still under-investigated in the domain of sales promotions. We first acknowledge some of the limitations of this thesis, and then we provide recommendations on how to extend the analysis of price promotion effectiveness (1) from price wars to recessions, (2) to
environments characterized by sophisticated private labels portfolios, and (3) to discounters.

**General limitations.** In terms of the limitations, we use data from only one multinational manufacturer, in one country. Moreover, the set of categories (e.g. bread replacements, biscuits and snack) analyzed represents only a subset of the categories found in supermarkets. The nature of the category may influence the willingness of consumers to travel to another store. The cross-chain effects may be even stronger for categories characterized by higher prices (e.g. diapers) or for traffic builders (e.g. colas). Future research is therefore needed to validate our results with datasets from different manufacturers, in different product categories and countries. Second, we use only volume sales information. Promotional effectiveness may change once we incorporate the costs related to the implementation of sales promotions (the costs of features and displays, etc.), or when explicitly accounting for the level of trade deals. Our work could therefore be extended to analyze the profit implications of sales promotions. Third, when looking at the impact of price wars, one could extend our work to incorporate alternative scenarios: (1) when a brand is facing a direct price war but the competing brands are not reduced in price, or (2) when a brand is facing an indirect price war together with all its competing brands (which we called a category indirect price war). These additional scenarios may alter the effectiveness of sales promotions in different ways from the ones discussed above.

**From price wars to recessions.** Future studies could test whether the results presented in this dissertation hold in a recession scenario, given the high price sensitivity and competition characterizing both price wars and economic contractions. One important factor may however lead to other results: differently from a price war setting, in a recession, money is short for all the actors, i.e. manufacturers, retailers and consumers. In fact, during price wars, consumers’ discretionary income increases. During economic contractions, in contrast, it decreases, and consumers slow down their purchases and save where possible. This causes an increase in price sensitivity (Estelami et al. 2001), to which retailers as well as manufacturers react by proposing more price promotions to stimulate the demand (Lamey et al. 2008). As consumers reduce their purchases, it becomes more important for retailers and manufacturers to ensure that those sales still involve their stores/products. For example, Ma et al. (2010) show that households with lower incomes shop around more for deals during a recession. Thus, the competition among retailers and among manufacturers becomes fiercer. Managers modify their marketing strategy in response to recessions, although most companies indicate that they do not use any systematic procedure to determine the impact of such economic contraction on their
specific business (Shama 1993). In other words, managers feel the need to adapt their strategies to the new economic environment, but they do not know how exactly to assess the impact of recession on their marketing activities (Deleersnyder et al. 2009). Given the very elastic demand characterizing recessions, managers may have to rethink their pricing and promotional strategies. For example, should manufacturers and retailers decrease the regular price of their products, and/or implement more frequent and steeper sales promotion activities? How should they adapt their promotional activities? Should national brand manufacturer offer better trade deals to stimulate sales? Retailers may in fact push more private labels, as they offer lower prices for the consumers and higher margins for them (Ailawadi and Harlam 2004). Or, as both parties involved (manufacturers and retailers) have a strong interest in finding the right way to attract customers, are trade deals less needed? To answer these questions, future research should quantify the effects of recessions on sales and promotional effectiveness.

**Private labels.** Especially if a price war is initiated by retailers, future research should look at the role played by private labels. As retailers have higher margins on store brands, they can more easily cut temporary and permanent prices of private labels to signal lower in-store prices, and to fight hard discounters (Ailawadi et al. 2008, Geyskens et al. 2010). Indeed, during the Dutch price war, many price cut waves involved only private labels (see Table 3.2). Given the improved quality of the store brands and the strong presence of “premium” private labels in almost every product category, the (regular and promotional) sales of national brand manufacturers may be strongly influenced by the price of private labels.

