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# On consumer choice patterns and the net impact of feature promotions☆,☆☆

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ABSTRACT

Even in the digital age, feature promotions continue to receive significant investments from CPG manufacturers and retailers. Whether this is money well spent depends on consumers' (heterogeneous) tendency to switch brands or stores in response to features. This study proposes a 'Mixed-pattern Random-effects Nested Logit' (MRNL) model to analyse the effect of feature promotions in a multi-retailer multi-brand setting. Across 16 different CPG categories, our results reveal that in all cases a mixture of choice patterns prevails: about half of households exhibit a brand focus (i.e. rather substitute between stores offering that brand), the remaining half show evidence of a store focus (i.e. rather substitute brand offers within a visited store). We find that the size of the promotion lift and its underlying sources differ substantially between patterns. Brand-focused consumers are generally more responsive to feature ads than store-focused consumers – especially in low-concentration categories; while they imply much stronger cannibalization for the manufacturer, and much weaker cannibalization for the retailer. It follows that retailers reap much higher benefits in the brand-focused segment, while manufacturers may not prefer that segment in terms of net gains and must be wary of subsidizing those consumers. We identify household and category characteristics that underlie the choice patterns and offer opportunities for targeting.



## 1. Introduction

Feature promotions in consumer packaged goods (CPG) markets are ever-more pervasive. Even in the digital age, store flyers continue to be a key marketing instrument in many countries (Ziliani & Ieva, 2015), accounting for over 50% of retailers' marketing budget (Gázquez-Abad & Martínez-López, 2016), and involving huge investments from national brand manufacturers (Bia, 2010; Narasimhan, 2009). Business reports show that 83% of all households read the 'physical' store flyers while 26% access the digital version through an app or comparison website, and that such readership influences where and what they buy (Foldermonitor and GfK, 2016). Moreover, the share of national brands (NBs) sold on feature promotion at traditional supermarket chains has been steadily increasing (GfK, 2012; Guyt & Gijsbrechts, 2014).

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Yet, the net sales gains from such promotions have been called into question (Ailawadi, Beauchamp, Donthu, Gauri, & Shankar, 2009; Grewal et al., 2011; Srinivasan, Pauwels, Hanssens, & Dekimpe, 2004). For the NB manufacturer, the promotion lift may come at the expense of the NB's sales in other stores where it is not on deal. Likewise, for the retailer, the lift for the promoted brand may come from within-store brand switching. In such cases, the feature investments fail to enhance sales volume and, to the extent that deal prices and margins are lower than usual, even reduce the revenues and profitability of the promoted brand (or, for the retailer, category). These issues become more pressing as consumers' willingness to pay for NBs decreases (Steenkamp, van Heerde, & Geyskens, 2010), while their propensity to patronize multiple stores goes up (Baltas, Argouslidis, & Skarmeas, 2010). So, whether feature advertising investments are money well spent, depends on how consumers switch between the available brands and stores for their CPG purchases.

Extant studies suggest that households are heterogeneous in their CPG purchasing patterns, and in their promotional response within these patterns (Bucklin & Lattin, 1992; Gauri, Sudhir, & Talukdar, 2008; Gupta, 1988; Inman, Shankar, & Ferraro, 2004; Mehta & Ma, 2012). However, these studies typically focused either on households' brand choice (e.g. Mehta & Ma, 2012) or store choice (e.g. Gauri et al., 2008) separately. Papers that document both brand and store switching do so at the aggregate (market or store) level (Nijs, Dekimpe, Steenkamp, & Hanssens, 2001; Srinivasan et al., 2004; van Heerde, Leeflang, & Wittink, 2004). Little is known about how individual households trade off their category purchases across both brands and stores, and how these - possibly heterogeneous - purchase patterns align with the effect of feature promotions. Especially at times where budgets are strained and managers are increasingly held accountable, understanding how shoppers switch among brands and stores, and how this affects the net sales gains of feature ads, is critical for the effective allocation and targeting of manufacturer and retailer store-flyer budgets.

The primary objective of this study is to shed light on the patterns of brand-store choice (i.e. which brand is bought at which retailer), conditional upon a category purchase in CPG categories; and to explore how these patterns are related to the impact of feature promotions on the manufacturer and retailer. Our research questions are fourfold. First, given a category purchase, how do consumers trade off different brand-store choices, and are consumers heterogeneous in their switching patterns? Second, does the promotion lift (i.e. the share increase) for a national brand featured at a supermarket chain differ depending on the choice pattern? Third, what is the impact on the manufacturer and retailer's net gains from the feature promotion, after accounting for within-brand and within-store cannibalization, respectively? Finally, if feature promotions lead to different outcomes depending on the choice pattern, can we profile which consumers in which categories will yield 'bigger bang for the feature-buck'?

To answer these questions, we propose and estimate a 'Mixed-pattern Random-effects Nested Logit' (MRNL) model that flexibly captures shoppers' brand and store choice for a given category purchase. We estimate this model on household scanner panel data across sixteen categories, spanning a period of 4 years. Our MRNL model allows the choice of a brand-store combination to materialize through two different substitution patterns, (i) one in which the households' focus is on retailers, and brands disproportionately compete with each other within a retailer ('store focus'), and (ii) another in which the households' focus is on brands, and retailers disproportionally compete for a brand ('brand focus'). We expect a mixture of choice patterns to prevail in each category, but possibly with different importance weights. Moreover, our model allows the impact of feature ads to differ between the two choice patterns. We use the outcomes of this model to empirically document the prevailing mixture of choice patterns in each category and, for each category-choice pattern, to quantify the impact of store flyer appearances for the promoted brand-store alternative and for the brand and store as a whole. We also explore the drivers of the choice patterns, and reflect on managerial implications.

We contribute to extant literature in several ways. To the best of our knowledge, we are the first to: (i) simultaneously consider (inter- and intra-) brand- and store-competition, taking an individual shopper perspective and allowing for a flexible interplay between the two choice dimensions, (ii) empirically document the relative importance of these choice patterns across multiple shoppers and product categories; and (iii) explore the effectiveness of store-flyer ads in these choice patterns. As such, our paper fits in with a 'shopper marketing' perspective (Shankar, Jeffrey Inman, Mantrala, Kelley, & Rizley, 2011), in which brands' marketing activities are tailored to specific retail accounts for maximum shopper response (Kushwaha & Shankar, 2013). Effective shopper marketing hinges on fine-grained insights into shoppers' buying tradeoffs and 'paths-to-purchase', and we answer a call to enhance such knowledge (Shankar et al., 2011). Moreover, by shedding light on the choice shifts among brands and stores, we contribute to the promotion decomposition literature-indicating how the portion of the promotion lift that benefits the manufacturer or retailer is shaped by the consumers' choice pattern, thereby providing a more refined perspective on the decomposition. Uncovering how these choice patterns influence the 'net' share increase from price cuts and store-flyer appearances for both parties may provide guidance for feature-ad investments and targeting.

Below, we briefly review relevant background literature. We then outline the methodology, followed by a description of the data and setting. Having presented the estimation results, we identify the resulting patterns of brand-store competition and ensuing feature effects. We end with a discussion of implications, limitations, and future research areas.

## 2. Background

### *2.1. Impact of feature promotions on brand and store choice*

An extensive body of literature has documented the impact of feature ads in a wide range of CPG categories (e.g. Ailawadi, Harlam, César, & Trounce, 2006; Ataman, Mela, & van Heerde, 2008; Gázquez-Abad & Martínez-López, 2016; Gupta, 1988; Haans & Gijsbrechts, 2011; Narasimhan, Neslin, & Sen, 1996; van Heerde et al., 2004; Zhang, 2006). An established finding from these papers is that features for CPG products may lead to both substantial brand switching *and* shifts in purchase location where the latter mostly take the form of indirect store switching (i.e. consumers reallocating category purchases among stores they visit anyway) (Guyt & Gijsbrechts, 2014). Moreover, extant studies indicate that the (relative) size of these brand and store switching components strongly affects the net promotion benefits for the manufacturer and the retailer (Srinivasan et al., 2004).

The majority of these studies, however, have been conducted on an aggregate level, using market- or store-wide data to document promotional changes in brand and store-category sales (e.g. Srinivasan et al., 2004; van Heerde et al., 2004). Yet, households are known to be heterogeneous in their purchase patterns and choices: some being more committed to their favorite brand(s) and/or likely to engage in cross-store shopping, others being more willing to switch brands yet stay with their usual store(s) (Bucklin & Gupta, 1999). Given that households' choice processes determine the competitive shifts among choice options, the magnitude of the promotion response (i.e. whether a consumer is enticed by a feature ad for a certain brand and store) as well as the sources of the promotion bump (i.e. the portion that stems from brand and/or store switching) may well vary depending on their choice mechanisms regarding what and where to buy (e.g. Gupta, 1988; Zhang, 2006). Nevertheless, extant studies on individual households' response to (feature) promotions have either focused on brand choice (e.g. Mehta & Ma, 2012), or store choice (e.g. Gauri et al., 2008), but have not considered the interplay between the two – something we turn to below.

### *2.2. Choice patterns and promotional brand-store switching*

CPG categories present consumers with multiple options on what to buy (i.e. which brand), and where (i.e. at which store). Consumers' brand selection is based on the brands' utility, which is driven by their familiarity, availability, intrinsic quality, price and promotional offers (e.g. Ataman et al., 2008). The 'where' decision is governed by the shopping costs/utilities of alternative stores, which have a fixed component (depending on the travel time and distance to, and familiarity with the store) and a variable component (depending on the store's assortment, prices and promotions for items on the consumer's shopping list (Bell, Ho, & Tang, 1998; Briesch, Chintagunta, & Fox, 2009; Rhee & Bell, 2002).

Temporal factors like feature promotions, may alter these utilities and give consumers an incentive to 'change allegiance' (Rhee & Bell, 2002). Whether, and how, consumers respond to such factors depends on their switching costs (Campo, Gijsbrechts, & Nisol, 2000). As indicated by Campo et al. (2000), the cost of switching brands includes the utility loss from moving to a less familiar and possibly lower-quality brand. The cost of switching stores, in turn, comprises changes in fixed shopping cost (e.g. having to travel to a more remote or less familiar store, having to incur an extra visit) and/or variable shopping costs (e.g. having to also switch other items on the shopping list for which the new store has lower appeal).

The relative level of these costs is bound to differ between consumers, and drive their choice (switching) patterns (Throughout the text, we use the terms 'choice patterns' and 'switching patterns' interchangeably). For some consumers (for instance, infrequent shoppers for whom accessible stores are more remote and geographically spread, Gauri et al., 2008), the costs of switching stores are quite prohibitive, whereas (possibly because they view brand qualities as similar, or value variety) the costs of switching brands are not. We expect such consumers to exhibit a 'store focus' choice pattern, i.e. to primarily switch among brands available within a visited, focal store. For other consumers, changing brands implies a large utility loss (e.g. because they are risk-averse and/or perceive brands as differentiated), while store switching is far less 'costly' (e.g. because they frequently shop at multiple stores, such that they can easily engage in "indirect store switching", i.e. shift the purchase of a particular brand between those locations and visits; Bell & Lattin, 1998; Guyt & Gijsbrechts, 2014). Such consumers are bound to follow a 'brand focus' pattern, i.e. to primarily switch between the offers of different stores carrying their focal brand.

