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"One-deal-fits-all?"

On category sales promotion effectiveness in smaller versus larger supermarkets.

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ABSTRACT

Even within a store chain and format, supermarket outlets often exhibit substantial differences in selling surface. For chain managers, this raises the issue of correctly anticipating the promotion lift, and of profitably managing promotion activities, across these outlets. In this paper, we conceptualize why and how store size influences the category sales effectiveness of four promotional indicators (depth of the promotional discount, display support, feature support, and whether the promotion is quantity-based). We then estimate the net moderating effect on four product categories for 103 store outlets belonging to four chains. For each of the promotion instruments, we find the *percentage* sales increases to be lower in large stores. For instance, whereas a 10 % point increase in feature activity enhances category sales by about 1.64 % in a 700m2 store, this figure drops to only 1.03 % in a 1300m2 store - a 59% reduction. This moderating effect is especially pronounced for discount depth, the relative sales lift from a typical price cut being about 78 % lower in the larger-sized (1300m2) outlet. However, since large outlets also have larger base sales, the picture changes when we consider *absolute* sales effects. The net outcome is that deeper discounts or quantity-based promotions do not systematically generate larger or smaller absolute sales bumps in large stores, whereas for in-store displays and features, we obtain a clear positive (be it less than proportional) link between store size and absolute category sales lift. When it comes to margin implications, we show that large stores gain higher profit from price cuts than small outlets only as long as the retailer *keeps* part of the manufacturer discount to himself. Managers can use these insights to improve their promotional forecasts across outlets, as well as to tailor their mix of instruments to store selling surface.

Recent changes in the retail food business have led to intensified retail competition (Morganosky and Cude 2000), and have motivated grocery retailers to continuously increase the number of store outlets within their (umbrella) chain (see e.g. Dawson 2006). Even within a given store format, these outlets often exhibit substantial differences in selling surface. For instance, within the Albert Heijn supermarket format, store sizes easily range from a low 200 to a high 2800 square meters - comparable within-format size differences being observed for other chains. Effectively managing these differently sized-outlets, and specifically, the pricing and promotional program for these outlets, has become a paramount concern for retail format managers (Bolton et al 2009). Given the vast budgets spent on sales promotion activities, the cost of maintaining these activities, and the lack of profitability of prevailing sales promotion efforts for retailers (Ailawadi et al 2009; Kim et al 1999; Srinivasan et al 2004), effective promotion management continues to be a key point of attention among academics and practitioners. Managing promotions *across stores that widely differ in size* adds to the complexity of this task, and raises several additional issues.

First, headquarters need to accurately *forecast the sales lift* from promotional activities in the different stores, in order to anticipate the product quantities that need to be shipped to these different outlets. It is well-known that logistical efficiencies associated with trade dealing are crucial for retailer profitability (Hoch et al 1994). Overestimating promotional demand in a store will lead to high storage costs or to perished items, whereas promotional stock-outs may be costly in terms of lost sales (Mantrala et al 2009) or decreased customer goodwill (Fitzsimons 2000; Olsen and Parker 2008). In a recent interview, the chief promotion manager of a major Dutch retail chain estimated the margin losses from inaccurate store-level predictions at three million Euros annually - a sizable amount. Yet, while common sense seems to dictate that the *sales lift* from a promotion *increases with store size*, little is known about the magnitude of the store size effect. For instance: will the relative sales increase due to the promotion, be the same in an outlet that is twice as large? Moreover, based on the scarce available evidence, even the *direction* of the effect remains equivocal (Ailawadi et al 2006; Boatwright et al 2004; Montgomery 1997), leaving retailers with little guidance on what to expect.

Second, if promotion effectiveness varies with store size, retailers may need to *adjust their promotional programs* accordingly. Following Bolton et al (2009), successful retailers are developing customized pricing practices, that are neither chain- nor store-wide, and in which promotion intensity depends on store size and clientele. There is evidence that some retail chains, indeed, tailor their dealing activities to outlet selling surface. In an empirical analysis of retailer pricing decisions, Shankar and Bolton (2004) observe that retailers price promote more intensively in their larger stores. Ellickson and Misra (2009), in contrast, report that large stores within a chain more strongly engage in EDLP (rather than Hi-Lo) pricing. This begs the question: which of these approaches is more advisable, and why is that so? To further complicate matters, the impact of store size on promotion effectiveness may well vary with the type of promotion. For instance, even if the percentage sales lift from a display would be the same in a $1000m^2$ as in a $500m^2$ store, this might not hold for a price cut. Unfortunately, the literature to date offers little insight into such instrument differences or their underlying drivers (Ailawadi et al 2006) – thereby hampering proper adjustment of promotion programs to the stores' selling surface.

In this paper, we shed more light on the relationship between promotion effectiveness and store size, and – hence – on the potential payoffs from tailoring promotional programs to store size. Given the extensive accumulated knowledge on the drivers of promotion response, what could we gain from such an analysis? We see four reasons why analyzing the impact of store size on promotion effectiveness is fruitful. First, as we argue below, the sheer selling surface of the store, through its effect on fixed in-store shopping costs and search costs, exerts an impact on the promotion's category sales lift not captured by other drivers. Second, apart from its effect on promotional sales lift, store size shapes the profitability of alternative promotion instruments. As we will empirically document below, large stores – because of their larger (base) sales - are less suited for promotion activities with a large per-unit cost component. Third, store size may serve as a valuable proxy for (a multitude of) other factors that are difficult or costly to measure and integrate. Even after local *inhabitant* characteristics are controlled for, differently-sized stores will attract different types of *customers*, for different types of shopping *trips* (Fox and Sethuraman 2006). While trip-specific shopping goals and customer profiles (including their distance to the store) have been documented to influence promotion response (Gauri et al 2009; Lee and Ariely 2006; Seetharaman et al 1999), such data may be unavailable to retailers (for instance shoppers' time constraints or shopping goal abstractness, Lee and Ariely 2006) or difficult to integrate with their promotion databases[3]. Store size, in contrast, is immediately accessible, and may then proxy for these trip- or customer- related drivers. Finally, tailoring the promotional program to store size is appealing from an implementation viewpoint. Recognizing the vast size discrepancies, retailers have often adjusted their logistic operations to accommodate supermarket outlets of different selling surface. An example is Albert Heijn’s store replenishment system called Cels, which distinguishes five different logistical procedures tailored to different supermarket size classes (Beerens 2002; Verhoef et al 2009). Promotion programs that exploit differences in promotion response among these size classes would, then, be easily integrated into the logistical systems already in place.

In sum, while reflecting on the ‘unique’ store size effects (first and second point above) may add to our academic knowledge on promotion effectiveness and shopper response, we believe that an important contribution of our study lies in its managerial usefulness. By documenting the role of store size (either in itself or as a proxy for other drivers), we also hope to offer a practical perspective on how retailers can better anticipate the promotional sales lift across differently-sized outlets, or differentiate their promotion programs across these outlets. Hence, our research fruitfully combines a shopper marketing perspective, with the need for improved resource allocation tools - two points on the Marketing Science Institute's 2010-2012 research priority list.

Our analysis proceeds as follows. First, we aim to uncover why the sales lift from promotions may vary with store size, and how this effect differs across promotional instruments. To this end, we develop a conceptual framework that clarifies the store size effect on four promotion variables: discount depth, display, feature, and promotion format (i.e. whether the promotion involves a quantity discount or a straight price cut). From the retailer’s perspective, especially the promotion impact on category sales is important (Ailawadi et al 2009; Nijs et al 2001; Raju 1992). Hence, we will use the category as our focal level of analysis. Second, we set out to empirically quantify the promotion effect across supermarket stores of ‘umbrella branded’ grocery retail chains. These outlets share the same ‘retail chain image’ and format positioning, but widely differ in selling surface – thereby offering the opportunity to separate store size

[3] Contacts with several major retailers reveal that, even though they collect background data from their loyalty card holders, these data are often not integrated with their ‘transactional’ databases (containing information by receipt), nor with their product-based sales and promotion databases (containing information by SKU). Also, receipt data alone do not provide a good indication of consumers' shopping goals (Bell, Corsten and Knox, 2010) and hence their implied promotion response.

effects from chain or other format characteristics. To further enhance the validity of our findings, we conduct the analysis in four different product categories and four chains, and control for a broad set of store trading area characteristics. Moreover, as recently advocated by Grewal et al (2009), we explore the store size implications for complementary promotional store metrics: immediate and net incremental category sales, and incremental category margin. Figure 1 provides an overview of our focal constructs and their interrelationships.

< Insert Figure 1 about here>

The outcomes of this research are relevant to both academics and practitioners. To academics, we offer an improved understanding of what drives the moderating impact of store size on the effectiveness of various promotion instruments. We also empirically document the direction and size of the moderating effect, and show that it differs with the type of promotional activity, and with the promotional metric. For display and feature actions, we find that promotional sales lift is higher in large stores, but that this increase is less than proportional. Interestingly, for straight price deals and for quantity-based offers, our results indicate that the absolute sales lift is not significantly higher in large selling areas. Store baseline sales, however, go up almost proportionally with store size and thus become a dominant driver of the profitability of price cuts in large outlets. Such price deals reveal *less* appealing in *large* than in small stores if the retailer *bears* part of the discount himself, yet far *more* appealing if he *keeps* part of the manufacturer discount to himself. From a *managerial* perspective, retailers can use these insights to improve their promotional forecasts across outlets, as well as to tailor their mix of instruments to the stores' selling surface.