Manufacturers may want to know which private label tier is mining their market share and how to react to it. Geyskens et al. (2010) find that private labels are not always negatively influencing national brands’ sales, as the responses are asymmetric. The introduction of premium (economy) store brands may sometimes even benefit premium-quality (mainstream-quality) national brands. However, Geyskens et al. (2010) suggest that their findings may not hold if manufacturers react to private labels by decreasing their prices or increasing their promotional activities, as this will modify the quality perception of their products, changing the performance implications of their brands. Given that during price wars many manufacturers cut their prices or discount their products more often, what will then be the consequences for national brands? How should retailers manage the promotion implementation tools (e.g. promotional calendar, depth of the discount) across their portfolio of private labels and national brands?
Hard discounters. Discount stores make strong gains in Europe (e.g. Aldi and Lidl), as well as in the USA (e.g. Save-A-Lot). In comparison to traditional retailers, their assortment is very limited (e.g. from a minimum of 800 SKUs at Aldi to more than 20,000 in a typical outlet), as well as their selection of products (mainly focused on private labels). The increased acceptance and popularity of private labels (Geyskens et al. 2010) facilitates even further the growth of hard discounters. Between 2004 and 2009, their sales (in value) increased by 45% in the States, and by 40% in Europe (Planet Retail 2010). As this channel expands, it becomes even more appealing for national brands to reach those consumers that shop at discounters (Steenkamp and Kumar 2009). Moreover, the low number of national brands carried by the discounters increases the pressure for manufacturers to take action before their competitors, preventing them from occupying the limited space available on the discounters’ shelves. At the same time, the high competition across retailers pushes the discounters to ask national brands to sell their products in their stores, in order to increase their assortment variety and quality perception.

Even though this is a growing phenomenon, to the best of our knowledge, only the studies of Clareen et al. (2010), Deleersnyder et al. (2007) and Steenkamp and Kumar (2009) have so far focused on the (hard) discount phenomenon. However, there are several important issues that are still uncovered by the extant literature. For example, manufacturers are increasingly concerned that the sales realized through discounters may not come from new shoppers, but may be the result of cross-chain cannibalization. Similarly, also hard discounters are questioning the true benefits of national brands. In particular, they wonder whether they do significantly increase store traffic. As a consequence, some discounters have already started delisting them (IRI France 2009). If national brands do not attract new customers to discount stores, they may simply dilute existing consumers’ purchases across a higher number of SKUs. Given the higher price of national brands, this may significantly affect the sales of their private labels and/or of products in other categories. Nevertheless, Deleersnyder et al. (2007) find that it is better for discounters to keep a large price difference between the national brands and the discounters’ private labels (as both brands are targeted at different consumer segments or purchase occasions). Should then discounters offer more price promotions on national brands to stimulate traffic? Or would that be just a waste of money, as consumers may be drawn to national brands anyway? Moreover, while from the perspective of the retailer, promoting national brands at discounters may decrease sales of private labels inside the store, from the perspective of the manufacturer, it may as well induce higher levels of cross-chain cannibalization.
Conclusions

Furthermore, the presence of some national brands at hard discounters may lead all retailers and manufacturers to change their pricing and promotional strategies in order to keep the status quo. Traditional retailers may, for example, decide to lower the prices of the national brands, or offer more frequent/steeper promotions to prevent consumers from switching to discounters. Similar changes may be implemented by the manufacturers of brands not available at discounters, in order not to lose market share. Such changes may affect promotional effectiveness of every brand at rival retailers, and/or become an impetus for yet another price war among retailers.
SAMENVATTING: (SUMMARY IN DUTCH)