We contend that within a category, each pattern comes with different feature-ad effects for manufacturers and retailers. For one, factors that drive consumers' brand vs. store switching costs may also affect their sensitivity to feature ads. For instance, consumers who primarily shop around for a particular brand ('brand focus'), may be more alert to price offers (Vanhuele & Drèze, 2002) and/or more actively look for brand appearances in the store flyer. Conversely, consumers who tend to concentrate purchases at one store to save on shopping time ('store focus') may be less inclined to search flyers. So, depending on the focal pattern, the promotion lift (i.e. choice-share increase of the featured brand-store alternative) may already be different.

More importantly, though, the consumers' choice patterns affect the underlying 'competitive shifts' between manufacturers and retailers. For the manufacturer, promoting its NB at a given store is more likely to: (i) lead to share gains at the expense of other brands in the store in case of a store-focused choice pattern, yet (ii) induce consumers who would buy the brand anyway to merely shift locations in a brand-focused pattern. Similarly, for the retailer, featuring a NB in the store flyer will primarily lead to within-store brand shifts in case of a store focus, and to store switches in case of a brand focus. For either party, the net promotion gain will thus depend on the type of choice pattern, but also on the degree of disproportionality within the pattern, i.e. the 'strength' of consumers' tendency to stick to same-brand alternatives (in the brand focus) or to same-store alternatives (in the store focus).

### *2.3. Heterogeneity in choice patterns*

As argued above, adherence to a brand-store choice pattern and feature responsiveness within that pattern depend on consumer characteristics. On the one hand, consumers differ in their opportunity cost of time and access to alternative stores, which drive their visit timing (weekend vs. week), visit frequency and number of stores visited (Baltas et al., 2010; Gauri et al., 2008). Households' overall and category-specific needs, also, affect their inclination to shop around (e.g. Baltas et al., 2010; Haans & Gijsbrechts, 2011). These, in turn, determine the possibility of indirect store switching (i.e. of simply shifting the brand purchase to the promoting store which is visited anyway), and/or the cost of direct store switching (i.e. of engaging in an extra trip to buy the promoted brand - or shifting the entire shopping basket - at the promoted store). On the other hand, consumers are heterogeneous in their brand- preference strength, risk aversion and degree of variety seeking, factors that will drive their cost of switching brands. Together, these characteristics will shape which cost component prevails, and whether the consumer's choices are store-focused vs. brand-focused.

Moreover, product category characteristics may play a role. For frequently-needed categories (e.g. coffee, where indirect store switching is less of an option), consumers are less likely to shop around for a particular brand, but rather engage in a category purchase ("pick a product from the shelf") whenever they shop at a given store (Gijsbrechts et al., 2008; Krider and Weinberg, 2000) – consistent with a store focus. Conversely, one expects consumers to rather maintain a brand focus for categories where quality differentiation (and hence the cost of brand switching) is high (Bell, Chiang, & Padmanabhan, 1999). Category concentration may matter as well, though the impact on pattern adherence is not clear upfront: On the one hand, presence of only a few dominant brands could enhance brand loyalty (Narasimhan et al., 1996) and induce a brand focus; on the other hand, it could be indicative of taste homogeneity and make stores' assortments more likely to overlap (which fosters a store focus). In all, depending on the category, the 'what' and 'where' decisions may be more or less prevalent.

In the remainder of this paper, we empirically examine the prevalence of the two proposed choice patterns, and the implications of feature ads for the promoted brand-store alternative in each of these patterns. We then zoom in on the net share gains for the manufacturer and retailer under the different choice patterns, and explore their underlying drivers. In the next section, we present the model that allows us to assess these issues.

## 3. Methodology

To answer our research questions, we need a (i) household-level model that (ii) considers both brand and store choice within a category, (iii) allows for different switching patterns, with (iv) possibly differential marketing mix effects across these patterns, and (v) unobserved household heterogeneity within patterns. The Mixed-pattern Random-effects Nested Logit (MRNL) model that we propose meets these requirements.

### 3.1. Model structure

Let $c$ be a category indicator, $h$ be a household indicator, and $t$ an indicator for a category purchase occasion (trip). We use $b$ and $j$ as brand indicators, and $r$ and $s$ to denote stores. On each category purchase occasion, $t$, the household selects a brand-store combination ($br$) from the available brands and stores (any combination $js$) based on its utility.

As a starting point, one could model this choice through a (random coefficients) MNL specification, in which the utility for a specific brand-store combination is given by:

$$\begin{aligned} U_{c,h,br,t} &= V_{c,h,br,t} + \varepsilon_{c,h,br,t} \\ &= X_{c,h,br,t}\beta_{c,h} + \varepsilon_{c,h,br,t} \end{aligned}$$

where $V_{c,\ h,\ br,\ t}$ are the systematic utility components, $X_{c,\ h,\ br,\ t}$ is a vector of observable utility drivers, $\beta_{c,\ h}$ is the corresponding parameter vector, which we assume to be normally distributed across households, and $\varepsilon_{c,\ h,\ br,\ t}$ are independent extreme value-distributed unobserved components. With utility-maximizing consumers, the probability that household $h$ buys brand $b$ in store $r$, given a category purchase at time $t$, would then be given by:

$$P_{c,h,br,t} = \frac{\exp\left(V_{c,h,br,t}\right)}{\sum_j \sum_s \exp\left(V_{c,h,js,t}\right)}$$

This random-coefficients MNL model has several appealing properties: it is consistent with random utility maximization (RUM), offers a closed-form probability expression, and allows for unobserved heterogeneity in households' response to the utility drivers. However, for any given household, it imposes IIA substitution patterns: changes in a utility driver for one choice alternative producing a change in the choice probability of other alternatives in proportion to its original level:

$$\frac{\partial P_{c,h,br,t}}{\partial X_{c,h,js,t}} = -\beta_{c,h} P_{c,h,js,t} * P_{c,h,br,t}$$

This is a deficiency in our setting. Indeed, while the "proportional" substitution assumption is often-used and quite acceptable when modeling consumers' choice among stores (see, e.g. Bell et al., 1998; Briesch et al., 2009; Briesch, Dillon, & Fox, 2013) or, alternatively, brands (Erdem, Zhao, & Valenzuela, 2004; e.g. Guadagni & Little, 1983; Shin, Misra, & Horsky, 2012), it becomes questionable if one considers the tradeoff between brand-store combinations, some choice alternatives pertaining to different brands in the same store, others to the same brand in different stores.

In the presence of groupings, a natural way to break IIA is to generalize the MNL model to a Nested logit structure (Train, 2009). In such model, choice alternatives are grouped into mutually exclusive nests and, while the random utility components of alternatives in different nests are still independent, they are now allowed to be correlated within nests. For instance, if we would place brand-store combinations that pertain to the same store in one 'nest', the (random coefficients) nested logit model would be:

$$U_{c,h,br,t,focus_{store}} = V_{c,h,br,t,focus_{store}} + \varepsilon_{c,h,br,t,focus_{store}} = \beta_{c,h,focus_{store}} X_{c,h,br,t} + \varepsilon_{c,h,br,t,focus_{store}} \tag{1}$$

where the random utility components would now follow a generalized extreme value distribution (GEV) function given by $\exp\left(-\sum_s \left(\sum_j e^{\varepsilon_{c,h,sj,t}} \Big/ _{\gamma_{c,store}}\right)^{\gamma_{c,store}}\right)$ with 'nesting parameter' $\gamma_{c,\ store}$; and where $(1-\gamma_{c,\ store})$ is an indicator of the degree of correlation among the unobserved utility components of choice alternatives within a store nest (see, e.g., Train, 2009 p. 79). The choice probabilities associated with this structure are given by:

$$\begin{aligned} P_{c,h,br,t|focus_{store}} &= \left[\frac{\exp\left(V_{c,h,br,t,focus_{store}}/\gamma_{c,store}\right)}{\exp\left(IV_{c,h,.r,t,focus_{store}}\right)}\right] * \left[\frac{\exp\left(IV_{c,h,.r,t,focus_{store}}{}^{*}\gamma_{c,store}\right)}{\sum_s \exp\left(IV_{c,h,.s,t,focus_{store}}{}^{*}\gamma_{c,store}\right)}\right] \\ &= [P_{c,h,br,t|focus_{store}} \mid r]^{*}[P_{c,h,.r,t|focus_{store}}] \end{aligned} \tag{2}$$

where $P_{c,\ h,\ .\ r,\ t|focus_{store}}$ is the total share of store $r$ (summed across brands), and $IV_{c,\ h,\ .\ r,\ t,\ focus_{store}}$ is the inclusive value of store r (i.e. the expected maximum utility across brands in the store), given by $IV_{c,h,.r,t,focus_{store}} = \ln(\sum_j \exp(V_{c,h,jr,t,focus_{store}}/\gamma_{c,store}))$.

This model remains consistent with RUM as long as the nesting parameter is between zero and one (Koppelman & Wen, 1998). Moreover, though still IIA within a nest, it now allows for more flexible substitution patterns among alternatives. This is clear from the marginal cross-effects:

$$\frac{\partial P_{c,h,br,t|focus_{store}}}{\partial X_{c,h,js,t}} = -\beta_{c,h,focus_{store}} P_{c,h,js,t|focus_{store}} * P_{c,h,br,t|focus_{store}}$$

for alternatives in a different store ($r{=}/{=}s$), and

$$\frac{\partial P_{c,h,br,t|focus_{store}}}{\partial X_{c,h,jr,t}} = -\beta_{c,h,focus_{store}}\left(P_{c,h,jr,t|focus_{store}} + \left(\frac{1}{\gamma_{c,store}} - 1\right) * P_{c,h,jr,t|focus_{store}}|r\right) * P_{c,h,br,t|focus_{store}}$$

for same-store alternatives. As these expressions show, for $0 < \gamma_{c,\ store} < 1$, changes in a utility driver (e.g. a feature promotion) of a brand in a given store, have more pronounced effects on other brands in the same store compared to different stores. This is what we expect for consumers with a store focus.

However, based on our conceptualization, households may alternatively exhibit a brand focus. In that case, the appropriate grouping would be to place same brand alternatives in one nest, and the model would become:

$$U_{c,h,br,t,focus_{brand}} = V_{c,h,br,t,focus_{brand}} + \varepsilon_{c,h,br,t,focus_{brand}} = \beta_{c,h,focus_{brand}} X_{c,h,br,t} + \varepsilon_{c,h,br,t,focus_{brand}} \tag{3}$$

with GEV random components, and choice probabilities given by:

$$\begin{aligned} P_{c,h,br,t|focus_{brand}} &= \left[\frac{\exp\left(V_{c,h,br,t,focus_{brand}}/\gamma_{c,brand}\right)}{\exp\left(IV_{c,h,b.,t,focus_{brand}}\right)}\right] * \left[\frac{\exp\left(IV_{c,h,b.,t,focus_{brand}}{}^{*}\gamma_{c,brand}\right)}{\sum_j \exp\left(IV_{c,h,j.,t,focus_{brand}}{}^{*}\gamma_{c,brand}\right)}\right] \\ &= \left[P_{c,h,br,t|focus_{brand}}|b\right] * \left[P_{c,h,b.,t|focus_{brand}}\right] \end{aligned} \tag{4}$$

with $0 < \gamma_{c,\ brand} < 1$, and where $P_{c,\ h,\ b.\ ,\ t|focus_{brand}}$ is the total share of brand $b$ (summed across stores), and $IV_{c,\ h,\ b.\ ,\ t,\ focus_{brand}}$ is the inclusive value of brand b (i.e. its expected maximum utility across stores), given by $IV_{c,h,b.,t,focus_{brand}} = \ln(\sum_s \exp(V_{c,h,bs,t,focus_{brand}}/\gamma_{c,brand}))$.