The discussion is organized as follows. In the next section, we provide a brief overview of the literature, and present our conceptual framework. Section 3 describes the data and model used for empirical testing, and reports the estimation results. Section 4 discusses the ensuing effects for absolute category sales and category profit. Section 5, finally, summarizes the findings and discusses managerial implications, limitations and areas for further research.

Available literature

While it is well documented that promotion effectiveness varies with chain and shopping pattern characteristics (Gijsbrechts et al 2003; Mittal 1994; Montgomery 1997; Shankar and Krishnamurthi 1996), only few studies have focused on the relation between promotion effectiveness and store size within a chain – that is, controlling for chain and format characteristics. Table 1 lists key papers on this topic. Together, the studies provide somewhat mixed evidence on the moderating impact of store size. Whereas Boatwright et al (2004) do not find any influence; Montgomery (1997), Hoch et al (1995) and Gijsbrechts et al (2003) report significant negative effects of store size. Ailawadi et al (2006) postulate a positive influence, yet observe a small negative impact of store square footage on promotion lift.

These diverging results may be attributed to differences in study characteristics. First, the analyses are often confined to a single chain (Ailawadi et al 2006: one drug chain, Hoch et al 1995: Dominick's, Gijsbrechts et al 2003: Belgian retailer), which hampers comparability. Second, some papers focus on price cuts (Hoch et al 1995; Montgomery 1997) while others exclusively look at feature ad effects (Gijsbrechts et al 2003). The impact of display and especially quantity-based promotions has rarely been linked to store size. Third, the studies differ in their measure of promotional impact (Boatwright et al 2004 and Montgomery 1997: brand sales, Gijsbrechts et al 2003: store traffic). Though *category* level outcomes are key for promotion effectiveness from the retailer's perspective (Ailawadi et al 2009; Nijs et al 2001), these seldom are the focal variable of interest - notable exceptions being the papers by Hoch et al (1995) and Ailawadi et al (2006). In addition, these studies use different outcome *metrics*: Hoch et al (1995) explore the drivers of promotion effectiveness (including store size) on category sales elasticities; Ailawadi et al (2006) focus on absolute incremental sales and margins. Finally, as store size is not a focal variable in these papers, they do not discuss or explore what underlies their divergent or unexpected effects. In summary, what seems to be missing is a unifying framework and empirical support for why and how store size shapes the influence of various promotion types, on distinct retailer performance metrics.

<Insert Table 1 about here>

Below, we offer a framework on how stores' selling surface affects the category sales and margin impact of discount depth, feature, display, and quantity-based offers. In so doing, we not only focus on the effect of store size *as such.* We also acknowledge an *indirect* effect of selling surface– through its appeal to different customer profiles for different types of shopping trips - thereby highlighting the link with other promotional drivers.

Conceptual Framework

To develop our understanding of why store size moderates the effectiveness of various promotion instruments, we build on earlier work by Lam et al (2001), Chandon et al (2000) and Urbany et al (2000). Lam et al (2001) break down store sales into four components, namely front traffic (number of people walking along the front of the store), store-entry ratio (fraction of those people coming into the store), closing ratio (fraction of in-store shoppers converted to buyers), and average spending. They then identify which promotion instruments affect store performance through attraction (increasing front traffic or the store-entry ratio), conversion (enhancing the closing ratio) or spending effects. As indicated below, this breakdown offers an excellent starting point for our purpose, i.e. to conceptualize the moderating impact of store size on various promotion instruments. Note that our focus is *not* on testing the separate promotion effects, and the moderating influence of store size on each of these effects, per se. Instead, our objective is to investigate which particular promotion mechanisms are affected by the store's selling surface, and how this ultimately leads to differences in category sales lift, across promotion instruments, between smaller and larger stores.

Given our interest in category-level effects, we adjust the framework of Lam et al (2001) by distinguishing between store traffic (consumers entering the store) and aisle traffic (consumers getting in front of the category shelf). Moreover, in view of our focus on grocery supermarkets, we consider households in the outlet's trading area, rather than people passing by the store, as the potential customer base. Like Lam et al (2001), we do not expect isolated promotion activities to alter a store's Trading Zone Potential. Rather, promotions will elicit different *responses* from these potential customers, through the subsequent category sales components. Hence, in our framework, promotional category sales come about as a result of four mechanisms, depicted as columns in Figure 2: (1) the promotion's ability to draw potential customers into the store ("Store traffic ratio"), (2) its propensity to attract store visitors to the category shelf ("Shelf traffic ratio"), (3) its conversion of shelf visitors into category buyers ("Category closing ratio"), and (4) its impact on the number of units bought, given that a category purchase occurs ("Average category purchase quantity"). Total category sales in a store are then simply obtained by multiplying the store's trading area potential with these four components.

<Insert Figure 2 about here>

Similar to Lam et al (2001), we can conjecture about the main effect of alternative promotion instruments on each of the category sales components. We consider four category promotion variables: (1) Feature, i.e. the out-of-store promotional ads for the category, (2) Display, i.e. in-store visual support in the form of shelf tags or end-of-aisle displays, (3) Discount Depth or the economic value of the temporary promotional gain to the consumer and (4) Quantity-based format, i.e. whether the promotion takes the form of a 'per-unit' promotion (straight price cut) or a quantity-based discount. Note that this latter variable only looks at the promotion *format* and not the size of the benefit, which is captured in discount depth. Differently stated, the quantity-based format variable could capture the difference in effect between a Buy-One-Get-One-Free (BOGO) promotion and a 50% straight price cut, both of which offer the same percentage reduction to the consumer.

The anticipated effects of these variables are indicated in Figure 2, Panel a, where '+' indicates that the promotion variable is expected to increase the category sales component, '-' points to an expected decrease, and '' indicates that we do not anticipate any effect. Specifically, out-of-store *feature advertisements* are expected to draw a larger fraction of potential customers to the store ('+' effect on Store Traffic Ratio) and, to the extent that consumers plan these promoted purchases, convert them into buyers ('+' Category Closing Ratio) (Chandon et al 2000; Lam et al 2001). *In-store displays* can only influence consumers once inside the store (no impact on Store Traffic Ratio), but may well draw their attention to the category shelf ('+' impact on Shelf Traffic Ratio) or remind them of buying ('+' Category Closing Ratio) (Boatwright et al 2004; Chandon et al 2000; Kahn and McAlister 1997). *Deeper discounts* may increase the fraction of potential customers visiting the store ('+' for Store Traffic Ratio) (Lam et al 2001): even if they are not supported by a feature ad, consumers may become aware of those deals through other sources (e.g. word-of-mouth) (Urbany et al 2000). Their dominant impact, however, is to convert shelf visitors into category buyers (‘+’ Category Closing Ratio) and to enhance the average quantity per category purchase (‘+’ Average Category Purchase effect) (Chandon et al 2000; Lam et al 2001). Finally, we expect the effect of a deal to be different for quantity discounts (e.g. ‘Buy-One-Get-One-Free’) than for per unit-promotions (e.g. a straight 50% price cut), even if they offer similar economic value (Chandon et al 2000). On the one hand, because it imposes a quantity restriction, the quantity-based format is considered more of a hurdle (Foubert and Gijsbrechts, 2007), and signals a less appealing deal. Hence, for a given discount depth, it may convince a smaller fraction of shelf visitors to engage in a category purchase (‘-‘Category Closing Ratio) (Wansink et al 1998). At the same time, the quantity restriction is likely to enhance the average purchase quantity of category buyers (‘+’ Average Category Purchase Quantity effect) (Uncles 1996; Wansink et al 1998).

This breakdown of promotion effects along the category sales components becomes especially relevant when considering the moderating effect of store size. Clearly, store size has a positive 'main' effect on the store's Trading Zone Potential. Even within a given chain and format, larger stores typically offer consumers higher fixed shopping benefits, such as more parking spaces, additional services and – through their depth and breadth of assortment - increased variety and opportunity of one stop shopping (Bell et al 1998; Kahn and McAlister 1997; Messinger and Narasimhan 1997). This increases their potential customer base: larger stores serving more customers from larger geographic areas (see, e.g., Campo et al 2000). However, store size also affects the other four, promotion-related, category sales components (columns in Figure 2). The reason is that each of these components is linked to specific costs and benefits of shopping for the consumer, which is related to the size of the store outlet for reasons we outline below. This is explained in panel b of Figure 2, which spells out the type of shopping cost or benefit driving each component, as well as its relationship with store size.

First, large stores tend to enhance the fixed cost of shopping, that is, the cost inherent to each store trip. Consumers may have to travel longer distances to the store, and spend more time traveling the aisles or waiting at the checkout (see e.g., Bell et al 1998; Fox and Sethuraman 2006). This makes households visit these stores less frequently (but for larger, stock-up trips), thereby lowering the fraction of potential customers patronizing the store at a given point in time.

For these same reasons, large stores are less likely to lure customers into the store for an extra 'cherry picking' visit. Hence, we expect a negative effect of store size on the 'Store Traffic Ratio', and on the promotions' ability to enhance that ratio.

Second, large stores typically involve higher in-store search costs. Their broad category offer, displayed in numerous and spatially distant aisles, as well as their deeper category assortments, may make specific category discounts and in-store displays less accessible to the consumer (Boatwright et al 2004; Iyer 1989; Kahn and Schmittlein 1992; Kahn and McAlister 1997; Mantrala et al 2009). Also, once inside the store, consumers may find it harder to quickly find feature-advertised items, having to more extensively scan shelves to locate categories and brands (Broniarczyk and Hoyer 2006; van der Lans 2006). We therefore expect a negative impact of store size on the Shelf Traffic Ratio, and on the fraction of store visitors actually confronted with the promotion on the category shelf.