Jaarlijks besteden fabrikanten en detaillisten een substantiel deel van hun marketing budget aan sales promotions. Het is daarom niet verwonderlijk dat veel academici zich hebben geconcentreerd op dit onderwerp. Het uitvoeren van promties voor nationale merken gezamenlijk met detaillisten is een complexe taak in de hedendaagse competitieve markt. Een brand manager neemt beslissingen over welke vorm van promties uit te voeren en op welk moment. Daarbij moet hij rekening houden met de gevolgen van de promties niet alleen in een stabiele marktomingving, maar ook tijdens een prijsoorlog, zowel bij de focale retailers als bij de concurrerende detaillisten. Eerdere studies zijn vooral gericht op het eerste aspect en geven brand managers inzicht welk merk beter verkoop tijdens promties en bij welke retailer. Echter, voor een specifiek merk kunnen managers nog steeds niet vaststellen hoeveel en welke promties daadwerkelijk in staat zijn om de verkoop te laten toenemen. Wij vertrekken van de bestaande literatuur en breiden deze in drie richtingen uit door het identificeren van welke promties een beter resultaat geven tijdens (1) stabiele marktomstandigheden, tijdens (2) een prijsoorlog, en (3) niet alleen bij de focale retailer, maar ook bij concurrerende retailers.

In ons onderzoek introduceren we een nieuwe methode op basis van de intervention analysis van Leone (1987). Deze methode stelt ons in staat om op flexibele wijze het effect van individuele promties vast te stellen en zodoende beter te begrijpen hoeveel promties daadwerkelijk effectief zijn. In ons onderzoek vinden we dat ongeveer 80% van de promties in staat zijn om de verkopen van het merk aanzienlijk te doen toenemen bij de focale retailer. In vergelijking met een "gemiddelde-effect"-model, zoals het SCAN*PRO-model, krijgen we een meer gedetailleerd overzicht van wat echt werkt en wat niet. In een "gemiddelde-effect" model, zoals bij het SCAN*PRO-model, berekent de onderzoeker een gemiddelde coëfficiënt over verschillende promties waardoor het aantal effectieve promties niet geïdentificeerd kan worden. Onze meer verfijnde benadering biedt gedetailleerde inzichten in wat werkt en wat niet. Bijvoorbeeld:

(1) Een niet-significante parameter in het SCAN*PRO-model geeft aan dat de promotionele activiteiten van dat merk niet in staat zijn om hogere verkopen te genereren. Met onze aanpak echter kunnen we vaststellen dat bijna 40% van deze promties wél effectief zijn en resulteren in gemiste kansen als fabrikanten besluiten ze stop te zetten.
(2) In plaats daarvan zijn 13% van de merkpromoties waarvoor het SCAN*PRO model aangeeft dat het effectieve promoties zijn, weggegooid geld aangezien deze promoties niet in staat zijn om de verkoop significant te doen laten toenemen.

(3) Slechts voor 17% van de merken zijn alle promoties daadwerkelijk in staat om de verkoop te stimuleren.

Om deze redenen moeten managers verder kijken dan het gemiddelde effect van hun promotionele activiteiten voor een specifiek merk. Als ze het rendement van hun marketinguitgaven willen maximaliseren is het van belang voor hen om te begrijpen welke promotie beter werkt en waarom. Enkel kijkend naar het gemiddelde resultaat van promoties kan leiden tot gemiste kansen of weggegooid geld. Zoals eerder vermeld, indien promoties gemiddeld niet in staat zijn om de verkoop te stimuleren, betekent dit niet dat ze allemaal weggegooid geld zijn.

Daarnaast vergelijken we de effectiviteit van de verkoopbevordering in een business-as-usual scenario met een prijsoorlogscenario. In dit proefschrift onderzoeken we de Nederlandse supermarktprijsoorlog welke in 2003 door de marktleider is ontketend. We dragen bij aan zowel de promotie- en prijsoorlogliteratuur door ons niet te richten op de gevolgen voor de initiatiefnemer van de prijsoorlog (detaillist) dan wel voor de andere direct betrokken partijen (andere detaillisten), maar we richten ons juist op de gevolgen voor een derde partij. In onze situatie is deze derde partij een merkartikelenfabrikant die gedwongen wordt om zijn producten af te zetten via een verkoopkanaal dat verwikkeld is een prijsoorlog. In het bijzonder laten we zien wat er gebeurt met de verkoop en promotie-effectiviteit van een A-merk wanneer de prijs van het product door de detaillist wordt verlaagd (directe prijsoorlog) dan wel niet wordt verlaagd (indirecte prijsoorlog). In ons onderzoek vinden we dat fabrikanten hun prijzen en promotionele strategie zouden moeten heroverwegen. Verlaging van de prijzen van hun merken helpt de verkopen en promotionele effectiviteit te verhogen. Omgekeerd, wanneer concurrerende merken hun prijzen verlagen terwijl het focale merk dit niet doet, zullen zowel de verkopen en promotionele effectiviteit afnemen. In beide scenario’s neemt de promotionele effectiviteit af over tijd.