The pattern of marginal cross-effects now implies IIA substitution within a brand nest, but allows for weaker substitution across than within nests:

$$\frac{\partial P_{c,h,br,t|focus_{brand}}}{\partial X_{c,h,bs,t}} = -\beta_{c,h,focus_{brand}}\left(P_{c,h,bs,t|focus_{brand}} + \left(\frac{1}{\gamma_{c,brand}} - 1\right) * P_{c,h,bs,t|focus_{brand}}|b\right) * P_{c,h,br,t|focus_{brand}}$$

for same-brand alternatives,

$$\frac{\partial P_{c,h,br,t|focus_{brand}}}{\partial X_{c,h,js,t}} = -\beta_{c,h,focus_{brand}} P_{c,h,js,t|focus_{brand}} * P_{c,h,br,t|focus_{brand}}$$

for alternatives involving a different brand (b=/=j).

Because we do not observe which of these substitution patterns (store, or brand) a household adheres to,[1] we use a latent class approach, in which households have a (latent) propensity of being assigned to the store-focused or the brand-focused segment, and the probability that household $h$ selects brand $b$ from store $r$ on category purchase occasion $t$ becomes a mixture of expressions (2) and (4):

$$P_{c,h,br,t} = \Psi_{c,h,focus_{store}} * P_{c,h,br,t|focus_{store}} + \Psi_{c,h,focus_{brand}} P_{c,h,br,t|focus_{brand}} \tag{5}$$

where $\Psi_{c,\ h,\ focus_{store}}$ and $\Psi_{c,\ h,\ focus_{brand}}$ are the (prior) probabilities that household $h$ is in the store-focused or brand-focused segment for category $c$.[2] As indicated in the conceptual part, we expect households' tendency to exhibit a store or a brand focus, to be household- and category-specific. As such, we use a concomitant variable approach, in which we specify the segment membership probabilities as a function of category and household characteristics:

$$\Psi_{c,h,focus_{brand}} = \frac{e^{\alpha_{0,h}+\sum_{l=1}^{L}\alpha_l * Z_{c,h,l}}}{1+e^{\alpha_{0,h}+\sum_{l=1}^{L}\alpha_l * Z_{c,h,l}}} \text{ and } \Psi_{c,h,focus_{store}} = 1-\Psi_{c,h,focus_{brand}} \tag{6}$$

where $a_{0,\ h}$ are random-effect parameters assumed to be normally distributed across households, and $Z_{c,\ h,\ l}$, $l = 1, \ldots, L$; represent category and household characteristics (which we list in detail in the operationalization section) with coefficients $a_l$.

Together, expressions (1) to (6) make up our full model, which we refer to as the 'Mixed-pattern Random-effects Nested Logit' (MRNL) model. Several points are worth noting. First, this latent class choice model allows households to exhibit different choice patterns, in a parsimonious way[3] that is still consistent with RUM as long as each of the nesting parameters are between zero and one (Koppelman and Wen 1998). By specifying the membership probabilities as a function of household- and category drivers, it allows managers not only to gauge the size of the brand-focused vs. the store-focused segment for their categories, but also to target those segments with tailored promotion strategies.

Second, as indicated earlier, while the two nesting structures differ in the *nature* of the disproportionality, i.e. *whether* disproportional substitution occurs among alternatives of the same store (store focus pattern) or of the same brand (brand focus pattern); the nesting parameters further reflect the *degree of disproportionality within each pattern*: In the store focus pattern, $\gamma_{c,\ store}$ governs the intensity of competition within stores, in the brand-nesting structure, $\gamma_{c,\ brand}$ governs the degree of competition within the national-brand nests. A nesting parameter closer to (0) 1 indicates a (stronger) weaker within-group competition/substitution effect. The model collapses to a model with proportional switching among all brand-store alternatives (similar to the MNL-model) if both $\gamma_{c,\ store}$ and $\gamma_{c,\ brand}$ equal 1. Because we expect that, even for consumers that are store-focused (brand-focused), this degree of disproportionality may differ between categories (for instance: even store focused consumers may be more inclined to shop around for diapers than for toilet tissue), we allow the nesting parameters to be category-specific.

Third, in the spirit of Swait, Brigden, and Johnson (2014) we allow the coefficients of the utility drivers (including feature ads) to differ between the two choice patterns. Moreover, because households can differ not only in the structure of their choice patterns but also in their sensitivity to utility drivers (read: promotions) within these patterns, we allow for unobserved heterogeneity.[4] We use normal mixing distributions for the parameter vectors $\beta_{c,\ h,\ focus_{store}}$ and $\beta_{c,\ h,\ focus_{brand}}$, the means and standard deviations of which are choice-pattern specific.

Fig. 1 provides an overview of the model structure. It also indicates how feature promotions intervene. We elaborate on the latter, and on other utility drivers, below.

### 3.2. Utility drivers

Our main purpose is to assess the impact of feature promotions on brand-store choice. We include a dummy variable (*Feature*), which equals one if the brand is on feature in the flyer of the considered store in that week, and zero otherwise. Because feature-ad response may depend on the actual offer, we add a separate variable for promotional price cuts (*Discount*) and also include its interaction with the feature variable.

To separate out the feature effect from other factors, we control for various previously identified drivers of brand and store utility. The brand-specific controls comprise a set of brand dummies (to capture differences in 'base' preference between brands), a dummy indicating whether the household's last category purchase pertained to the same brand (*State Dependence Brand*), and the brand's

[1] Of course, alternative nesting structures are conceivable. We focus on brand vs. store nests here, because they are aligned with our conceptual focus and meaningfully carry through to multiple categories.

[2] We emphasize upfront that, like the Nested Logit model, our model does not impose (nor document) a strict decision sequence on the part of consumers. Rather, it documents asymmetries in consumers' ultimate choice switches among brands and stores, through a flexible pattern of correlations among their random utility components. As such, in our empirical analysis, 'choice pattern' (or 'substitution pattern') refers to the pattern of choice outcomes: brand-focused consumers are those with stronger probability shifts between stores than brands, and store-focused consumers those with stronger probability shifts between brands than stores.

[3] An even more flexible approach to break IIA would be a multinomial probit model with freely estimated variance-covariance matrix of the unobserved utility components. However, given the large number of brand-store alternatives, such a model would be intractable here, and lead to unstable parameters. Moreover, instead of providing closed-form probability and elasticity expressions, the substitution patterns would only be revealed through the error covariances (which, as underscored by Train 2009, p. 108–109, may not be interpretable directly), and it would be hard to handle household heterogeneity in the substitution patterns.

[4] As such, our model is a generalization of Grigolon and Verboven's (2014) random-coefficients nested logit specification, and of Keane and Wasi's (2013) latent class mixed MNL model.

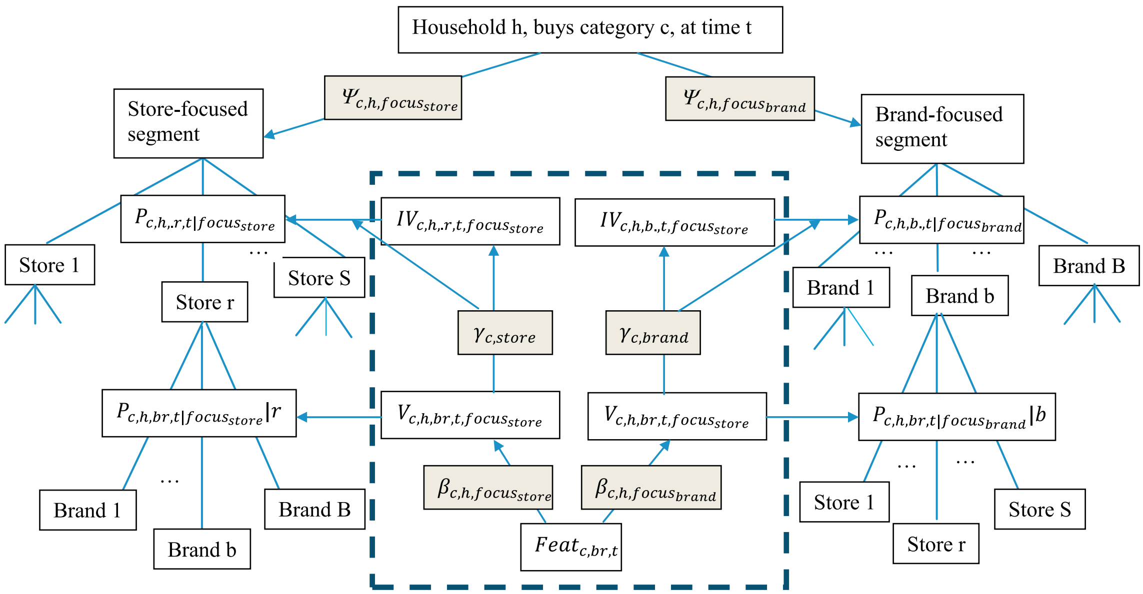


**Fig. 1.** Model overview.

regular price level (*Price*) and number of SKUs (*Assortment*) in the considered store. As for store-level controls, we include as determinants of fixed shopping utility: the retailer's share of the household's trips in an initialization period (*Retailer Share*), and the household's distance to the store (*Distance*). The variable shopping utility depends on the store's appeal for the focal category (which, next to the brand prices and assortments, is taken up by retailer dummies[5] and a dummy indicating whether the household's last category purchase pertained to the same retailer; *State Dependence Retailer*), but, as indicated by Bell et al. (1998), also on other categories that the consumer needs. To accommodate this, we adopt an approach similar to Briesch et al. (2009, 2013): we first predict which categories are on the household's shopping list on a given trip, based on its use rate and previous purchases; and use these predictions to calculate, for each store, household and trip, a *Basket-price*, *Basket-assortment* and *Basket-promotion* variable reflecting the store's overall marketing mix for the needed categories. Details of this approach are provided in Web Appendix 1.

### *3.3. Drivers of segment membership*

As drivers of segment membership, we incorporate household and category characteristics that may affect the costs of brand and store switching. Store switching costs may decrease with households' overall shopping frequency, number of accessible (local) stores and category-assortment overlap across stores – making a brand focus more likely, while the reverse is expected for households who mainly shop at a high-end store, shop mostly during weekends, and buy the category more frequently. Households may have higher brand switching costs, and be more prone to exhibit a brand-focus, in categories with more quality differentiation and fewer brands, and if their main brand is a leading national brand. We also include age and household size, as previous literature has shown a link with consumers' shopping cost and brand adherence (Baltas et al., 2010). Finally, to explore whether there is a link with consumers' general price consciousness and tendency to engage in price search, we consider two items from a survey administered by GfK among its panel members capturing these constructs. Table 1 gives an overview of the variables and their operationalization.

### *3.4. Estimation*

We estimate the model with simulated maximum likelihood, using an EM (expectation-maximization) procedure (see e.g. Train, 2009, p. 355–360). In the *E*-step, we estimate the parameters of the segment membership probabilities across all households and categories, for given parameters in Eqs. (1) to (4). In the M-step, we fix these estimates and assess the parameters of the utility drivers and the nesting parameters. For reasons of tractability, we perform this M step by category. We iterate between the E-step and the M-step until convergence is reached, and initialize the procedure by first estimating the category models (1) to (5) with fixed segment sizes for each category. Details on the likelihood expression and estimation strategy can be found in Web Appendix 2. To ensure positive values of the nesting parameters, we estimate the log-transform of these parameters. Similarly, to ensure segment-membership probabilities between zero and one, and summing to one, we use a logit transformation

[5] Because we specify the choice model by category, the store intercepts reflect the appeal of the store for that category.