Third, whether consumers facing the promotion will actually respond to it and engage in a category purchase, depends on the promotion's perceived variable shopping utility. Building on the work of Chandon et al (2000), we distinguish between the perceived 'Monetary Savings' from the promotion (labeled: *economic* benefit in Figure 2) and its 'Convenience' value, i.e. the fact that it provides consumers with an easy decision heuristic and signals a good deal (labelled: *signal* value in Figure 2). Large stores predominantly attract large-basket shoppers, who are generally profiled as time-poor rather than money-poor (Bell and Lattin 1998; Bucklin and Lattin 1991; Kahn and McAlister 1997), and consumers with more abstract shopping goals (e.g. on weekly stock-up trips, rather than fill-in trips for daily essentials, or trips for immediate consumption; Bell, Corsten and Knox 2010; Popkowski-Leszczyc and Timmermans 1997). As these shoppers are more likely to use in-store cues as purchase reminders (Inman and Winer 1998; Iyer 1989), we expect the signal value of promotions to be higher in large stores. This leads to a positive moderating effect for signal value in Figure 2. Conversely, these large basket shoppers may not process the actual magnitude of the monetary savings (Chu et al 2008; Hansen and Singh 2009; Mantrala et al 2009), or may perceive these savings as less important, given that the promotional offer represents only a minor gain relative to the overall shopping basket size. This implies a negative moderation for economic benefit in Figure 2.

Last but not least, store size may influence the quantity bought by the consumer, given that he engages in a category purchase. This category purchase amount will be higher if consumers face low transaction cost, i.e. have less difficulty in handling these larger quantities. On the one hand, we expect purchasing large (extra) quantities to be more congruent with the 'stock up' shopping goal typical of major trips, both in terms of mindset and physical setting (i.e. consumers shop by car and use a shopping cart) (Uncles 1996). On the other hand, shoppers who already buy large amounts and who have to handle many categories may be more *reluctant* to further increase their basket size – be it only as a result of the physical constraint imposed by the shopping cart. Hence, as indicated in Figure 2, we expect that the impact of store size on the promotional category purchase quantity can be either positive or negative.

Since the direction of the moderation effects differs among the category sales components, we cannot make unequivocal predictions on their net outcome[4]. Still, the framework in Figure 2 helps us to better understand *how* and *why* store size plays a role, through identifying the underlying theoretical mechanisms. Moreover, given that different promotion variables affect different category sales components (Figure 2, panel a) and that store size influences the benefits and costs underlying these components in different directions (Figure 2, panel b), the framework also clarifies why the moderating impact of store size may vary by instrument. For instance, all promotion instruments will benefit from the larger trading zone potential of large stores (which, as indicated above, we consider exogenous to temporary and specific category promotion activities). Yet, for feature ads, this positive effect is (1) reduced by the higher fixed shopping costs of large outlets (which make it harder to increase the Store Traffic Ratio), but (2) enhanced by the higher promotional signal value of their clientele (which drives up the Category Closing Ratio). In contrast, deeper discount promotions, (1) suffer from the large outlet's higher fixed shopping costs (lower Store Traffic Ratio) and (2) the lower perceived economic benefits by its clientele (lower Category Closing Ratio), and (3) may benefit (suffer) from their lower (higher) transaction costs (resulting in higher (lower) Average Category Purchase Quantities given a promotional purchase). The tradeoffs for Display and Quantity-based promotions can be derived in a similar way from Figure 2. In the empirical section, we quantify how these different effects net out for each promotion variable, and for different levels of store selling surface.

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[4] Also, we emphasize – again – that it is not our objective to separately measure the subsequent promotion effects, and our data would not allow us to disentangle them.

DATA AND METHODOLOGY

Data.

Two years of Dutch IRI data on weekly category sales volume and promotions (discount depth, feature, display and quantity-discount) in combination with store (trading area) specific data from Claritas, are used for model estimation. These data contain information on four product categories (softener, diapers, cereals and cola) and four chains. For each chain we have information on a 'representative' sample of outlets included in the IRI database. Table 2 provides some summary statistics by chain. While the average store size is in line with typical supermarket selling surfaces reported in the literature (Gonzales Benito 2005), the variation across outlets in each chain is substantial.

In addition, the data set comprises consumer trading area characteristics. These include competition intensity (*Comp*: number of competing supermarkets in the store's trading area), the local inhabitants' age and income profile (*Age*: percentage older than 65, *Income*: percentage of households with income above the national mode), and their shopping pattern variables (*BasketSize*: average size of local households' purchase basket and *Impulse*: percentage of impulse buyers). Details on the measures are given in Table 3. The operationalizations are similar to those adopted in previous studies (see, e.g., Boatwright et al 2004; Hoch et al 1995; Kim et al 1999; Montgomery 1997). As can be seen from Table 2, the averages of these variables do not differ much between chains, although within-chain differences can be noticed.

<Insert Tables 2 and 3 about here>

Table 2 reports the promotional characteristics by chain, averaged over the four categories. It indicates, next to the percentage of items on discount, the average discount depth of the promotion (*DiscDepth*, expressed as a fraction of regular price), the percentage of items on display (*Disp*) or feature (*Feat*), and the percentage of items on quantity - rather than straight price cut - discount (*QuanDisc*) (for details, see Table 3). Similar to previous studies on category-level promotion effectiveness (see, e.g., Raju 1992; Putsis and Dhar 2001, Nijs et al 2007), we use share-weighted measures of promotion activity. Table 2 shows that, overall, the promotional activities appear comparable across chains. At the category level, some differences exist. The diaper and cola category show high promotion activity, whereas the cereal category appears much less promotion-intense. The quantity-based promotion in this category is only used in one week, in two chains. As a result, this promotion tool will not be taken into further consideration for the cereal category. Each of the considered chains adopts a highly centralized approach: the promotion program is negotiated with manufacturers by the head office, and implemented chain-wide. It follows that, as promotion decisions in our chains are not tailored to local performance or store size, endogeneity will not be an issue when estimating the model.

Model.

To empirically address our research questions, we develop a model linking category sales volume in a store to that store's promotion activity and store size, adding price and several trading zone characteristics as control variables (see Figure 1). The model is given by:

[1]

$$lnSales_{t,s}^{p,c} = \beta_{0\,s}^{\,p,c} + \beta_{1s}^{\,p,c} lnPrice_{t,s}^{p,c} + \beta_{2\,s}^{\,p,c} DiscDepth_{t,s}^{p,c} + \beta_{3\,s}^{\,p,c} Feat_{t,s}^{p,c} + \beta_{4\,s}^{\,p,c} Disp_{t,s}^{p,c} +$$
$$\beta_{5\,s}^{\,p,c} QuanDisc_{t,s}^{p,c} + \beta_{6\,s}^{\,p,c} LagDiscDepth_{t,s}^{p,c} + \beta_{7\,s}^{\,p,c} LagFeat_{t,s}^{p,c} + \beta_{8\,s}^{\,p,c} LagDisp_{t,s}^{p,c} + \beta_{9\,s}^{\,p,c} LagQuanDisc_{t,s}^{p,c} + \varepsilon_{t,s}^{p,c}$$

[2a] $$\beta_{0s}^{\,p,c} = \delta_{00}^{\,p,c} + \delta_{01}^{\,p,c} \ln StoreSize_s^c + \delta_{02}^{\,p,c} lnAge_s^c + \delta_{03}^{\,p,c} lnIncome_s^c + \delta_{04}^{\,p,c} \ln Comp_s^c + \varpi_{0s}^{\,p,c}$$

[2b] $$\beta_{1s}^{\,p,c} = \delta_{10}^{\,p,c} + \delta_{11}^{\,p,c} \ln StoreSize_s^c + \varpi_{1s}^{\,p,c}$$

[2c] $$\beta_{2s}^{\,p,c} = \delta_{20}^{\,p,c} + \delta_{21}^{\,p,c} \ln StoreSize_s^c + \varpi_{2s}^{\,p,c}$$

[2d] $$\beta_{3s}^{\,p,c} = \delta_{30}^{\,p,c} + \delta_{31}^{\,p,c} \ln StoreSize_s^c + \varpi_{3s}^{\,p,c}$$

[2e] $$\beta_{4s}^{\,p,c} = \delta_{40}^{\,p,c} + \delta_{41}^{\,p,c} \ln StoreSize_s^c + \varpi_{4s}^{\,p,c}$$

[2f] $$\beta_{5s}^{\,p,c} = \delta_{50}^{\,p,c} + \delta_{51}^{\,p,c} \ln StoreSize_s^c + \varpi_{5s}^{\,p,c}$$

[2g] $$\beta_{6s}^{\,p,c} = \delta_{60}^{\,p,c} + \delta_{61}^{\,p,c} \ln StoreSize_s^c + \varpi_{6s}^{\,p,c}$$

[2h] $$\beta_{7s}^{\,p,c} = \delta_{70}^{\,p,c} + \delta_{71}^{\,p,c} \ln StoreSize_s^c + \varpi_{7s}^{\,p,c}$$

[2i] $$\beta_{8s}^{\,p,c} = \delta_{80}^{\,p,c} + \delta_{81}^{\,p,c} \ln StoreSize_s^c + \varpi_{8s}^{\,p,c}$$

[2j] $$\beta_{9s}^{\,p,c} = \delta_{90}^{\,p,c} + \delta_{91}^{\,p,c} \ln StoreSize_s^c + \varpi_{9s}^{\,p,c}$$

where superscripts refer to the product category (p) and chain (c), subscripts indicate the week (t) and store(s), β and δ are parameters, and ε and ϖ are normally distributed errors.