Verder vinden we dat de prijsoorlog de effectiviteit van instrumenten voor verkooppromoties verandert. Wanneer de prijs van het focale merk niet wordt verlaagd, zou de brand manager frequenter verkooppromoties moeten uitvoeren met hogere kortingen en ondersteunen met verkoopfolders. In feite, gezien het ongunstige relatieve
Samenvatting (Summary in Dutch)

Prijsbeeld (wanneer concurrenten hun prijzen verlagen), zullen zijn promoties minder effectief zijn en heeft het merk meer ondersteuning nodig om hetzelfde verkoopniveau gedurende de promotie te behouden. Als in plaats daarvan de prijs van het merk direct wordt verlaagd, zal de effectiviteit van in-store displays afnemen terwijl folders belangrijker worden om verkoop te stimuleren. In een prijsoorlog hebben consumenten de neiging om hun verkoopbeslissing te baseren op prijzen en folders vergemakkelijkt hun keuze daarin. Hoewel men om deze reden een toename in het belang van display communicatie zou verwachten, verlaagt het overmatig gebruik van displays bij tijdelijke en permanente prijsverlagingen hun doeltreffendheid.

Tot slot richten we ons niet alleen op de effecten van verkooppromoties binnen de focal retailer, maar ook op die bij concurrerende detailwinkels, een onderzoeksgebied dat grotendeels is genegeerd in de literatuur. Hoewel de cherry-picking literatuur concludeert dat in een bepaald marktsegment consumenten alleen in prijs verlaagde producten kopen en dusdanig hun winkelkeuze maken, is er beperkt onderzoek verricht naar de gevolgen van prijspromoties op concurrerende winkelketens. Vanuit het perspectief van de fabrikant is een promotie succesvol wanneer deze in staat is om verkoop op te tellen zonder de verkoop in concurrerende winkels te kannibaliseren. Daarom moet een fabrikant die via meerdere concurrerende winkelketens verkoopt gedegen aandacht besteden aan de gevolgen van zijn promoties niet alleen binnen de focal chain, maar ook de gevolgen voor concurrerende ketens. Doet hij dat niet, dan loopt hij de kans om de effectiviteit van de verkoopbevordering te overschatten en te negeren dat een deel van de incrementele verkooptoename ten koste gaat van verkoop bij andere ketens. Hoewel deze kannibaliseringseffecten onopgemerkt blijven binnen een individuele keten, worden ze significant wanneer gekeken wordt naar het totale effect over alle concurrerende ketens. Om mogelijke kannibaliserings te voorkomen dienen fabrikanten een duidelijk inzicht te hebben in de positionering van de verschillende winkelketens. Inderdaad, we vinden dat de cross-chain effecten afhankelijk zijn van de winkelformule. Een winkelketen gekenmerkt door hoge prijzen en een hoog niveau van dienstverlening haalt minder klanten weg van concurrerende ketens met lage prijzen en laag niveau van dienstverlening.

Tekenen van mogelijke kannibaliserings zijn reeds duidelijk wanneer we kijken naar de determinanten van sales promoties in stabiele marktcondities, evenals tijdens een prijzenoorlog. In beide situaties wordt de effectiviteit van een promotie verlaagd wanneer deze gelijktijdig of kort op elkaar volgend plaatsvindt in concurrerende winkelketens. Echter, indien de prijs van het merk niet is verlaagd tijdens een prijsoorlog, zijn promoties
effectiever als ze vaker en kort na de promotie in een concurrerende keten worden uitgevoerd.