**Table 1**
Variables and operationalization.

Panel A: utility drivers

| Variable name | Operationalization |
|---|---|
| Feature | Dummy equal to 1 if there was a feature promotion for (more than half of the brand's SKU line) at the retailer in that week, and 0 otherwise |
| State dependence retailer | Dummy equal to 1 if household's last purchase in the category occurred at the same retailer, and 0 otherwise |
| State dependence brand | Dummy equal to one if the same brand was purchased on the household's last purchase in the category, and zero otherwise |
| Assortment | Number of SKUs in the brand's line at the retailer (prior moving average of number of SKUs encountered in the panel, over 26 weeks) |
| Price | Average price per unit volume (across SKUs) for a brand in a given week, as observed in the panel data. Missing observations were replaced by four-week moving average of the brand price at the same retailer, outliers (>5 SD) were replaced by the series mean |
| Discount | Difference between the brands' regular and promotion price, where promotion prices are identified as prices more than one standard deviation below the mean (similar to Geyskens, Gielens and Gijsbrechts 2010) |
| Retailer basket promotion | Mean-centered promotion pressure across categories for each retailer, weighted by household category and retailer share (in initialization period), as well as the category need for each household (see Web Appendix 1) |
| Retailer basket assortment | Mean-centered assortment availability across categories for each retailer, weighted by household category and retailer share (in initialization period), as well as the category need for each household (see Web Appendix 1) |
| Retailer basket price | Mean-centered price levels across categories for each retailer, weighted by household category and retailer share (in initialization period), as well as the category need for each household (see Web Appendix 1) |
| Retailer share (hh) | Household-specific retailer share of visits in the initialization period |
| Brand share (hh) | Household-specific brand share of category purchases in the initialization period |
| Distance | Log-transformed distance (in km) of household to the closest outlet of each retailer (updated quarterly) |

Panel B: drivers of segment membership

| Variable name | Operationalization |
|---|---|
| Dependent variable | |
| *Brand_Focus_Member* | Latent |
| Explanatory variables | |
| Household: | |
| Shopping frequency | Average weekly number of trips per household |
| Price consciousness (reverse scaled) | Survey item[a], rated between 1 (not at all price conscious) and 4 (highly price conscious) |
| Cross-price comparison (reverse scaled) | Survey item[a]: "Before I buy something, I check whether it is not cheaper elsewhere", rated between 1 (completely agree) and 5 (fully disagree) |
| Fraction trips on weekends | Fraction of the household's total shopping trips on weekend-days rather than weekdays |
| Retailer density | Number of stores within 5-km radius |
| Household size | Number of persons in household |
| Main Hi end store | Whether store indicated by household as their "main store", is a high-end chain (Albert Heijn or Super de Boer); (GfK Survey) |
| Main Hi end brand | Whether most-often bought brand by household in category, is a high-end brand |
| Age head of household | Age of head of household (Based on mean age in 11 categories provided by GfK). |
| Category: | |
| Assortment overlap | Category specific availability of brands at retailers $\frac{\sum_{\text{brands}}\left(\frac{\#\text{of rets with brand}}{\#\text{of rets}}\right)}{\#\text{of brands}}$ |
| Quality differentiation | Average rating from three independent experts on "In this category, there are big differences in quality between the various brands" (1: strongly disagree – 5: strongly agree)" (Vroegrijk, Gijsbrechts, & Campo, 2016) (mean-centered across categories, Cronbach's alpha: 0.73). |
| Number of brands | Number of brands in the category |
| HH-category: | |
| Purchase frequency | Number of times household purchased from category |

[a] Based on a survey administered by GfK among its panel members.

(see Zhang & Breugelmans, 2012 for a similar approach, and Table 5). To test for predictive power, we split the sample into an estimation sample (the first 90% of each panelist's trips) and a holdout sample (with the remaining 10% last trips).

## 4. Data and setting

### 4.1. Setting

To examine consumers' brand-store choice patterns for grocery items, we use panel data comprising household purchases in the CPG-industry in the Netherlands, spanning a period of 4 years (2007–2011). We study the households' purchases in 16

**Table 2**
Category descriptives[a].

| Category | # of brands | # of choice alternatives across all 8 stores | Average # of purchases/hh | Average # of different brands/hh | Average # of different stores/hh | Concentration (share of top 3 national brands) | Quality differentiation[b] |
|---|---|---|---|---|---|---|---|
| Beer | 13 | 52 | 56 | 4.10 | 2.90 | 0.07 | 1.150 |
| Chocolate bars | 14 | 43 | 34 | 3.87 | 2.77 | 0.21 | 0.490 |
| Coffee | 9 | 25 | 65 | 3.16 | 2.98 | 0.28 | 0.820 |
| Custard | 10 | 27 | 81 | 4.40 | 2.95 | 0.25 | 0.150 |
| Diapers | 8 | 23 | 34 | 3.06 | 2.53 | 0.17 | 0.820 |
| Dish soap hands | 11 | 26 | 15 | 2.51 | 2.21 | 0.16 | 0.150 |
| Dog food | 16 | 38 | 96 | 3.82 | 2.94 | 0.23 | −0.180 |
| Frozen pizza | 7 | 20 | 38 | 3.04 | 2.54 | 0.48 | 0.490 |
| Hairspray | 9 | 30 | 15 | 2.38 | 2.00 | 0.15 | 1.150 |
| Ketchup | 9 | 31 | 17 | 2.69 | 2.29 | 0.29 | −0.180 |
| Kitchen tissue | 16 | 39 | 21 | 3.74 | 2.40 | 0.09 | −0.510 |
| Laundry detergents | 13 | 46 | 21 | 3.49 | 2.42 | 0.16 | 1.150 |
| Margarine | 10 | 30 | 50 | 3.08 | 2.77 | 0.25 | −0.510 |
| Mayonnaise | 10 | 35 | 22 | 2.95 | 2.37 | 0.18 | −0.180 |
| Muesli | 13 | 31 | 27 | 3.16 | 2.47 | 0.20 | 1.150 |
| Toilet Tissue | 14 | 29 | 28 | 3.37 | 2.48 | 0.13 | −0.180 |

[a] Descriptives in all but the last column originate from the panel data described in the data section.
[b] Measures taken from (Vroegrijk et al., 2016), we thank the authors for making the data available.

different categories, listed in Table 2. These categories constitute a varied set, including food (frozen pizza, custard, muesli, chocolate bars and margarine), condiments (mayonnaise and ketchup), drinks (coffee and beer), personal care (hairspray, diapers and toilet tissue), household care (laundry detergents and dish soap), and other (dog food). The category share of retailer sales varies between 0.02% (hairspray) and 2.20% (beer) – figures that, for a given category, are similar across retailers.

For each shopping trip on which a category purchase is made, we consider which brand was chosen and where the purchase took place.[6] We include the top 7 retail chains, which jointly cover 60% of the Dutch grocery market, and group the remaining retailers into a 'rest' retailer. These chains' flyers are widely distributed physically, as well as accessible online (on the retailer's website and/or through comparison websites). For each category, we consider the top brands that, together, make up 80% of the (cross-retailer) sales within the category. If a brand contributes >10% of the sales within a specific retailer, we also retain it, leading to the inclusion of standard private labels in our setting.[7] Lastly, we consider a brand to be available at a retailer if its sales within the retailer exceed 1% of the total retailer-category sales (if a brand is not available at a retailer, that brand-store combination is not a choice option). We group the remaining brands into a 'rest' brand. We estimate the model on a random subsample of 300 households that buy from the considered categories and stay in the panel for at least 2 years.

### *4.2. Descriptives*

Table 2 presents category descriptives. The categories show wide variation in level of concentration (share of the top three national brands ranging between 9% for kitchen tissue and 48% for frozen pizza), purchase frequency (custard and dog food being the most and dish soap and hairspray the least often-bought categories), and quality differentiation (which is low for, e.g., kitchen tissue and margarine, and high for laundry detergents and hairspray). Each household typically buys more than one brand per category in the studied period (the average ranging from 2.38 in the hairspray category to 4.4 for custard) and procures each category from more than one retailer (2.6 on average). This further underlines the need to take multiple retailers into account when analyzing household responses to promotions.

Table 3 documents the feature activity of brands and retailers, indicating that there is ample opportunity and incentive for households to engage in promiscuous shopping behaviour. In select categories, brands are on feature within a single retailer roughly one out of every five weeks (e.g. toilet tissue: the 'average' brand is on feature in 21% of the weeks) and retailers advertise at least one product in their flyer every week (e.g. for beer, the average retailer has a likelihood of 0.66 that any NB has a promotion), whereas in other categories (e.g. margarine), retailers tend to only have a product on feature once every 10 weeks (e.g. the likelihood of any NB being on promotion at the 'average' retailer being 0.10) and specific brands are promoted even less frequently. Looking across retailers, chances of finding a specific brand on promotion at any of the retailers can be as high as 1 (e.g. the Fig. 1.03 for toilet tissue meaning that at least one store is carrying the brand on promo) to more moderate figures (e.g. for frozen pizza: 0.50, indicating

[6] As our model is at the trip level, we can easily handle consumers shopping for a category at different stores within a week. Only 1.1% of our trips are chained trips involving a category purchase at different stores visited during the same part of day. Because we do not know the temporal sequence of those visits, we treat them as separate trips.
[7] Though our primary interest is in the impact of feature ads for national brands in the store flyers of traditional retailers, to capture all options availabe to consumers, our choice model also includes standard PL brands and hard-discount retailers, along with their feature ads. Some chains also offered economy private labels and premium private labels, but these were too small to be part of the 'top brands' list, and thus taken up in the 'rest brand'.

**Table 3**
Feature promotion descriptives[a].

| Category | (Average) number of promotions per week for a *specific* brand at a *specific* retailer[b] | (Average) number of promotions per week for *any* brand at a *specific* retailer[c] | (Average) number of promotions per week for a *specific* brand at *any* retailer[d] | (Average) discount depth in case of a feature promotion |
|---|---|---|---|---|
| Beer | 0.10 | 0.66 | 0.51 | 0.10 |
| Chocolate bars | 0.05 | 0.19 | 0.21 | 0.08 |
| Coffee | 0.10 | 0.20 | 0.50 | 0.07 |
| Custard | 0.08 | 0.14 | 0.38 | 0.07 |
| Diapers | 0.10 | 0.19 | 0.50 | 0.09 |
| Dish soap hands | 0.09 | 0.18 | 0.46 | 0.08 |
| Dog food | 0.01 | 0.02 | 0.02 | 0.06 |
| Frozen pizza | 0.13 | 0.20 | 0.50 | 0.09 |
| Hair spray | 0.02 | 0.11 | 0.12 | 0.04 |
| Ketchup | 0.03 | 0.09 | 0.17 | 0.08 |
| Kitchen tissue | 0.06 | 0.21 | 0.28 | 0.15 |
| Laundry detergents | 0.15 | 0.67 | 0.70 | 0.07 |
| Margarine | 0.03 | 0.10 | 0.17 | 0.08 |
| Mayonnaise | 0.03 | 0.10 | 0.14 | 0.11 |
| Muesli | 0.04 | 0.12 | 0.22 | 0.08 |
| Toilet tissue | 0.21 | 0.39 | 1.03 | 0.11 |

[a] Fractions calculated for all NBs at traditional supermarkets.
[b] Weekly average of the number of brands that have a feature promotion divided by the total number of brands in a given retailer.
[c] Fraction of weeks in which a specific brand is on feature at a specific retailer.
[d] Weekly average of the number of retailers that have a feature promotion for a specific brand, divided by total number of retailers.

that roughly every two weeks the NB will be on promo at at least one retailer). For feature ads accompanied by a price cut (about 30% of the cases), the average price discount ranges between 4% (hairspray) and 15% (kitchen tissue) of the regular price.