Equation [1] expresses weekly category sales of an individual store (*Sales*), as a function of the store's regular weekly price (*Price*) and the four promotional variables (*DiscDepth*, *Feat*, *Disp*, and Q*uanDisc*). To account for possible post-promotion dips, we also incorporate lagged promotion instruments (*LagDiscDepth*, *LagFeat*, *LagDisp*, *LagQuanDisc*). Note that *DiscDepth* comprises the economic value of the offer irrespective of the promotional format: it represents the percentage price reduction for straight price cuts and the 'equivalent' discount depth for quantity-based promotions (for instance: the 50% price cut equivalent for BOGOs). The *QuanDisc* variable thus captures the mere-format effect (quantity-based as opposed to cents off), after the *value* of the offer is partialled out. To facilitate interpretation, all variables are centered around the (category- and chain-specific) mean (see Bijmolt et al 2005 and Karande and Kumar 1995, for a similar approach).

Like previous studies (see, e.g. Raju 1992; Putsis and Dhar 2001; Nijs et al 2007), Equation [1] uses the *log* of category sales as the dependent variable. Weekly sales of grocery products are skewed and characterized by a few extremely high values resulting from deep price cuts, and taking logarithms at least approximately normalizes the distribution of the dependent variable (Boatwright et al 2004; Raju 1992). While we also use a log-transform for price, the promotion variables - which can take on zero values - enter the model linearly. An advantage of the semi-logarithmic link between category sales and promotion is that this model automatically takes interactions between the promotional tools into account (Bijmolt et al 2005; Karande and Kumar 1995), which is particularly important since most display and feature activities are used in support of price cuts. Comparison with a linear specification, furthermore, indicates that the semi-logarithmic model fits the data substantially better, as indicated below.

Equation [2] specifies the parameters in [1] as a function of outlet-specific variables. The sales intercept $\beta_{0s}^{p,c}$ for product category (p), chain (c) and store (s) is influenced by the store's size (*StoreSize*) and by a set of control variables capturing trading zone characteristics: competition intensity (*Comp*), the local inhabitants' age (*Age*) and their income profile (*Income*). For similar reasons as before, we log-transform these variables prior to inclusion in the model. In line with our conceptual framework and Figure 1, store size also influences the effectiveness of regular price and, more importantly for our study, the immediate and lagged impact of promotion activities. Random error terms ($\varpi_{0_s}^{p,c}$ to $\varpi_{9_s}^{p,c}$) are included for the intercept, base price effect, and promotional variables' effectiveness, to capture unobserved heterogeneity as in Degeratu et al (2001). As a sequential procedure is inefficient (Boatwright et al 2004), we use Hierarchical Linear Modeling (by using Proc Mixed in SAS) to simultaneously estimate Equations [1]-[2], across stores, categories and chains. At the same time, to ensure that the moderating effect of store size is not confounded with chain or category characteristics, we keep separate parameters (δ), and separate distributions for the random components (ε, ϖ), for each category and chain. To accommodate the relatively small number of stores within each category and chain (which ranges between 15 and 43), we use Restricted Maximum Likelihood (REML) and the Huber/White estimator (Maas and Hox 2004). The results are reported below.

ESTIMATION RESULTS

Model Fit.

To test whether the moderating effect of store size on the promotion parameters significantly contributes to model fit, we compare the results of the full model (FM hereafter) with those of (i) a model without any store-size promotion interactions and of (ii) a model where store size interacts with the immediate, but not with the lagged promotion effects. We use the Consistent Akaike Information Criterion (CAIC) (Ashok, Dillon and Yuan 2002) and Likelihood Ratio tests to compare these models. We find that adding store size-promotion interactions yields a substantially better model fit – both in terms of a lower CAIC and a significant likelihood ratio test ($p<.05$). Including lagged promotion effects (and their store-size interactions) provides an additional and significant fit improvement. In addition, we compare the results of our (semi-) logarithmic specification [1]-[2], with those of a linear model (in which neither the dependent variable nor the store size variable and the controls are log-transformed). The semi-logarithmic model provides a substantially better fit, its average MAPE (mean absolute percentage error) being 8.6% lower than that of the linear specification. Finally, the Variance Inflation Factor (VIF) scores of model FM are, in most cases, well below 3.0 and they never exceed 6.4 – indicating that we do not have collinearity problems. We therefore retain model FM as the final model.

<Insert Table 4 about here>

Parameter estimates.

Table 4 summarizes the main effect estimates of the full model. On average, the estimated coefficient of *lnStoreSize* is close to one, implying that category sales go up proportionally with the outlet's selling surface. The coefficients of regular price, discount depth, feature and display are mostly significant with the expected sign (since all variables are mean-centered by category and chain, these coefficients capture the promotions' impact in the average-sized supermarket for each chain). Except in two instances, the effect of Quantity-Discount is also positive and significant, suggesting that the lower propensity of quantity-based promotions to convert non-buyers into buyers (lower Category Closing Ratio) is generally outweighed by their positive effect on the purchase quantity of those who buy (higher Average Category Purchase Quantity). While category sales are lower in weeks following a discount, the other post-promotion effects are much less significant and in some instances positive, reflecting a delayed positive reaction or a 'persistence' of the offer after the 'official' promotion week (Nijs et al 2001; Nijs et al 2007). The trading zone variables (*lnAge, lnIncome, lnComp),* finally, exhibit a mixed pattern of effects and explain only a small portion of category sales variation across outlets – a finding also reported in other studies (Mittal 1994; Teunter 2002).

Our primary interest, however, is in the interaction coefficients between the promotion variables on the one hand, and the store's selling surface on the other. Given the form of the model and the fact that all variables are mean-centered, these coefficients can be interpreted as the *relative change in promotion effectiveness* (percentage increase in category sales resulting from a marginal increase in the category promotion activity) *when moving from an averaged-size outlet of the chain* (e.g. 1000 square meters), *to an outlet with a one percent larger selling area* (e.g. 1010 square meters). Zero interaction coefficients, therefore, would point to a promotional lift proportional to the (larger or smaller) outlet's base sales, whereas positive (negative) interactions would reflect more (less) than proportional promotion effects. To test the significance of the estimated interactions between store size and each promotion variable, across chains and categories, we use Stouffer's meta-analytic test (Rosenthal 1991)[5]. The outcomes for

[5] This test is also referred to as the method of 'adding *z*s'. This test statistic corresponds to the *p* value that the results of the chain/category combinations combined could have occurred under the null hypothesis that there is no

both the immediate and net promotion effect are shown in Table 5, with combined 2-tailed significance levels indicated in the fifth column in the table. The results point to a significant and negative moderation effect (for regular price as well as) for the promotion variables. For each of these instruments, the *promotional sales increase thus represents a smaller fraction of baseline sales, as the store becomes larger*. Based on the average value of the interaction coefficient, this effect is most pronounced for discount depth (-.42, p<.01), followed by the feature (-.17, p<.01), quantity-based format (-.15, p<.01) and display variable (-.03, p<.01). The *net* moderating effects (-.41, -.16, -.17 and -.02, respectively, see Table 5) remain very close to the *immediate* moderating influence of store size. This indicates that the difference in promotion impact between small and large stores remains after post-promotion dips are accounted for. These moderating effects are not only statistically significant, they are also quite sizable. For instance, for feature ads, the net interaction coefficient implies that whereas a 10 % point increase in feature activity enhances category sales by about 1.64 % in a 700m2 store, this figure drops to only 1.03 % in a 1300m2 store - a 58.65% reduction. The moderating effect is especially strong for discount depth: the relative sales lift from a typical (say, 25%) price cut on a typical (say, 10% category-share) brand being about 78.33 % lower in the larger-sized (1300m2) outlet compared to the small-sized (700m2) outlet.

<Insert Table 5 about here>

Robustness checks.

Alternative explanations. To ensure that our promotion-store size interactions stem from the store's selling surface and are not an artefact of the types of trading areas in which large stores are typically located, we estimate several additional models. These models also incorporate moderating promotion effects for various trading zones characteristics: local supermarket competition, age and income distribution of the local population, and general shopper characteristics of local inhabitants (specifically: Percentage Impulse Buyers and Average Basket Size, see Table 3). (In Figure 1, this would imply an additional moderating arrow from the control variables to the promotions' category sales effects). For reasons of space, the estimation

effect of store size. To accommodate the correlations between the jointly estimated parameters, we apply the correction suggested by Strube (1985).

results are not presented here, but can be obtained from the first author. We find that these extra interactions do not lead to an improvement in model fit. More importantly: adding these extra moderating effects has virtually no impact on the promotion variable-store size interactions. While this is surprising at first, it should be interpreted against the fact that these variables reflect the profile of *all* local inhabitants and of their *average* shopping behavior, rather than characterizing the clientele and shopping trips of the store *itself*. Given the high retail density, and the fact that all local markets contain small as well as large-sized supermarkets, a store's own customers and shopping trips need not reflect the characteristics of the whole local market. Rather, in line with Hansen and Singh (2009), we expect consumers to 'self select', and patronize large (small) outlets for major (minor) trip missions. Hence, even if the overall profile of households in the local market (trading zone) does not moderate the promotional effectiveness in the store, characteristics of the store's own clientele and shopping trips may remain an important driver of the promotional lift in that store. In all, the findings strongly support that our moderating effects of store size are not an 'artefact' of characteristics of the stores' trading area.