Ten slotte biedt dit proefschrift een nieuwe manier om promotionele effectiviteit te meten. Middels dit proefschrift hopen we meer inzicht te hebben gekregen in welke promotie effectiever is en waarom dankzij het individuele promotiemodel dat wij hebben toegepast We bestudeerden de sales promoties niet alleen tijdens stabiele marktcondities, maar ook tijdens een grote verstoring in de markt, die van een prijzenoorlog. We toonden aan dat promoties op verschillende manieren moeten worden uitgevoerd in deze twee scenario's. Bovendien hebben we gewezen op de noodzaak om rekening te houden met factoren welke tot nu toe genegeerd zijn door de bestaande literatuur, zoals cross-chain effecten.
### APPENDIX

Appendix 1. Moderator analysis – Chapter 2 – full set of results (see Table 2.5)

<table>
<thead>
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<th>Dependent variable: $TE^*$</th>
<th>Parameter estimate</th>
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<th>Two-sided p-value</th>
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</table>

**PLANNING**

| $\beta_1$ Log TIMING       | .440               | 1.800   | .073              |
| $\beta_2$ Log TIMING_COMP  | .510               | 2.480   | .014              |
| $\beta_3$ SIMULTANEOUS     | -1.264             | -2.590  | .010              |
| $\beta_4$ Log DEPTH       | .932               | 1.850   | .065              |
| $\beta_5$ Log DURATION     | -1.770             | -3.000  | .003              |

**FRAMING (vs. pure price cut)**

| $\beta_6$ QUANTITY         | -.056              | -.080   | .935              |
| $\beta_7$ LOYALTY          | -1.653             | -1.010  | .312              |
| $\beta_8$ OTHER            | 4.261              | 1.870   | .062              |

**COMMUNICATION (vs. in-store shelf tag)**

| $\beta_9$ FEATURE         | 1.496              | 2.950   | .003              |
| $\beta_{10}$ DISPLAY      | 2.365              | 2.210   | .027              |
| $\beta_{11}$ Log ADSTOCK  | -.001              | -.030   | .978              |

**CONTROL VARIABLE**

| $\beta_{12}$ Log MKTSHARE  | -.900              | -2.280  | .023              |
| $\beta_{13}$ Log CONCENTRATION | 5.032           | 2.420   | .016              |
| $\beta_{14}$ Log INVENTORY | -1.392             | -1.480  | .140              |
Appendix 2. Moderator analysis – Chapter 3 – full set of results (see Table 3.11)

<table>
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<tr>
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Vries-van Ketel E. de, How Assortment Variety Affects Assortment Attractiveness:


NOT ALL PROMOTIONS ARE MADE EQUAL
FROM THE EFFECTS OF A PRICE WAR TO CROSS-CHAIN CANNIBALIZATION

Despite the huge amount of money allocated every year to sales promotions, brand managers still do not know how often and in what circumstances promotions are truly effective. This dissertation proposes an approach that allows managers to assess the impact of individual promotion events rather than the average effect of total promotional efforts. As such, more detailed information is gained on how promotions should be implemented.

Moreover, sales promotions are not only evaluated in a business-as-usual environment, but their role and effectiveness during retailer induced price wars is also critically examined. As retailer competition tends to degenerate more often into price wars, this research offers recommendations to brand managers on whether they should accommodate retailers’ wishes to lower regular, list prices rather than focusing on temporary promotions.

Finally, a brand manufacturer, when planning his promotional events for a retailer, should consider that a promotion can steal sales from rival supermarket chains. While these cross-chain effects are often negligible for the retailer, they are quite substantial for the manufacturer. Thus, to increase promotional effectiveness, a brand manager should carefully plan the promotional calendar across rival retailers.

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