On the whole, these descriptives show that households do patronize a variety of stores and opt for different brands, and that feature ads are frequently used by manufacturers and retailers to influence this selection process. The question remains: how do these choices come about, and what are the shifts produced by the store flyer ads under different choice patterns? Our MRNL model sheds light on this issue.

## 5. Results

### 5.1. Model fit and estimation results

For each category, we estimate a series of four models (three benchmark models and the 'full' MRNL model). As benchmarks we consider (i) a random-effects MNL model, (ii) a random-effects nested logit (NL) model with alternatives nested within a store, and (iii) a random-effects NL model with alternatives nested within a brand. We note that these models are special cases of our proposed MRNL model. Table 4 provides an overview of the models, along with some key fit statistics. The results show that the proposed MRNL specification outperforms each of the benchmark models; in-sample (with lower AIC, AIC3 and BIC values) as well as in the holdout period (higher loglikelihood).

Table 5 summarizes the estimates of the MRNL model for each category. To save space, we report only the population-mean estimates (and their standard errors) for the focal parameters, that is, the segment sizes, and the nesting parameters and feature coefficients for each of the two choice patterns (the full set of estimation results and posterior segment memberships are given in Web Appendix 3). Below, we discuss what these estimates imply for (the relative importance of) consumers' store vs. brand focus, and for the impact of feature ads on brand-store choice.

**Table 4**
Model fit.

| | In-sample | | | Out-of-sample |
|---|---|---|---|---|
| | AIC | AIC3 | BIC | LL |
| MNL | 428,658 | 429,742 | 439,553 | −50,396 |
| NL (Store) | 408,209 | 409,309 | 419,265 | −48,657 |
| NL (Brand) | 406,055 | 407,155 | 417,112 | −48,984 |
| MRNL | 396,419 | 396,853 | 416,865 | −47,815 |

**Table 5**
Estimation results[a].

Panel A: within-segment parameters[a]

| | Nesting parameter[b] | | Feature parameter[c] | | Feature * discount[c] | |
|---|---|---|---|---|---|---|
| | Store focus | Brand focus | Store focus | Brand focus | Store focus | Brand focus |
| Beer | −1.042 (0.132)** | −0.378 (0.045)** | 0.109 (0.038)** | 0.715 (0.066)** | 1.656 (0.402)** | 3.025 (0.629)** |
| Chocolate bars | −0.073 (0.068) | −0.206 (0.038)** | 0.54 (0.111)** | 1.039 (0.081)** | 2.485 (0.769)** | 0.826 (0.578) |
| Coffee | −0.554 (0.049)** | −0.329 (0.034)** | 1.209 (0.068)** | 0.867 (0.071)** | −3.706 (0.519)** | −1.276 (0.704)* |
| Custard | −0.729 (0.064)** | −0.4 (0.029)** | 0.697 (0.074)** | 0.618 (0.073)** | 0.676 (0.588) | 3.218 (0.822)** |
| Diapers | −0.734 (0.032)** | 0.022 (0.033) | 0.578 (0.044)** | 0.739 (0.079)** | 3.414 (0.227)** | 1.97 (0.426)** |
| Dish soap hands | −0.668 (0.106)** | −0.306 (0.094)** | 0.74 (0.163)** | 0.664 (0.171)** | 3.155 (1.065)** | 2.933 (1.203)** |
| Dog food | −1.536 (0.012)** | −0.814 (0.025)** | 0.13 (0.051)** | 0.364 (0.21)* | −0.203 (0.589) | −3.372 (3.296) |
| Frozen pizza | −0.575 (0.082)** | −0.146 (0.049)** | 0.455 (0.079)** | 0.714 (0.092)** | 2.358 (0.638)** | 0.759 (0.97) |
| Hairspray | −1.653 (0.512)** | −0.802 (0.168)** | 0.064 (0.057) | 0.478 (0.097)** | 0.581 (0.606) | 2.408 (0.75)** |
| Ketchup | −0.119 (0.107) | −0.488 (0.068)** | 0.875 (0.269)** | 0.691 (0.168)** | 2.381 (1.71) | −0.081 (1.296) |
| Kitchen tissue | −0.84 (0.139)** | −0.085 (0.077) | 0.579 (0.112)** | 1.45 (0.139)** | 1.116 (0.597)* | 1.606 (0.808)** |
| Laundry detergents | −0.357 (0.103)** | −0.304 (0.048)** | 0.825 (0.105)** | 1.452 (0.071)** | 1.338 (0.601)** | 0.214 (0.422) |
| Margarine | −0.38 (0.049)** | −0.415 (0.042)** | 0.69 (0.117)** | 0.459 (0.166)** | 2.759 (0.882)** | 2.146 (1.269)* |
| Mayonnaise | −0.416 (0.135)** | −0.505 (0.071)** | 0.911 (0.17)** | 0.919 (0.166)** | 0.872 (1.104) | 1.45 (1.1) |
| Muesli | −1.257 (0.134)** | −0.354 (0.059)** | 0.378 (0.072)** | 1.67 (0.119)** | 0.006 (0.374) | 1.557 (0.844)* |
| Toilet tissue | −0.651 (0.076)** | −0.239 (0.056)** | 0.996 (0.113)** | 0.862 (0.103)** | −0.754 (0.534) | 2.027 (0.659)** |

[a] * = $p < .05$, ** = $p < .01$. Standard errors of the estimates are between brackets.
[b] Nesting parameter is log-transformed for estimation purposes.
[c] For exposition purposes, we only report the means of the random coefficients here. The standard deviations of the mixing distributions are given in the Web Appendix.

Panel B: drivers of brand segment membership

| Variable | Estimate | Variable | Estimate |
|---|---|---|---|
| Constant: mean across households SD across households | −0.330 (0.378)<br>0.029 (0.044) | Cross-price comparison (reverse scaled) | −0.010 (0.034) |
| Shopping frequency | −0.001 (0.029) | Age head of household | 0.006 (0.003)* |
| Retailer density | −0.026 (0.020) | Assortment overlap | 0.247 (0.264) |
| Household size | −0.019 (0.033) | Quality differentiation | 0.138 (0.064)** |
| Main hi end store | −0.010 (0.076) | Number of brands | 0.043 (0.017)** |
| Main hi end brand | 0.165 (0.076)** | Purchase Frequency | −0.010 (0.006)* |
| Price consciousness (reverse scaled) | −0.023 (0.049) | Fraction Trips on Weekends | −0.696 (0.257)** |

[a] ** = $p < .05$, * = $p < .10$. Based on two-tailed tests (Standard errors of the estimates between brackets). Given the small sample size, we also consider a 10% significance cutoff.

### 5.2. Choice patterns

Starting from the model estimates in Table 5, Table 6, Panel A reports the average segment sizes, and associated nesting parameters, for all categories. As can be seen from the table, categories exhibit a mixture of store-focused and brand-focused choices, segment sizes ranging between 50% and 75% for the brand focus pattern and between 25% and 50% for the store focus pattern.

What drives these choice-pattern differences? Table 6, Panel B reports the coefficients of the concomitant variables in the segment membership probabilities for the brand-focused segment (clearly, the opposite profile pertains to the store-focused segment). As expected, households are more likely to follow brand-focused patterns in categories they purchase only infrequently: the fact that they do not *need* to buy them whenever they shop at a particular store facilitates indirect store switching. Moreover, brand-focused choice patterns are more prevalent in categories with more national brands (in which taste heterogeneity may be stronger) and high levels of quality differentiation (making brand shifts more risky). Similarly, a brand focus is more common among households with a leading NB as their main brand.

While households' overall shopping frequency and main-store positioning have no significant effect, those who concentrate more of their trips on weekends are less likely to shop around for a brand. Somewhat surprisingly, households living in areas with many stores are not more prone (but rather, if anything, less inclined) to shop around for their favorite brand – possibly because these are more urban areas, where mobility and parking space are a problem. The coefficients of price consciousness and propensity to engage in price comparisons (reverse scaled), though negative, fail to reach significance. Of the socio-demographics, household size does not have an effect, whereas older consumers are more brand-focused. On the whole, both factors that shape the cost of brand switching and the cost of store switching play a role.

The estimated nesting parameters shed further light on the strength of the disproportionality (i.e. on the 'degree' of within store or brand switching for each of the two choice patterns). As Table 6 shows, the nesting parameters always exceed zero, implying that even among store-focused consumers *some* store switching occurs, and that even brand-focused consumers have *some* propensity to switch brands. At the same time, they are often substantially below one, pointing to a high degree of disproportionality (average nesting parameter 0.529 and 0.714 in the store-focused and brand-focused patterns, respectively). Differently stated, consumers

**Table 6**
Overview of choice patterns.

| | Store focus | | Brand focus | |
|---|---|---|---|---|
| | Importance of choice pattern[a] | Nesting parameter | Importance of choice pattern[a] | Nesting parameter |
| Beer | 0.381 | 0.353 | 0.619 | 0.685 |
| Chocolate bars | 0.451 | 0.930 | 0.549 | 0.814 |
| Coffee | 0.465 | 0.575 | 0.535 | 0.720 |
| Custard | 0.491 | 0.482 | 0.509 | 0.670 |
| Diapers | 0.252 | 0.480 | 0.748 | 1.022 |
| Dish soap hands | 0.474 | 0.513 | 0.526 | 0.736 |
| Dog food | 0.331 | 0.215 | 0.669 | 0.443 |
| Frozen pizza | 0.482 | 0.563 | 0.518 | 0.864 |
| Hairspray | 0.419 | 0.191 | 0.581 | 0.449 |
| Ketchup | 0.479 | 0.888 | 0.521 | 0.614 |
| Kitchen tissue | 0.485 | 0.432 | 0.515 | 0.918 |
| Laundry det. | 0.397 | 0.700 | 0.603 | 0.738 |
| Margarine | 0.503 | 0.684 | 0.497 | 0.661 |
| Mayonnaise | 0.466 | 0.659 | 0.534 | 0.603 |
| Muesli | 0.450 | 0.284 | 0.550 | 0.702 |
| Toilet tissue | 0.503 | 0.522 | 0.497 | 0.787 |
| Average | 0.439 | 0.529 | 0.561 | 0.714 |

[a] Table entries indicate the size of the choice pattern's latent segment in the category, using the average values of estimated segment memberships.

with a store focus switch *far* more strongly among brands than stores, while those with a brand focus are *much* more likely to shift stores than brands – a point that we will come back to below.