Additional model checks. To further evaluate the robustness of the findings, several additional checks were conducted. First, our reading of the quantity discount variable coefficient as a mere format-effect (compared to straight price cuts), assumes that the 'presence' of a promotion is already captured by the discount depth variable, which becomes nonzero as soon as a promotional offer is in place. To check for any remaining confounding effects between the occurrence of a promotion and its format, we also estimated a model in which a separate promotion dummy was introduced – capturing the presence of a promotion – with main and store size interaction effects. Adding this variable did not alter the main or interaction effects for the quantity discount variable – confirming its interpretation as a promotion format indicator. Second, we estimate a pooled model including chain-and category-specific constants, but common main- and moderating effects for the remaining variables. While a pooling test (Cramer and Ridder 1991) reveals that the model with chain- and category-specific coefficients is to be preferred, we note that the sign of the promotion-store size interaction effects remain negative and strongly significant in the pooled model – in line with the findings above.

Taken together, these extended robustness checks support the descriptive validity of the models, and help ascertain that our estimated interaction coefficients are indeed attributable to store size, and not to external trading zone characteristics. Given the semi-log form of our estimated sales-promotion relationship (which, we recall, fits the data much better than a linear model), the main-effect promotion coefficients reflect the *percentage* change in sales from a change in the promotion variables; and the interaction coefficients indicate how these percentage changes vary with store size. The retailer, however, will ultimately be interested in *absolute* performance metrics. We derive the implications of our estimates for absolute sales and margins below.

ABSOLUTE SALES AND MARGIN IMPLICATIONS

While the conceptual framework and hypotheses refer to absolute effects, the model parameters reflect percentage changes. Therefore, this section translates the relative impact of the promotion variables given by the model coefficients, into *absolute* performance metrics in differently-sized stores. To save space, we report the results for net (immediate minus post-deal) effects only – the pattern for immediate effects being highly similar.

Absolute Category Sales Implications from Promotions in larger stores.

Consider a price cut of depth $DiscDepth_{bo}$ (e.g. 25% off the regular price) for a brand b0 with a share of category base sales equal to $Share_{b0}$ (e.g. 10%). The category-level discount depth is then given by[6] $DiscDepth = DiscDepth_{b0} Share_{b0}$ (or 2.5%). Also, let $\beta_{dd}^{s,net}$ be the 'net' discount depth effectiveness parameter in store s, after post-promotion dips have been accounted for (e.g. for a price cut without feature or display support: the sum of $\beta_{2_s}^{p,c}$ and $\beta_{6_s}^{p,c}$ in equation [1]). As indicated above, this parameter decreases with store size. Our estimation results reveal, however, that larger store outlets also entail higher category baseline sales. Hence, the lower (relative) effectiveness parameter may still generate a higher absolute category sales lift. To properly assess the retailer category sales implications, we must translate the promotion effectiveness estimates obtained above into absolute movement data, where the change or 'movement' in category sales for store s is given by (Sivakumar and Raj 1997):

[6] This follows from our definition of the category-level discount depth variable (see Table 3) which is a share-weighted average of brand-level discount depth. For simplicity, we let the promoted brand's category share be the same in large as in small stores, while in practice it could be higher (if it has more SKUs in the large store) or lower (if (more) competing brands offer more SKUs).

[3] $$\underbrace{\Delta Sales^{s}}_{Movement} = \underbrace{\beta_{dd}^{s,net}}_{\substack{promotion\ effectiveness \\ parameter}} * \underbrace{DiscDepth}_{\substack{value\ of\ the \\ promotion\ variable}} * \underbrace{Sales^{s}}_{\substack{Outlet\ base \\ sales}}$$

Using our estimated model coefficients, Table 6, panel a, illustrates the net absolute sales effects, across categories and chains, for two levels of store size. It presents the change in category sales volume when the category promotion variable goes up by 10% points (for display or feature support, and quantity-based format) and 2.5 % points (for discount depth, which is the equivalent of a 25% price cut on this same 10% of the category offer). For display and feature, we report both the 'stand alone' effects ('Feature only' and 'Display only'), as well as their combined impact with a price deal. As for store size, we consider a selling surface (i) 300 m^2 below, and (ii) 300 m^2 above the average of a particular chain. We use a 300 m2-deviation, as this represents a realistic difference in store size for each of the studied chains. The table gives a flavor for the change in promotion effectiveness as store surface increases or decreases. For the two levels of store size, it reports the mean effect[7] across chains and categories, as well as the fraction of cases (chain-category combinations) in which the absolute sales bump (expressed in units, not in money spent) is larger in the small or the large outlet.

< Insert Table 6 about here>

For Discount Depth, though the *mean* absolute sales effect is somewhat higher in large stores compared to small stores (14 460 compared to 11 710 units), the pattern of underlying effects across chains and categories is highly mixed (9 cases with a higher sales lift in the small store, compared to 7 in the large store). Hence, the (net) promotional sales bump does not seem to systematically increase with store size. Figure 2 offers a tentative explanation. When implemented in large stores, deeper discounts are made available to a larger customer base (of mostly large basket shoppers), who have lower transaction costs and, hence, can easily handle larger purchase quantities. At the same time, however, these customers are also less sensitive to the discount's economic benefit, and hence more difficult to convert into buyers. The results in

[7] Because category sales are expressed in different units (e.g. liters for softeners versus ounces for cereals), we transform them into equivalent monetary units first by multiplying with the average regular unit price of the category (across chains and weeks).

Table 6 suggests that, on the whole, the positive impact of a higher trading zone potential and average category purchase quantity is offset by the lower category closing rate.

The same pattern is observed for Quantity-based deals. While the absolute sales lift is somewhat higher in large stores on *average* (for Quantity-based offers: 11990 units in large compared to 8230 in small stores), there are as many instances in which the difference is positive (6 cases) as negative (6 cases)). Figure 2 offers an explanation for this ‘tie’. As argued above, quantity-based discounts have lower ‘signal’ appeal whereas large store shoppers are particularly sensitive to the promotion signal. Moreover, these large store (large basket) shoppers often buy large-enough quantities to qualify for the deal without making an extra effort (e.g. they already buy two units under non-promotional conditions, which suffices to benefit from a BOGO deal, Foubert and Gijsbrechts, 2007). Also, they may find it inconvenient to handle even larger basket sizes, such that the average category purchase quantity is less likely to go up. Our results suggest that these negative effects caused by the characteristics of large store shoppers, cancel out the positive impact of the larger customer base.

A different outcome is obtained for feature and display (either alone or in support of a price cut). Not only is the absolute sales lift bigger in large stores *on average* (e.g. for ‘Feature only’: 10 850 units in small versus 15 930 units in large stores, for ‘Display only’: 13 940 units in small versus 21 600 units in large outlets), this same pattern is found in almost all underlying category-chain combinations (11 out of 16 cases for feature only, 15 out of 16 cases for display only). As indicated in Figure 2, the larger base of potential customers, who more heavily rely on promotion signals to decide on a category purchase, favorably moderates the impact of Feature and Display activities. Based on our findings, this more than offsets the fact that large stores have higher fixed shopping costs – which would make it more difficult for feature ads to generate extra store traffic. It also offsets the higher in-store search costs – which would reduce the display’s drawing power to the category shelf. The net result is that both out-of-store and in-store promotional communication instruments lead to higher sales lift in large outlets. At the same time, this increase is far less than proportional: in an outlet twice as large, the absolute sales bump from a display is only 55% higher in the absence of a price cut, and only 41% higher when its supports a price deal. For feature ads, these figures even drop to 47% and 10%, respectively.

For the immediate promotion effects, the pattern of differences between small and large stores is highly similar. As a further check on these absolute sales effects, we conduct two additional analyses. First, since the FM parameter estimates on which our calculations are based have inherent uncertainty, we simulate the difference in absolute sales lift between the small and large stores based on 10000 draws from the multivariate normal parameter distributions. We do this for each category-chain combination, and for each promotional activity. Having obtained the means and standard errors by category and chain, we again conduct a Stouffer test on the overall difference in absolute sales lift between small and large outlets, for each promotion variable. The results confirm the previously observed pattern. For straight price cuts (not supported by feature or display) and for quantity-based discounts, we do not find a significantly higher sales bump in large outlets ($p>.10$ and $p>.09$, respectively). For feature and display activities, in contrast, the sales lift is significantly higher in the larger outlet ($p<.01$). Second, we consider the coefficients of the linear specification (with sales rather than logarithm of sales as the dependent variable, please see the section on robustness checks). The coefficients of these models directly reflect the absolute sales bumps triggered by promotions and their interaction with store size. Based on the Stouffer test, we find that the (combined) moderating effect of store size in these linear models is not significant for Discount Depth and Quantity-based format ($p>.10$), and significantly positive for Feature and Display ($p<.01$), which further corroborates the findings above.

Margin implications of price cuts in larger stores

Having assessed the promotions' absolute category sales effect for different store sizes, we briefly explore their margin implications. For promotions that involve a discount to the consumer, the extra revenues from the promotional sales bump must compensate for the possibly reduced margins on units that would have been sold without the deal anyway. The promotion is profitable if the margin gain from net incremental category sales exceeds the margin loss on sales that would have been made without the promotion anyway. If the absolute sales change is larger in larger outlets, this will positively influence the margin in those large stores. On the other hand, large stores also entail substantially higher *base* sales. Whether these larger base sales will further enhance the margin in large stores, or lower it, depends on the retailer's participation in the discount, i.e. the fraction φ of the discount borne by the retailer. If $\varphi > 0$, the retailer earns less on promotional than on regular sales (a setting commonly referred to as 'retailer pass through above one', Besanko et al 2005), and the large stores' higher level of base sales results in stronger subsidization. If $\varphi < 0$, the retailer – instead of *paying* for (a portion of) the deal himself - *cashes in* on part of the promotional discount granted by the manufacturer ('retailer pass-through smaller than one'). In that case, the higher base sales in large stores become an asset - allowing the retailer to reap additional margins.