### 5.3. Impact of feature ads

Having established the prevalence of different choice patterns, the question remains whether they lead to distinct promotion effects. The coefficients of feature in Table 5 are all positive (and almost all significant, except for hairspray in the store focus pattern), showing that in either choice pattern consumers are responsive to store flyer ads; while the feature-discount interaction coefficients (which are mostly positive, and significant in more than half of the cases) indicate that having both a feature ad and a discount often works synergetically. Moreover, the estimates often differ between the store-focused and the brand-focused segment – underscoring the importance of accommodating parameter differences between choice patterns. Still, given the structure of the model, the coefficients in Table 5 cannot be interpreted in isolation. Instead, we use them as a starting point to calculate the impact of feature actions on the choice probability of the promoted (brand-store) alternative, as well as on other alternatives, under each choice-pattern regime (i.e. store focus vs. brand focus). Given that our feature variables are dummies, we do not compute elasticities or marginal effects, but calculate 'average partial effects' (APEs, see e.g. Minnema, Bijmolt, & Non, 2017), i.e. changes in choice share if the feature variable jumps from zero to one (Web Appendix 4 provides the expressions for the own- and cross-effects). To isolate the pure-feature effect, we first consider a situation where the discount depth equals zero – a realistic setting, given that a considerable number of store flyer ads do not come with a price cut. (We consider features accompanied with a discount in the next section). We do so for each national brand-traditional store combination, and for each category.

#### 5.3.1. Impact on the promoted alternative: promotion lift

Table 7 (column "Promoted alternative"), reports the average lift in choice probability for the featured brand-store alternative, in absolute terms (percentage points) as well as in relative terms (increase relative to the base share without promotion), for consumers in a store-focused or a brand-focused choice pattern.

As the table shows, features lead to a choice share increase for the promoted alternative among both store-focused and brand-focused consumers: with an average absolute increase of 3.1 percentage points, the sales share of the promoted brand in the promoted store is about two times higher compared to non-promotion periods.[8] On the whole, brand-focused consumers appear the most feature-responsive, with an average relative increase of 2.645 (3.4% points absolute increase) in case of a brand focus, compared to 1.804 (2.7% points absolute increase) in case of a store focus – the difference being significant ($p < .05$). This difference in responsiveness is most pronounced in categories with high quality differentiation and many brands, like laundry detergents, beer, muesli and chocolate bars.

#### 5.3.2. Brand and store cannibalization

The question remains: where does the promotion lift come from? Table 7 (columns "Fraction Cannibalized"), displays the fraction of the promotion lift due to switches from the same brand at other stores (manufacturer cannibalization) and from another brand in the same store (retailer cannibalization). The table points to non-negligible cannibalization for either party: on average, 25.5% of the promoted alternative's choice share lift is at the expense of other brands in the store, and 23% to the detriment of the

[8] Though these effects may seem large, this is related to the fact that we consider increases for the promoted brand within the promoted store, while previous studies have often focused on market-level outcomes. Similarly high effects have been reported by (Foekens, Leeflang, and Wittink, 1998; Macé and Neslin, 2004).

**Table 7**
Feature effects by category and choice pattern[a].

| Category | Impact on choice-share of promoted alternative | | | | | | Fraction cannibalized | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Absolute (% points) | | | Relative (absolute/base share) | | | Manufacturer[b] | | | Retailer[c] | | |
| | Store focus (1) | Brand focus (2) | Sig. (2)–(1) | Store focus (3) | Brand focus (4) | Sig. (4)–(3) | Store focus (5) | Brand focus (6) | Sig. (6)–(5) | Store focus (7) | Brand focus (8) | Sig. (8)–(7) |
| Beer | 0.002 | 0.018 | ** | 0.279 | 2.054 | ** | 0.029 | 0.294 | ** | 0.663 | 0.090 | ** |
| Chocolate bars | 0.007 | 0.017 | ** | 0.873 | 2.258 | ** | 0.073 | 0.184 | ** | 0.203 | 0.112 | * |
| Coffee | 0.083 | 0.051 | ** | 4.178 | 1.998 | ** | 0.255 | 0.492 | ** | 0.270 | 0.063 | ** |
| Custard | 0.042 | 0.024 | ** | 2.18 | 1.266 | ** | 0.090 | 0.359 | ** | 0.458 | 0.069 | ** |
| Diapers | 0.029 | 0.019 | ** | 1.619 | 1.018 | ** | 0.108 | 0.157 | ** | 0.417 | 0.065 | ** |
| Dish soap hands | 0.031 | 0.033 | | 2.101 | 2.045 | | 0.088 | 0.384 | ** | 0.456 | 0.060 | ** |
| Dog food | 0.008 | 0.015 | | 0.685 | 1.199 | | 0.036 | 0.558 | ** | 0.758 | 0.059 | ** |
| Frozen pizza | 0.042 | 0.063 | * | 0.973 | 1.320 | | 0.389 | 0.532 | ** | 0.211 | 0.048 | ** |
| Hairspray | 0.027 | 0.011 | ** | 2.712 | 0.856 | * | 0.030 | 0.594 | ** | 0.833 | 0.029 | ** |
| Ketchup | 0.042 | 0.040 | | 2.067 | 2.016 | | 0.134 | 0.407 | ** | 0.118 | 0.063 | * |
| Kitchen tissue | 0.008 | 0.015 | | 2.161 | 4.018 | | 0.018 | 0.118 | * | 0.564 | 0.077 | ** |
| Laundry det. | 0.017 | 0.046 | ** | 2.087 | 6.086 | ** | 0.079 | 0.271 | ** | 0.294 | 0.083 | ** |
| Margarine | 0.017 | 0.011 | | 1.026 | 0.695 | | 0.113 | 0.423 | ** | 0.291 | 0.058 | ** |
| Mayonnaise | 0.038 | 0.057 | | 1.818 | 2.718 | | 0.155 | 0.416 | ** | 0.336 | 0.091 | ** |
| Muesli | 0.020 | 0.100 | ** | 1.916 | 10.852 | ** | 0.042 | 0.316 | ** | 0.713 | 0.111 | ** |
| Toilet tissue | 0.026 | 0.022 | ** | 2.182 | 1.913 | ** | 0.039 | 0.194 | ** | 0.412 | 0.076 | ** |
| Segment average | 0.027 | 0.034 | | 1.804 | 2.645 | ** | 0.105 | 0.356 | ** | 0.437 | 0.072 | ** |
| Overall average | 0.031 | | | 2.224 | | | 0.230 | | | 0.255 | | |

[a] Column entries give the change in choice probability of the promoted brand-store alternative, resulting from a change in the feature variable from zero to one; in absolute terms (percentage points) and in relative terms (absolute change divided by the base share without feature), within each choice pattern (store focus or a brand focus) – see Web Appendix 4 for the underlying expressions. For each metric, the table also reports whether the difference between the choice patterns is significant, based on 500 draws from the sampling distributions of the estimates. For each drawn parameter set, the associated difference is calculated, and the empirical distribution of the calculated differences is considered. A '**' indicates that the difference is positive in more than 95 (or less than 5) instances; a '*' that the difference is positive for >90 (or <10) instances.
[b] Fraction of the absolute probability change of the promoted brand-store alternative that comes from the same brand in a different store.
[c] Fraction of the absolute probability change of the promoted brand-store alternative that comes from a different brand in the same store.

same brand in other stores. Interestingly, beneath these averages, we find a huge difference between choice patterns. While the manufacturer suffers, on average, only 10.5% cannibalization among store-focused consumers (that primarily switch to other brands within a store), this figure goes up to 35.6% in case of a brand-focused choice pattern (where consumers primarily switch stores, but not brands) – a significant difference ($p < .01$). The opposite holds for the retailer, with 7.2% of the sales bump cannibalized in the brand-focused pattern, compared to 43.7% in the store-focused pattern (difference: $p < .01$). These asymmetries are found (and statistically significant) in each of the categories, be it with differences in the size of the effects: categories with low concentration (i.e. many brands, like muesli and kitchen tissue, see Table 2) implying lower cannibalization for the manufacturer, especially among store-focused consumers; yet higher cannibalization for the retailer, especially among brand-focused consumers.

### *5.3.3. Net manufacturer and retailer gains*

Although the results confirm the presence of two different choice patterns the question remains: how do these choice patterns drive the net promotion gains for the manufacturer and for the retailer; after accounting for cannibalization, and what drives the difference in these net gains? This is not obvious a priori: for instance, if brand-focused consumers are more numerous or more responsive to feature ads to begin with, this may compensate for the larger portion of the promotion lift that is cannibalized for the manufacturer. Hence, to gauge the net gains that each party can reap from either segment, we need to combine the underlying forces.

For either party, the total net gains can be written as:

$$NetGains^{X}{}_{c} = NetGains^{X}_{c,focus_{store}} + NetGains^{X}_{c,focus_{brand}} = \Psi_{c,focus_{store}} * PromoLift_{c,focus_{store}} * \left(1 - Cannib^{X}_{c,focus_{store}}\right) + \Psi_{c,focus_{brand}} * PromoLift_{c,focus_{brand}} * \left(1 - Cannib^{X}_{c,focus_{brand}}\right) \quad (7)$$

where superscript X refers to the *manufacturer* or the *retailer*, and $\Psi$ represents the segment sizes from Eq. (6), averaged across households based on their characteristics. That is, the total net gains for each party can be split into those obtained in the store-focused segment plus those obtained in the brand-focused segment, where these gains from each segment consist of the segment size, multiplied by the promotion lift for the promoted brand-store alternative, multiplied by the fraction of that lift that is "incremental" (i.e. not cannibalized). For example, for a retailer this comes down to subtracting, in each segment, the cannibalized sales (i.e. drop in sales of other brands at his store) from the sales that the promoting brand gained in the store.

Starting from Eq. (7), we can quantify for each party the fraction of total net gains contributed by each segment: $NetGains_{focus_{brand}}{}^{X}/NetGains^{X}$ and $NetGains_{focus_{store}}{}^{X}/NetGains^{X}$. The difference between these segment contributions can then be decomposed into its underlying drivers (segment size, promotion lift and cannibalization rate) as follows:

$$\begin{aligned}
\Delta NetGainShare^{X}{}_{c} &= \frac{NetGains^{X}_{c,focus_{brand}}}{NetGains^{X}{}_{c}} - \frac{NetGains^{X}_{c,focus_{store}}}{NetGains^{X}{}_{c}} \\
&= \left(\Psi_{c,focus_{brand}} - \Psi_{c,focus_{store}}\right) * \\
&\frac{\left(PromoLift_{c,focus_{store}}{}^{*}\left(1-Cannib^{X}_{c,focus_{store}}\right) + PromoLift_{c,focus_{brand}}{}^{*}\left(1-Cannib^{X}_{c,focus_{brand}}\right)\right)}{2^{*}NetGains^{X}{}_{c}} \\
&+ \left(PromoLift_{c,focus_{brand}} - PromoLift_{c,focus_{store}}\right) * \frac{\left(1-Cannib^{X}_{c,focus_{brand}}/2 - Cannib^{X}_{c,focus_{store}}/2\right)}{2^{*}NetGains^{X}{}_{c}} \\
&- \left(Cannib^{X}_{c,focus_{brand}} - Cannib^{X}_{c,focus_{store}}\right) * \frac{\left(PromoLift_{c,focus_{brand}} + PromoLift_{c,focus_{store}}\right)}{2^{*}NetGains^{X}{}_{c}}
\end{aligned} \tag{8}$$

The larger $\Delta NetGainShare^{X}{}_{c}$ for a given party X (where X is the manufacturer or the retailer), the larger the contribution of the brand-focused relative to the store-focused segment (and the larger the stakes in focusing on that segment). As the right-side of Eq. (8) shows, this could be: (i) because the brand-focused segment is bigger (larger segment-size difference $\Psi_{c,\, focus_{brand}} - \Psi_{c,\, focus_{store}}$), (ii) reacts more strongly to store flyer ads (larger difference in promotion lift, $PromoLift_{c,\, focus_{brand}} - PromoLift_{c,\, focus_{store}}$), (iii) implies less disproportional switching at the cost of the focal party (lower cannibalization-rate difference $Cannib_{c,\, focus_{brand}}{}^{X} - Cannib_{c,\, focus_{store}}{}^{X}$), or a combination of these factors.

Table 8 reflects the total and segment-specific 'net gains' for the (average) retailer and manufacturer, in each category and overall. Comparing the net gains across the two choice patterns we find that for the retailer, the net gains from the brand-focused segment by far exceed those from the store-focused segment. On average, more than two-thirds of the retailer's total net gains (71%) stem from brand-focused consumers, which account for a (statistically significant) larger portion of the gains in 14 (10) out of the 16 categories. The decomposition in Table 9 shows that though differences in segment size or promotion responsiveness play a role, this is predominantly due to the much lower cannibalization rate in the brand-focused segment.

The situation is very different for the manufacturer, for whom both segments, on average, contribute about equally to the gain in overall brand share (53.8% for the brand vs. 46.2% for the store-focused segment, see bottom of Table 8). As the decomposition in Table 9 shows, the segment difference in net gains now results from a trade-off between differences in segment size and feature responsiveness on the one hand, and within-brand cannibalization on the other – all of which are typically higher among brand-focused consumers. Again, category characteristics play a role here: the manufacturer reaping higher net gains in the brand-focused segment relative to the store focused segment in less concentrated and more differentiated categories – where that segment is larger and more feature-responsive, while the opposite holds in other categories.

**Table 8**
Net manufacturer and retailer choice-share gains from feature[a].

| Category | Retailer | | | | | Manufacturer | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total | Store focus | | Brand focus | | Total | Store focus | | Brand focus | |
| | | Absolute | Fraction of total | Absolute | Fraction of total | | Absolute | Fraction of total | Absolute | Fraction of total |
| Beer | 0.010 | 0.000 | 0.030 | 0.010 | 0.970 | 0.009 | 0.001 | 0.102 | 0.008 | 0.898 |
| Chocolate bars | 0.011 | 0.003 | 0.232 | 0.008 | 0.768 | 0.011 | 0.003 | 0.277 | 0.008 | 0.723 |
| Coffee | 0.054 | 0.028 | 0.525 | 0.025 | 0.475 | 0.042 | 0.029 | 0.675 | 0.014 | 0.325 |
| Custard | 0.023 | 0.011 | 0.490 | 0.012 | 0.510 | 0.027 | 0.019 | 0.701 | 0.008 | 0.299 |
| Diapers | 0.018 | 0.004 | 0.242 | 0.013 | 0.758 | 0.019 | 0.007 | 0.351 | 0.012 | 0.649 |
| Dish soap hands | 0.024 | 0.008 | 0.334 | 0.016 | 0.666 | 0.024 | 0.014 | 0.562 | 0.011 | 0.438 |
| Dog Food | 0.010 | 0.001 | 0.066 | 0.009 | 0.934 | 0.007 | 0.003 | 0.374 | 0.004 | 0.626 |
| Frozen pizza | 0.047 | 0.016 | 0.341 | 0.031 | 0.659 | 0.028 | 0.012 | 0.449 | 0.015 | 0.551 |
| Hairspray | 0.008 | 0.002 | 0.232 | 0.006 | 0.768 | 0.014 | 0.011 | 0.807 | 0.003 | 0.193 |
| Ketchup | 0.037 | 0.018 | 0.479 | 0.019 | 0.521 | 0.030 | 0.017 | 0.587 | 0.012 | 0.413 |
| Kitchen tissue | 0.009 | 0.002 | 0.191 | 0.007 | 0.809 | 0.011 | 0.004 | 0.358 | 0.007 | 0.642 |
| Laundry det. | 0.030 | 0.005 | 0.155 | 0.025 | 0.845 | 0.026 | 0.006 | 0.231 | 0.02 | 0.769 |
| Margarine | 0.011 | 0.006 | 0.524 | 0.005 | 0.476 | 0.011 | 0.007 | 0.692 | 0.003 | 0.308 |
| Mayonnaise | 0.040 | 0.012 | 0.298 | 0.028 | 0.702 | 0.033 | 0.015 | 0.456 | 0.018 | 0.544 |
| Muesli | 0.051 | 0.003 | 0.051 | 0.049 | 0.949 | 0.046 | 0.009 | 0.189 | 0.038 | 0.811 |
| Toilet tissue | 0.018 | 0.008 | 0.427 | 0.010 | 0.573 | 0.021 | 0.012 | 0.582 | 0.009 | 0.418 |
| Average | 0.025 | 0.008 | 0.288 | 0.017 | 0.712 | 0.022 | 0.011 | 0.462 | 0.012 | 0.538 |

[a] Table 8 shows the increase in sales share in the category due to the feature promotion, for the store (Retailer 'Total') and brand (Manufacturer 'Total') as a whole, split into the portion gained in the store- vs. brand-focused segment.

**Table 9**
Difference in net gains between segments: decomposition[a].

| | Retailer | | | | Manufacturer | | | |
|---|---|---|---|---|---|---|---|---|
| | D Net gain share brand – store focus | Portion due to | | | D net gain share brand – store focus | Portion due to | | |
| | | D segment size | D promotion lift | D cannibal. rate | | D segment size | D promotion lift | D cannibal. rate |
| Beer | 0.941** | 0.196** | 0.464** | 0.280** | 0.796** | 0.205** | 0.745** | −0.154** |
| Chocolate bars | 0.536** | 0.094** | 0.391** | 0.051* | 0.447** | 0.095** | 0.414** | −0.063** |
| Coffee | −0.050 | 0.071** | −0.250** | 0.129** | −0.350** | 0.073** | −0.236** | −0.186** |
| Custard | 0.019 | 0.018** | −0.283** | 0.284** | −0.402** | 0.018** | −0.254** | −0.167** |
| Diapers | 0.516** | 0.488** | −0.212** | 0.240** | 0.297** | 0.559** | −0.230** | −0.032** |
| Dish soap hands | 0.332 | 0.051** | 0.020 | 0.261** | −0.124 | 0.053** | 0.020 | −0.197** |
| Dog food | 0.868** | 0.269** | 0.197 | 0.403** | 0.253 | 0.348** | 0.333 | −0.429** |
| Frozen pizza | 0.317** | 0.036** | 0.190** | 0.091** | 0.101 | 0.036** | 0.201** | −0.136** |
| Hairspray | 0.537** | 0.151** | −0.554** | 0.940** | −0.614 | 0.182** | −0.402** | −0.395** |
| Ketchup | 0.043 | 0.042** | −0.030 | 0.030** | −0.175 | 0.043** | −0.030 | −0.188** |
| Kitchen tissue | 0.617** | 0.030** | 0.270 | 0.318** | 0.283 | 0.030** | 0.307 | −0.054** |
| Laundry Det. | 0.690** | 0.185** | 0.396** | 0.110** | 0.538** | 0.191** | 0.461** | −0.114** |
| Margarine | −0.048 | −0.006** | −0.187 | 0.144** | −0.384** | −0.006** | −0.175 | −0.203** |
| Mayonnaise | 0.405* | 0.067** | 0.190 | 0.147** | 0.087 | 0.069** | 0.208 | −0.189** |
| Muesli | 0.898** | 0.093** | 0.454** | 0.352** | 0.621** | 0.095** | 0.703** | −0.177** |
| toilet tissue | 0.147 | −0.006** | −0.073** | 0.226** | −0.165** | −0.006** | −0.071** | −0.087** |
| Average | 0.423** | 0.111** | 0.061* | 0.250** | 0.076** | 0.124** | 0.125** | −0.173** |

** = $p < .05$, * = $p < .10$. Based on 500 draws from the sampling distributions of the estimates. For each drawn parameter set, the associated segment difference is calculated, and the empirical distribution of the calculated differences is considered. A '**' indicates that the difference is positive in >95 (or <5) instances; a '*' that the difference is positive for >90 (or <10) instances.

[a] For each party (manufacturer or retailer), D Net Gain Share is the difference in net gain between the brand-focused and the store-focused segment, divided by the total net gains (reported in Table 8). It is split into a component due to (i) a difference in segment size, (ii) a difference in lift for the promoted alternative, and (iii) a difference in cannibalization rate. E.g. For Coffee, the retailer's D Net Gain Share equals 0.475–0.525 = −0.050, which can be split up as 0.071–0.250 + 0.129.

### *5.4. Impact of featured discounts*

So far, we focused on the effects of flyer ads as such, and considered their impact on the manufacturer's (brand) and the retailer's (category) choice share. However, store flyer appearances often go along with a price cut. This may not only alter the feature's choice-share gains (given that feature and discount-depth significantly interact, see Table 5) but also have wider revenue implications. We consider those in turn.

To document the choice-share effects, we calculate the promotion lift and net gains (i.e. counterparts of Tables 7 through 9) for feature promotions accompanied by a discount, with discount depth set at the average for category appearances in the store flyer (as indicated in Table 2). The full set of results is given in Web Appendix 5. As expected, the share increases from the promotion now become larger: across the two segments, the lift for the promoted alternative goes up from 3.1% points to 3.8% points, and net gains for the retailer (manufacturer) go up from 2.5 to 3.1% points (from 2.2 to 2.8% points). When it comes to segment differences, though, the previous pattern of results stands: brand-focused consumers are typically more promotion-responsive than store-focused consumers yet entail far less (more) cannibalization for the retailer (manufacturer), and this strongly drives the net volume gains.

Enticed by its typically higher feature responsiveness, the manufacturer may be inclined to target the brand-focused segment. Yet, even if it yields satisfactory net choice-share gains, this segment comes with high brand-cannibalization rates and, as the feature ad goes along with a (deeper) discount, such cannibalization will have a particularly detrimental revenue effect. Indeed, it implies that consumers who would otherwise have bought the brand or purchased at the store at the full regular price, now pay only the discounted price – thereby reducing the monetary gains from the promotion. This is especially relevant for the manufacturer who, next to paying for his brand appearance in the store flyer (see, e.g., Bia, 2010 for some going rates in the Dutch market), often bears the brunt of any accompanying price cuts (with retailer pass through below 100%, Ailawadi et al., 2006; Besanko, Dubé, & Gupta, 2005).

Using back-of-the envelope calculations, we can roughly gauge the revenue implications of the featured discounts in each of the segments. For the promoted alternative (i.e. the promoted brand at the promoting store), we obtain the revenue effect as the (absolute) choice-share increase times the discounted price, minus the baseline share times the discount. The *net* revenue impact for the manufacturer (i.e. for the brand as a whole), is then obtained by subtracting the portion of the choice-share increase that is cannibalized, evaluated at the full (undiscounted) price (see Web Appendix 4.2 for the full expressions). Using these calculations for featured discounts in our categories (averaged across NBs), we still find positive revenue effects for the promoted alternative, in both the brand-focused and the store-focused segment. When it comes to *net* revenue implications, though, the picture changes. Even in categories where brand-focused segments outperform store-focused segments in terms of net choice-share gains, this situation easily reverses with revenue as metric of interest. While featured price cuts still enhance net revenue in the store-focused segment (15 out of 16 categories); the manufacturer loses money on brand-focused consumers in the vast majority (11 out of 16) categories (see Web Appendix 5, Table A.5.4 for full set of results). The strong cannibalization in this segment leads to subsidization losses, and all the more so as price cuts deepen.