Table 6, panel b and c, documents the total margin effect based on our model estimates[8], for m=25%, and retailer participation equal to φ=-1 or φ=.05[9] (Details on the calculations can be obtained from the first author).With φ=-1, each promotion activity gives rise to higher margin gains in the large compared to the small store, even if that was not true for the absolute sales bump. For instance, for the Discount Depth variable, a .025 category-level price cut would now generate a 14.92 margin lift in the larger outlet, which is about twice the margin lift in the smaller store, and this pattern is observed in all sixteen category-chain combinations. For Displayed price cuts, the average margin lift would rise from 8.46 in the small compared to 16.35 in the larger outlet (a 93% increase), and this increase is consistently observed in all cases. The margin comparisons are quite different for positive levels of retailer participation (φ=.05). For instance, the straight 'Price cut' now results in an average margin loss of -0.71 in the larger store, which is more than 100% below the margin loss (-.35) in the small outlet. Similar losses can be observed for the featured price cut and quantity discount. For displayed price cuts, the average margin lift is still higher in large outlets (.58 in the large store compared to .48 in the small outlet), but the difference is much smaller than for φ=-1, and the pattern across chain-category combinations is somewhat less consistent. The reason is that, unlike the absolute sales bump, baseline sales almost proportionally increase with store size, such that subsidization becomes a more dominant problem in large outlets.

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[8] Since we do not have promotion estimates at the brand level, we adopt an approximation based on the meta-study of Bell et al (1999), which indicates that, on average, promotional brand sales elasticities are about four times as high as the corresponding category sales elasticities.

[9] Retailer pass through (or: PT) is typically defined as the portion of the reduction in the wholesale price (granted by the manufacturer to the retailer), passed on by the retailer to the consumer (Besanko et al 2005).With an average retail margin of 25% of the retail price p, levels of φ=-1, and .05 would correspond to pass through rates of PT=.8, and 1.05, respectively.

DISCUSSION, LIMITATIONS AND FUTURE RESEARCH.

Discussion.

Even though supermarket stores within a chain may dramatically vary in size, little is known about the differential effect of different promotion instruments in small versus large stores. This is surprising, given that a store's selling surface is bound to influence the impact of promotions on store category sales and margins, and that knowledge of these implications is important for efficient design of promotional programs as well as promotional logistics. In this paper, we conceptualize why and how store size influences the category sales effectiveness of four promotional indicators (depth of the promotional discount, display support, feature support, and whether the promotion is quantity-based), and estimate the net moderating effect on four product categories for 103 store outlets belonging to four chains.

Our research generates several *substantive* insights, which can be summarized as follows.

First, by decomposing category sales into its underlying components, our conceptual framework highlights *why store size influences promotion effectiveness*. On the positive side, large selling areas have a larger potential customer base, implying that more consumers are prone to be affected by the promotion. Moreover, large stores typically attract consumers on major, stock-up shopping trips. These consumers rely more heavily on promotions as a shopping heuristic. They may also have lower handling costs, which – once they are aware of the promotion - increases their propensity to engage in a category purchase, and buy larger quantities. On the negative side, however, large outlets typically entail larger fixed shopping costs and in-store search costs. These costs create larger hurdles to draw consumers into the store and to the category shelf. Also, the large outlet's major trip shoppers may pay less attention to the depth of the discount, or perceive it as less consequential relative to the total basket size. This makes it less likely that a price cut will convert category-non-buyers into buyers. In all, even though our focus is not on testing the behavioral mechanisms per se, the framework helps us understand the countervailing forces that underlie the moderating effect of store size.

Second, because different promotion instruments operate on different category sales components, they are also differentially affected by store size. Our empirical results reveal that deeper discounts do not systematically generate larger absolute sales bumps in large stores, despite the larger customer base of these stores. This is consistent with the observation that large store shoppers pay less attention to the value of the promotion as such, and are primarily affected by the presence of the promotional signal. Similarly, quantity-based promotions, probably because of their lower 'convenience-appeal', do not trigger higher incremental category sales in large outlets. For in-store displays and features, which primarily act as a 'purchasing cue' for major trip shoppers (Chandon et al 2000), we do obtain a systematic positive link between store size and category sales lift. Even so, the category sales bump increases less than proportionally with store size. An auxiliary regression analysis suggests that the positive link weakens if larger selling areas are more strongly associated with a larger number of brands in the category ($p<.067$) [10]. Interestingly, no such effect is found for discount depth and quantity-based promotions. This finding is in line with our conceptualizations: while larger assortments enhance the fixed shopping benefits (and, hence, the size of the potential customer base), they also entail higher fixed shopping costs (in-store travelling) and search costs (clutter) which, apparently, dampens promotion effectiveness for the non-price support variables.

Third, we also explore the implications of our findings for the link between promotion profitability and store size. For promotions involving a price cut, the profit difference between smaller and larger stores is driven by two components: the difference in absolute incremental sales from the promotion, and the difference in baseline sales. Unlike the promotional sales bump, we find that category baseline sales increase about proportionally with store size. This higher baseline will be detrimental or beneficial depending on whether the retailer bears part of the price cut himself (in which case he subsidizes current customers), or, alternatively, cashes in on part of the manufacturer's promotional offer (and reaps *extra* margin on baseline customers). Our empirical findings suggest that, as a result of these mechanisms, price cuts become less profitable in large than in small outlets as soon as the retailer *bears* part of the discount himself,

[10] Regression across chains, categories, and promotion instruments. The dependent variable is the estimated moderator coefficient. The independent variables are the correlations, within that chain and category, between outlets' size and their (i) average number of SKUs per brand, (ii) average number of brands, and (iii) instrument-specific dummies. The explanatory variables thus reflect to what extent larger store size is associated with deeper and larger category assortments. The auxiliary regression coefficients then indicate how this drives the observed moderating effects for store size. We use weighted least squares to accommodate the uncertainty (standard error) of our dependent variable, which is an estimated coefficient and – as conceptualized – allow the effects to differ between the non-price support variables (feature, display), and the other instruments. Because the number of observations is low, we use a 10% significance cut-off.

because of the larger subsidization effect. This especially holds true for price cuts not supported by a feature ad or a display. However, the situation is quickly reversed if the retailer cashes in on part of the manufacturer's per-unit discount, making promotional profit far higher in large stores.

Our findings also have important *implications for managers.*

As indicated by Grewal et al (2009), "Practitioners have a good handle on how to predict sales and provide an adequate service level for retail chains as a whole, but much more work is needed to fine-tune [assortments] by individual store". In a similar vein, industry reports suggest that, at present, there are "a handful of retailers that have looked into […] customization of their stores based on local demographics, […], adjusting their merchandising mix accordingly" (Planet Retail 2010), with only few reaching deeper levels of customization. Our results show that, even after local market differences (i.e. supermarket competition and population profiles) are accounted for, store size remains an important moderator of promotion effectiveness and as a result should be accounted for. Building on available literature, we conceptualize that this moderation stems not only from a direct but also from an indirect effect: larger selling surfaces attracting different types of shoppers (with different shopping tasks) into the store, which respond differently to promotion instruments[11]. Given that store size correlates heavily with these shopping trip characteristics – which are difficult to implement - it can serve as a valuable proxy for anticipating their promotion consequences. As indicated by Mantrala et al. (2009), the main barriers to practitioners' adoption of models from academic research relate to data requirements, model complexity, difficulty of integration into existing systems, and cost-benefit considerations. Store size information is 'objective', readily available, easy to align with the retailers' existing data and logistical systems, and – as we show here – an important driver of promotion effectiveness. Hence, it seems that refining promotion plans along store size holds the promise of implementability.

For one, our findings help retailers anticipate the amount of extra promotional sales, by store size. This is important for properly handling the operational or logistical aspects of the

[11] Such links between shopper/shopping trip profiles and store characteristics are well-rooted in the academic literature and corroborated empirically. For instance, a recent large scale survey among supermarket shoppers, conducted by a professional marketing research company, found that type of shopping trip matters in choosing a specific store size: whereas the vast majority of consumers on *weekly stock-up trips* mention size-related criteria (e.g. wide range of products, the store allows for one stop shopping) as a primary reason for store selection, this holds for only half of the consumers *shopping for daily needs*, and for less than one third of households on *urgent fill-in trips*.

promotional program. For price deals not accompanied by feature or display activities, and for quantity-based deals, there seems to be no need to adjust promotional shipments to store size. In contrast, feature ads or in-store announcements generate higher incremental sales in large outlets. Still, the increase is less than proportional with the store's selling area: if store size is doubled (e.g. from 600m2 to 1200 m2, a 100% increase), incremental category sales go up by only 55% for in-store displays, and by 47% for feature ads. For displayed or featured price cuts, these figures approximately drop to 41% and 10%, respectively. Retailers can use these numbers as a first indication of the sales lift from promotions in smaller versus larger outlets.

Second, by shedding light on the drivers underlying the moderating impact of store size, our results may help retailers improve the relative effectiveness of promotion instruments in large outlets. They may turn to different types of *display* activities in large selling areas, such as in-store demonstrations. These are more attention-catching, and particularly helpful to overcome in-store search costs. Similarly, end-of-aisle displays may make it easier for consumers to locate items from the promotional flyer, among the vast assortment inside large stores. Quantity-based discounts may be made more appealing to large store shoppers through shelf tags or on-pack messages, emphasizing the uniqueness of the offer and, hence, its signal value. Also, by offering BOGO-type deals as bundled packages, retailers may reduce the extra handling cost and enhance the appeal to large basket shoppers.

Last but not least, our results show how retailers can adjust their mix of promotion instruments to stores' selling surface, depending on whether sales or profit is their key performance metric. Shankar and Bolton (2004) find that supermarkets use more intensive price promotions in large stores, while Ellickson and Misra (2008) observe more emphasis on EDLP in large outlets. Our results shed some light on the desirability of such approaches. We find that for retailers aiming to enhance absolute category sales, featured and especially displayed price cuts appear particularly rewarding in large outlets. Display activity is easily customized across stores. In fact, having more or larger end-of-aisle displays in large stores is not only more effective, it also 'naturally' matches the less stringent space constraints in those stores. Differentiating feature support across outlets is less straightforward, as chains typically design their store flyer for the entire (national) market. Still, stores have been observed to place their own, outlet-specific, ads in local newspapers, and some chain flyers specify outlets in which selected feature promotions do (or do not) hold. So, even if tailoring feature support to store size is less likely to occur on a large scale, some options appear to remain.

For retailers who seek to enhance profitability, it appears good practice to offer more shallow discounts and use more non-price support in large stores, thereby avoiding large amounts of subsidization of these stores' substantially larger installed base. This holds true unless the manufacturer's promotional funding comes in the form of a per-unit discount instead of a lump-sum trade support budget (which, as observed by Ailawadi et al 2009, is the exception rather than the rule), and the retailer can keep part of this discount to himself. Also, retailers should avoid the use of retailer-induced promotions in large outlets (e.g. on their private labels), and adopt low levels of pass-through for manufacturer-funded price cuts in those outlets.

Limitations and future research.

Our study has a number of limitations, and opens up interesting opportunities for future research.

First, our conceptual arguments suggest that store size may play a different role in different categories. For instance, one could expect more negative promotion moderation effects for categories that are a fixed item on the shopping list of large basket shoppers, or have complex assortments. Unfortunately, our data set had too few categories to systematically analyse the role of such category characteristics – an issue that we leave for future research.

Second, our primary focus was on the effectiveness of category-level promotional activity. Category-level results are of key importance to the retailer (Nijs et al 2001), and retailers typically plan their purchases at the category level (Shankar and Bolton, 2004). Moreover, our current data set did not allow for brand-specific analyses. The category-level sales lift, as a function of store size, directly followed from our HLM estimates. To calculate the promotional *margin* implications at the category level, we could rely on previous meta-analytic results (Bell et al 1999) to approximate the portion of the category sales elasticity attributed to brand switching. Sensitivity analysis reveals that the pattern of outcomes for large versus small stores appears quite robust to changes in this brand switching portion. Still, an analysis at the brand level may reveal important extra insights for retailers (Shankar and Bolton 2004), and future studies could investigate how the moderating effect of store size on promotion effectiveness varies across individual brands within a given category.

Third, in a somewhat similar vein, the retailer's sales and gross margin implications may be further shaped by the *type of brand* placed on deal, i.e. whether the promotion applies to private label or manufacturer brands. Apart from margin differences (Ailawadi et al 2006) and differences in retailer pass-through (Ailawadi and Harlam 2009), these brand types may differ in their promotional appeal in small versus large outlets (Gijsbrechts et al 2003). Therefore, investigating the deal effectiveness of national brands and private labels across stores of varying selling areas may be a relevant topic for future study.

Last but not least, this paper only studied Hi-Low chains. Future research could assess the moderating impact of store size on promotions in discount chains, as they attract different (more price-sensitive) consumer segments that could differ in promotion response (Bell and Lattin 1998). Moreover, while our framework was built to explain the impact of supermarket size differences, we believe it offers a good starting point to study promotional differences across convenience, supermarket, and hypermarket outlets of a chain. We hope that this paper is a source of inspiration for further research on this topic.

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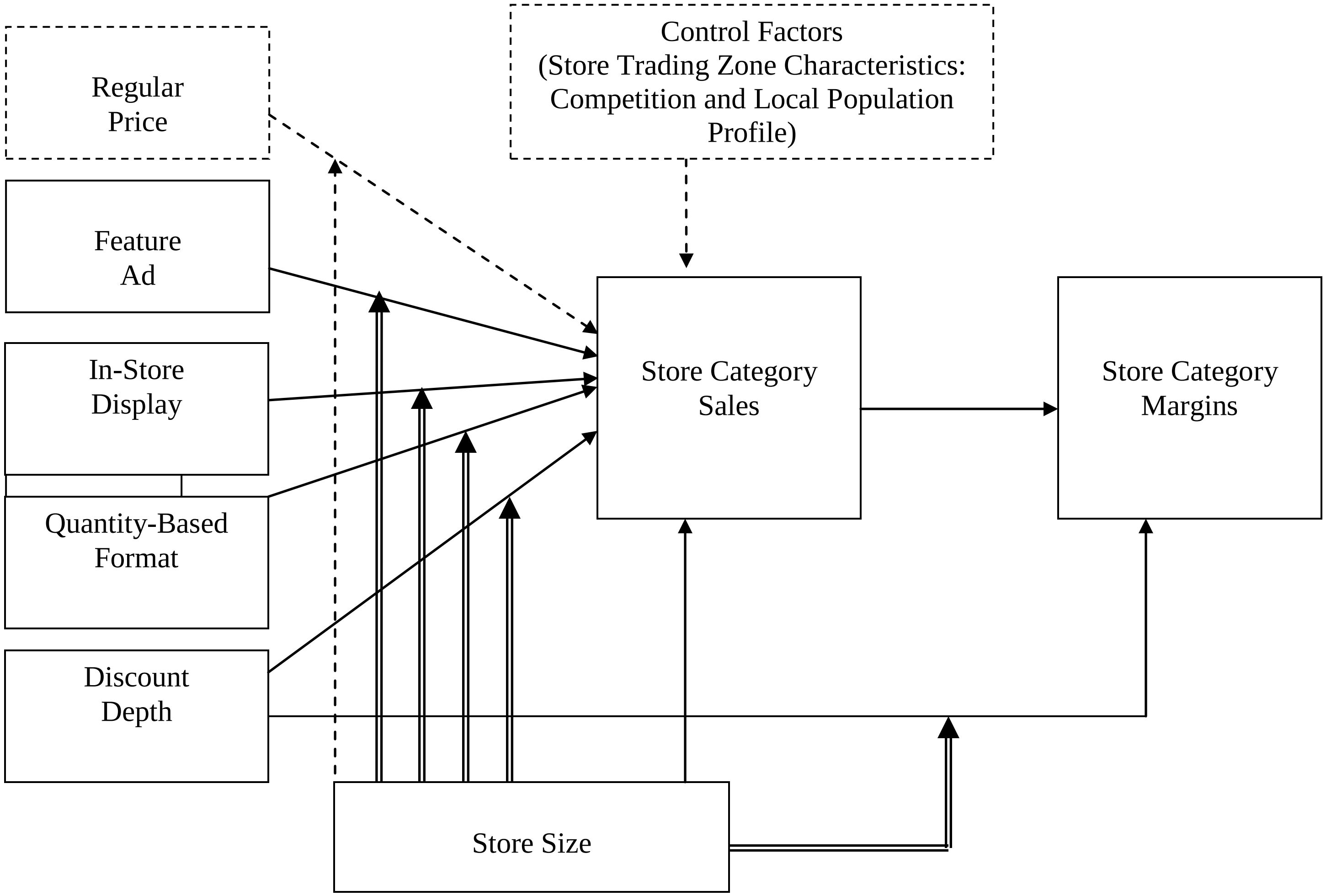
FIGURE 1: Overview of Constructs and Their Interrelationships



(Bold lines indicate main effects of interest, Double arrows moderating effects, and dotted lines are controls)

FIGURE 2: Conceptual Framework[a]

Category Sales Component	Store Traffic Ratio	Shelf Traffic Ratio	Category Closing Ratio		Average Category Purchase Quantity	Total Category Sales in Store
Panel a: Impact of Promotion Variable						
Feature	+		+			+
Display		+	+			+
Discount Depth	+			+	+	+
Quantity-based Format			-		+	?
Panel b: Moderating Effect of Store Size on Category Sales Component						
Driver of Category Sales Component	Low Fixed Shopping Cost	Low In-Store Search Cost	High Variable Shopping Utility		Low Transaction Cost	
			High Signal Value	High Economic Benefit		
Direction of Store Size effect	-	-	+	-	+/-	?

[a]Panel a in the framework reflects the impact of a promotion instrument (row) on each of the category sales components (columns). For instance, Features are expected to increase the Store Traffic Ratio and the Category Closing Ratio (indicated by a '+' in the corresponding cells in panel a). As another example: Quantity-based promotions are expected to decrease the Category Closing Ratio ('-'), but to enhance the Average Category Purchase Quantity ('+'). Panel b of the framework reflects how store size (row) affects the major benefit/cost driver of each category sales component (column). For instance, low fixed shopping costs are a main driver of a high Store Traffic Ratio. However, large store size does *not* lower fixed shopping costs ('-' in the corresponding column in panel b), and hence reduces the Store Traffic Ratio. As another example: larger store size goes along with a higher signal value of promotions ('+' in the corresponding column in panel b), which enhances the variable shopping utility and Category Closing Ratio.