This is further illustrated in Fig. 2, both for a category where the interaction between feature and discount is positive (muesli) or negative (coffee). The figure shows the monetary gains from featured discounts for an average NB, at different levels of discount depth, in each choice-pattern segment. It does so for the promoted brand-store alternative (dotted lines) as well as in 'net terms', for the manufacturer overall (the full lines). It shows that while offering a price discount may initially entail an increase (especially in case of a positive interaction, like for muesli), deeper discounts reduce the extra "monetary value" from the promotion, but far more quickly and strongly so in the brand-focused segment, where the manufacturer's degree of cannibalization is much higher. Hence, for the manufacturer, especially feature ads toward those brand-focused consumers should not come with deep price cuts.

## 6. Discussion

### 6.1. Main findings

Though feature promotions are widely used tools in CPG markets, their effectiveness has been called into question by extant studies at the market or store level (e.g. Srinivasan et al., 2004; van Heerde et al., 2004) indicating that a large portion of the promotion lift comes from within-brand or within-store shifts. We add to the literature on (asymmetric) promotion effects, by indicating that besides brand, store and category characteristics, consumers' choice pattern is a strong driver of net promotion gains. Our main findings are as follows.

First, households strongly differ in the way they choose among brands and stores. All categories under study are characterized by a mixture of different choice patterns: some households exhibit a 'store focus' and primarily switch between alternatives within the visited store(s), others exhibit a brand focus and are more likely to shop around for a (subset of) brand(s). Though there are differences in the relative size of the segments, each of them is economically meaningful – segment sizes within a category ranging between 25% and 75% of category shoppers. We find a brand focus to be more prominent among less-frequent buyers, whose primary brand is the leading NB, in less-concentrated and more quality-differentiated categories; and among older households and households that primarily shop on weekdays – the opposite holding for store-focused consumers.

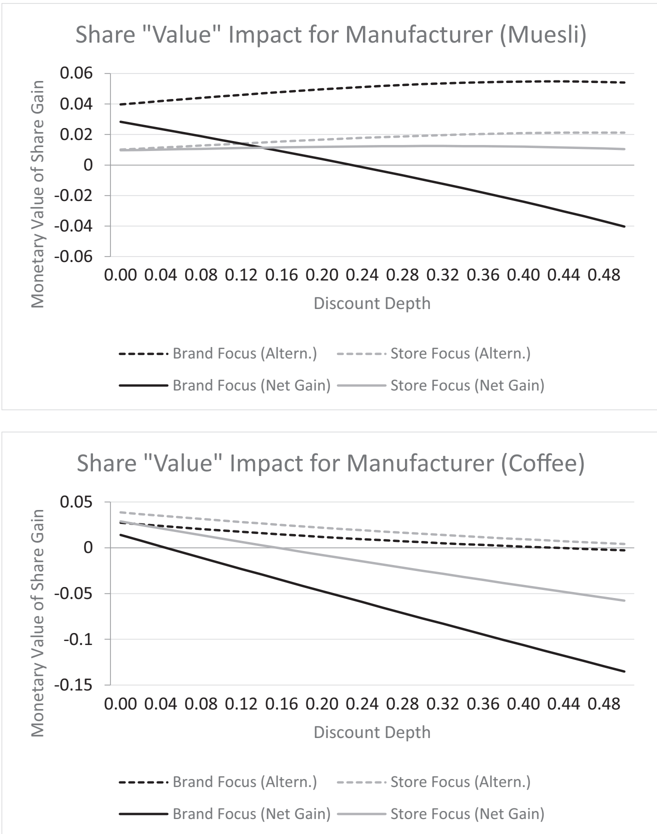


**Fig. 2.** Impact of featured discount on revenue. The curve for the promoted brand-store alternative ("Altern.") reflects (i) the volume-share increase from the feature ad multiplied by the promoted price, minus (ii) the discount multiplied by the baseline share of the promoted alternative. The curve for the brand overall ("Net Gain") reflects (i) the net volume-share increase multiplied by the promoted price, minus (ii) the discount multiplied by the baseline share of the promoted alternative, minus (iii) the discount depth multiplied by the cannibalized volume share.

Second, we find that though both segments significantly respond to feature ads, brand-focused households are generally more feature-sensitive. As such, the different choice patterns already entail differences in 'promotion lift'. Especially in categories with high quality differentiation and many national brands, the probability that the promoted brand in the promoted store will be chosen is higher in the brand-focused segment. However, for brand-focused households, feature ads primarily 'redirect' brand purchases from other stores to the promoting store, while for store-focused households, they rather lead to a brand shift within the store assortment. As such, the choice patterns come with very different sources of lift.

Third, indeed, while we find evidence of cannibalization overall (on average, about one fourth of the promoted alternative's choice-share lift being at the expense of other brands in the retailer's assortment, and of the manufacturer's own brand in other stores), these figures are dramatically different depending on the prevailing choice pattern. For the manufacturer, the cannibalization rate is only about 10% among store-focused, and nearly 40% among brand-focused consumers. For the retailer, the segment difference is even more pronounced: the fraction cannibalized drops below 10% among brand-focused households, and increases to over 40% among store-focused households.

Fourth, it follows that, depending on the household's choice pattern, the promotion lift entails very different net gains. While the bump in choice-share for the promoted alternative is typically highest in the brand-focused segment, in half of the categories the manufacturer reaps higher net share gains from store-focused consumers. For the retailer, the brand-focused segment is generally the most rewarding, the choice-share gain for its category assortment, on average, being twice as high among brand-focused than among store-focused households. So, for either party, the net gains observed at the market level conceal huge heterogeneity depending on consumers' choice patterns, where not only the size of the choice-pattern segments and difference in feature responsiveness matter, but especially the strength of the cannibalization produced by the feature ads in the different segments.

### 6.2. Managerial takeaways

Our results have several implications for managers. First, they caution retailers and manufacturers that market-level figures can conceal huge differences in net promotion outcomes. Given the high degree of cannibalization, investments in feature ads directed at the "wrong" segment might be less efficient, and better used otherwise. For the retailer, the brand-focused segment is typically far more rewarding. Feature ads targeted at this segment entail higher choice-share increases for the promoted item in many categories, and bring in more category buyers for the store – most of the promotion lift being at the expense of rival chains. For the manufacturer, a trade off is in order: the segment that is typically the largest and the most responsive to features, being the one with the highest cannibalization rate. So, while the retailer tends to have a clear preference for one segment over the other, the situation is very different for the manufacturer, whose net volume gains often originate from both segments and who has to reckon with strong cannibalization among brand-focused households.

Second, by profiling categories and households for which cannibalization is lower, our results suggest how the efficiency of the 'feature buck' can be improved. Previous guidelines for promotion targeting have often been based on consumers' 'last purchase' observed within the store (Rossi & Allenby, 1993; Zhang & Wedel, 2009). Our findings suggest that a broader perspective is called for, in which the household's switching pattern across brands and stores is considered. For the retailer, our segment profiles help to identify consumers and categories that should be prioritized to avoid within-store cannibalization. Manufacturers could tailor the depth of featured discounts to consumers' choice patterns, i.e. by avoiding deep price cuts in categories, areas and stores where the 'high cannibalization' segment is expected to be large.

Third, we show that when it comes to prioritizing segments, manufacturers' and retailers' interests are not necessarily unaligned. The reason is that, next to cannibalization, the difference in feature ad sensitivity is still a significant driver of net gains. It follows that in a number of (less frequently bought and less concentrated) categories, both the manufacturer and the retailer find brand-focused consumers to be the most rewarding. Exclusively targeting that segment is less appealing for the manufacturer, who misses out on potential gains and, in case of accompanying price cuts, loses revenue on established customers. The retailer may accommodate this by agreeing to more shallow price cuts or higher promotional pass through.

Fourth, an interesting observation for manufacturers is that having a customer base with many brand-focused consumers is a 'mixed blessing': while it contributes to a stable baseline, it also increases the risk of promotion subsidization and calls for a more selective use of promotion instruments – an arduous task in an industry known to have a high promotion intensity. The insights from this study may provide useful guidelines during the promotional planning process.

### 6.3. Limitations and future research

While our study provides new insights, it also opens up new research opportunities. First, we considered promotion effects conditional on a category purchase and hence only documented differential shifts in brand-store choice. Though we expect these to be the most distinct, it is possible that consumers' choice patterns also influence whether or when they buy, and trigger different stockpiling effects. Rough exploration suggests that promotion-induced purchase acceleration is not related to a household-category's segment membership probability,[9] but this could be further verified in future study. Moreover, even in the presence of

[9] In auxiliary regressions, we estimated the households' category purchase incidence as a function of promotional variables (next to controls like the time since the previous purchase, the previous purchase quantity, and the interaction between the two), using a random-effects specification. As expected, we found a positive main effect of feature promotions on category purchase incidence in all categories, with heterogeneity in this effect for 14 out of 16 categories. However, correlating these household-specific purchase-acceleration effects to the households' posterior membership of the brand vs store focused segment, we found no significant link (coefficient estimate: $-0.004$, $p > 0.05$), suggesting that our choice-segments do not show systematic differences in terms of dynamic promotion response.

strong cannibalization, manufacturer investments in feature ads may be helpful to maintain a top-of-mind position for their brand in the long run – an aspect our analysis did not include.

Second, we find that retailers are generally better off targeting the brand-focused segment, where feature response is high and within-store switching low; while manufacturers cannot afford to disregard one segment, and incur within-brand cannibalization from brand-focused consumers. However, while this pattern prevails in the vast majority of categories, it does not hold in all cases. In some categories (i.e. toilet tissue, coffee and margarine), store-focused households react more strongly to feature promotions than brand-focused households, up to a point where this segment becomes the most appealing for manufacturers and retailers alike. Purchase frequency, category concentration and (lack of) quality differentiation seem to play a role here, but this pattern is not entirely clear-cut. Future studies should shed further light on category characteristics underlying the differences in promotion lift and cannibalization rates.

Third, though our MRNL model is already quite flexible, further refinements may be called for. While we allowed for different promotion effectiveness *between* the two choice segments and among households within a segment, we used pooled coefficients across brands and retailers within a category. Though this is a commonly used approach (e.g. Ailawadi, Harlam, César, & Trounce, 2007; Foubert & Gijsbrechts, 2007; Zhang & Wedel, 2009), allowing for differential parameters across brands and/or retailers may be a fruitful extension.

Fourth, our data does not include information on in-store advertising, displays or temporary stock-outs. Store flyer appearances may be supported by communication inside the store, or substitution may be induced by out-of-stocks, and it may be useful to separate out these effects. Also, pattern adherence may depend on variables that were not available in our data set and vary over time. Future studies may explore other drivers, or allow for 'dynamic segment membership', in which the household's choice pattern depends on situational factors such as stock-outs or type of shopping trip, or on marketing-mix factors such as promotion calendars.

Finally, it may be instructive to combine and verify the outcomes of the MRNL model with more direct (survey) measures on the underlying process. Ideally, such data should be collected not only at the level of the category or household, but allow for idiosyncratic behaviors for household-category combinations. We hope that our work stimulates further research in that area.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2018.05.002.

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