TABLE 1

Key Papers Including Store Size Effects on Promotion Response

Author (year)	**Multiple Chains?**	**Multiple Categories?**	**Promotion Type**				**Promotion impact on Category Sales?**	**Within-chain Size differences?**
			(%) Price Cut	**Feature**	**Display**	**Quantity discount**		
Boatwright, Dhar and Hoch. (2004)	√		√	√	√			
Hoch, Kim, Montgomery and Rossi (1995)		√	√				√	√
Gijsbrechts, Campo and Goossens (2003)		√		√				√
Montgomery (1997)			√					√
Ailawadi, Harlam, César and Trounce (2006)		√	√	√	√		√	√
This study	√	√	√	√	√	√	√	√

TABLE 2

Descriptives

Variable[a]	Chain 1	Chain 2	Chain 3	Chain 4
Chain (Store) Characteristics				
# Outlets	43	24	21	15
Store Size (m2):				
Average	1181	960	765	832
Range	274 – 2673	427 - 1964	407 - 1153	314 - 1591
Trading zone characteristics				
% Local inhabitants with income above national mode				
Average	36.7	36.7	38.9	39.0
Range	14.7 – 54.2	22.3 – 50.5	20.2 – 57.5	26 – 47.4
Age: % > 65				
Average	26.8	21.8	25.2	25.8
Range	11.5 – 45.5	12.1 – 36.4	11.9 – 47.8	15.5 – 30.1
Basket Size (Euros):				
Average	64.5	66	66	65.5
Range	56.5 – 75	58 - 73	57.5 - 76	59.5 – 71.5
% Impulse Buyers:				
Average	47.9	47.3	46.0	47.0
Range	40.8 – 56.8	41.8 - 55.2	37.0 - 63.0	38.8 - 52.6
Competitive Pressure				
(# of supermarkets)***:***	26	15	23	17
Average	5 – 117	2 - 54	7 – 77	8 - 36
Range				
Promotion Characteristics				
Discount Depth				
% of items on discount[b]	7.0	8.0	8.2	7.6
average depth of discount [c]	0.07	0.10	0.10	0.04
Feature [b]	.05	.07	.04	.05
Display [b]	.04	.06	.03	.05
Quantity Discount [b]	.05	.04	.05	.04

[a] see Table 3 for measurement details

[b] average fraction of items in the category offered with a price cut (feature, display, quantity discount) per week, per store, over the four product categories

[c] average discount depth expressed as a fraction of the regular price

TABLE 3

Variable Description

Concept (variable name)	Measures
Category sales volume ($lnSales_{t,s}^{p,c}$)	Log of sales volume in week t, store s, chain c and product category p
Weekly regular price ($lnPrice_{t,s}^{p,c}$)	Log of the weekly regular price in week t, store s, chain c and product category p
Discount depth ($DiscDepth_{t,s}^{p,c}$)	Economic value of the promotional offer, expressed as a share-weighted percentage reduction off the regular price[12], in week t, store s, chain c and product category p (see e.g., Putsis and Dhar 2001; Raju 1992)
Feature advertising ($Feat_{t,s}^{p,c}$)	Share-weighted number of brand feature dummies in week t, store s, chain c and product category p
Display ($Disp_{t,s}^{p,c}$)	Share- weighted number of brand display dummies in week t, store s, chain c and product category p
Quantity discount ($QuanDisc_{t,s}^{p,c}$)	Promotional format indicator, measured as the share-weighted number of brands on which a quantity-based (BOGO or Extra Volume) format is offered in week t, store s, chain c and product category p
Store size ($lnStoreSize_{s}^{c}$)	Log of floor space in square meters for store s of chain c
Number of competitors ($lnComp_{s}^{c}$)	Log of the number of competitors in the trading zone (based on a 5 km radius) for store s of chain c
Percentage age > 65 ($lnAge_{s}^{c}$)	Log of the percentage of consumers older than 65 in the trading zone for store s of chain c
Percentage income > modal ($lnIncome_{s}^{c}$)	Log of the percentage of consumers with an income above the national mode in the trading zone for store s of chain c
Average basket size ($lnBasketSize_{s}^{c}$)	Log of average basket size of shoppers in the trading zone for store s of chain c, based on a Claritas local population survey
Percentage impulse buyers ($lnImpulse_{s}^{c}$)	Log of the percentage of impulse buyers in the trading zone for store s of chain c, based on a Claritas local population survey

[12] The weights are based on brands' average category sales share across weeks and chains (stores), and adjusted to brand availability in the store's assortment. For instance, suppose the category comprises three brands with average category sales shares (across weeks and chains) of .2, .5 and .3, respectively. Then, a 30% discount for brand 1, and no discounts offered on brands 2 and 3, would lead to a category-level discount depth of 6% (.3*(.2/(.2+.5+.3))=.06) in a store that carries all three brands. If the store's assortment only comprises brands 1 and 2, this same discount would lead to a category-level discount depth of 8.57% (.3*(.2/(.2+.5))=.0857), (see van Heerde et al (2008) for a similar weighting scheme).

TABLE 4

Summary of Main Effect Estimates

Variable (parameter)	**# positive effects**	**# significant positive effects[a]**	**# negative effects**	**# significant negative effects**
Base Price ($\delta_{10}{}^{p,c}$)	0	0	16	15
Discount depth ($\delta_{20}{}^{p,c}$)	14	13	2	2
Feature($\delta_{30}{}^{p,c}$)	13	11	3	2
Display ($\delta_{40}{}^{p,c}$)	16	13	0	0
Quantity Discount ($\delta_{50}{}^{p,c}$)	10	10	2	1
Lagged Discount depth ($\delta_{60}{}^{p,c}$)	3	1	13	9
Lagged Feature ($\delta_{70}{}^{p,c}$)	10	5	7	3
Lagged Display ($\delta_{80}{}^{p,c}$)	7	3	9	2
Lagged Quantity Discount ($\delta_{90}{}^{p,c}$)	7	3	5	4
Store Size ($\delta_{01}{}^{p,c}$)	16	16	0	0
Age ($\delta_{02}{}^{p,c}$)	4	0	12	5
Income ($\delta_{03}{}^{p,c}$)	12	6	4	3
Number of competitors ($\delta_{04}{}^{p,c}$)	9	0	7	2

[a] two-tailed tests, p<.05. Total number of cases is 16 (4 chains and 4 categories), except for the Quantity Discount variables which could not be estimated in the cereals category and for which 12 cases are retained.

TABLE 5

Summary of Store Size - Promotion Interaction Coefficients

Immediate interaction effect	**Number of negative effects**	**Number of significant negative effects[a]**	**Average parameter value[b]**	**Stouffer's test (two-tailed significance level)**
Store size – Regular Price	14	5	-.45	<.01
Store size – Discount depth	14	8	-.42	<.01
Store size – Feature	11	5	-.17	<.01
Store size – Display	12	2	-.03	<.01
Store size – Quantity discount[c].	9	3	-.15	<.01
Net interaction effect				
Store size – Discount depth	14	9	-.41	<.01
Store size – Feature	11	6	-.16	<.01
Store size – Display	11	3	-.02	<.01
Store size – Quantity discount[c].	9	4	-.17	<.01

[a] number of significant effects for $p < .05$, two-tailed.
[b] since all variables in the model are mean-centered, this coefficient represents the change in promotion effectiveness (% increase in category sales resulting from a marginal increase in the category promotion activity) when moving from an averaged-size store of the chain (e.g. 1000 square meters), to a store with a one percent larger selling area (e.g. 1010 square meters).
[c] Since there are no quantity discounts for cereals, the maximum number of effects is 12 instead of 16.

TABLE 6:

Absolute Net Sales and Absolute Net Margin Change from Promotion in Small versus Large stores

Promotion	Absolute Sales increase Panel a:				Absolute Margin increase for three levels of deal participation (regular margin=25% of retail price)							
					Panel b: $\varphi = -1$ (pass-through=.8)				Panel c: $\varphi = .05$ (pass-through=1.05)			
	Average sales increase from promotion in		Number of cases where sales increase is larger in[g]		Average margin increase from promotion in		Number of cases where margin increase is larger in		Average margin increase from promotion in		Number of cases where margin increase is larger in	
	Small Store	Large Store	Small Store	Large Store	Small Store	Large Store	Small Store	Large Store	Small Store	Large Store	Small Store	Large Store
Price cut only[a]	11.71	14.46	9	7	7.55	14.92	0	16	-.35	-.71	16	0
Price cut + Feature[b]	19.42	21.33	5	11	8.53	16.58	1	15	.28	.20	9	7
Price cut + Display[c]	25.64	36.06	2	14	8.46	16.35	0	16	.48	.58	2	14
Price cut as Quantity Discount[d]	8.23	11.99	6	6	9.57	18.78	0	12	.07	-.14	7	5
Feature only[e]	10.85	15.93	5	11	2.71	3.98	5	11	2.71	3.98	5	11
Display only[f]	13.94	21.60	1	15	3.49	5.40	1	15	3.49	5.40	1	15

[a]=price cut only: 25% off the regular price offered on brand with 10% category share, such that share weighted DiscDepth=.025, [b]=same price cut with feature support (DiscDepth=.025, Feat=.1), [c] =same price cut with display support (DiscDepth=.025, Disp=.1), [d] =same price cut in form of extra quantity (DiscDepth=.025, QuanDisc=.1), [e] = feature support only (DiscDepth=0, Feat=.1), [f] = display support only (DiscDepth=0, Disp=.1),
[g] Total number of cases is 16 (4 chains and 4 categories), except for the Quantity Discount variables which could not be estimated in the cereals category and for which 12 cases are retained.
The table should be read as follows: if DiscDepth changes from 0 to .025 (a 25% price cut on a 10% share brand is offered), weekly category sales in the small store, on average, increase by 11.71 units. The corresponding margin increase in that small store is 7.55 Euros for $\varphi=-1$, and -.35 for $\varphi=.05$.