

# Shelf Sequence and Proximity Effects on Online Grocery Choices

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November 2005

## *Acknowledgments*

We acknowledge the financial support of the Fund for Scientific Research, Flanders (FWO-Vlaanderen). The authors are much indebted to both the respondents that pre-tested the experimental design and the respondents that participated in the research. They further thank Patrick De Pelsmacker, Gilles Laurent, Annouk Lievens, Patrick Van Kenhove, Walter van Waterschoot and Philippe Verbeeck for their helpful suggestions on earlier versions of this manuscript.

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## Abstract

Research on traditional store shelf effects has shown that a product's absolute and relative shelf position may strongly affect consumer choices. In this paper, we examine whether such shelf effects are still at play in an online grocery store. While traditional 'eye-level' placement is no longer predominant, we find that a product's choice probability increases when presented on the first screen or located near focal (highly-preferred) items. Our results further demonstrate that these primacy and proximity effects depend on assortment size and composition. Larger and more difficult to process assortments complicate the choice process, thereby stimulating the use of shelf-based simplifying choice heuristics.

Keywords: retailing, shelf management, assortment, online shopping, choice decision

The Internet revolution has initiated a new era in which online shopping is a well-accepted way of purchasing products. Previous research has examined the effects of unique online store characteristics, such as interactive decision aids and more flexible customization procedures (e.g. Senecal and Nantel 2004; Zhang and Krishnamurthi 2004). Less attention has been paid to the equally intriguing question whether traditional marketing mix instruments affect online purchase decisions to the same extent and in the same way. A number of studies indicate, though, that online shoppers may react differently to marketing mix instruments such as price and brand name (e.g. Andrews and Currim 2004; Degeratu, Rangaswamy and Wu 2000; Lynch and Ariely 2000).

Given the differences in store environment, there are reasons to expect even stronger divergence in responses to merchandising instruments like shelf display. For one, in contrast to traditional stores, online stores typically allocate only one shelf 'facing' to each product,

thereby eliminating shelf space allocation effects. Second, search processes are greatly facilitated by the small and easily examinable electronic shelves. Limited (eye) movements and simple scrolling across screens may suffice to scan the entire assortment. As a result, shelf position may be less effective to draw customer attention to specific products. This even led to the conclusion that – though a dominant concern in traditional retail settings – shelf management might have become irrelevant in virtual stores (e.g. Yrjölä 2001; Menon and Kahn 2002). Yet, our study suggests that online shelf organization may – in its own way – affect consumers' shopping decisions. As will be explained in more detail below, the order in which products are displayed and their position relative to other items may still play an important role in directing customer attention and guiding online choice decisions.

Up till now, systematic analysis of online grocery shelf effects seems to be lacking. This research is a first step towards closing this gap. We examine *whether* traditional shelf effects prevail for online choices within fast moving consumer goods categories, and – if so – *how* they translate to a virtual store context. Using an online shopping experiment, we also provide indications on the magnitude of these effects and suggest guidelines for improved online shelf management. In the following section, we briefly review the traditional shelf literature and develop hypotheses on online shelf effects. Next, we describe the experiment and model used to test these effects. We then discuss implications for virtual shelf management and indicate directions for future research.

## **1. Traditional and online shelf effects**

### *1.1 Traditional shelf effects*

The impact of shelf organization on consumers' choice decisions in brick-and-mortar stores is widely supported in the literature. Items are more likely to be chosen when they receive more

shelf *space* (more facings) or are placed on more prominent shelf *positions* (e.g. Desmet and Renaudin 1998; Drèze, Hoch and Purk 1994). In terms of absolute shelf placement, vertical shelf position appears to have the strongest effect: products placed at eye- or hand-level having a significantly higher probability of being selected (Corstjens and Corstjens 1995; Campo and Gijbrecchts 2005). Horizontal shelf position tends to have a less pronounced effect, and results seemed inconclusive at first as to which position is best (Drèze et al. 1994). Recent research suggests, though, that much depends on the entrance point of the shelf. In line with the primacy effect observed in the communication literature, it was found that early encountered items are more likely to be chosen (Broere, Van Gensink and Van Oostrom 1999). Finally, a product's *relative shelf placement* may also affect its choice probability: a location near focal (e.g. highly-preferred) items increasing the probability that consumers will notice and select the item (Simonson and Winer 1992).

These shelf effects appear especially important when consumers are not much involved with the purchase decision, are pressed for time and/or face comprehensive shopping tasks (large shopping baskets). In such purchase situations, consumers will often pursue satisfying rather than utility maximizing purchase decisions (Hoyer 1984). Shelf organization may, in this case, play an important role in attracting/directing customer attention and serve as a 'cue' to simplify consumers' choice decisions.

Products with more facings or placed on more prominent shelf positions are more likely to be noticed by consumers – or catch *attention* first. Sequence of attention is especially important when consumers seek a satisfying and effortless solution. In this case, they will often stop their search procedure once a suitable product is found. As a result, only a subset of, first encountered, items will be evaluated (Simonson 1999). Even when the search process

continues, products encountered in a later stage may receive much less attention: consumers having settled for a specific product and merely scanning subsequent items to justify their choice. The probability that an item is chosen thus depends on where consumers start their search. This may be the shelf area that first catches their attention (triggered e.g. by the number of shelf facings, point of shelf entrance or vertical shelf position), or the shelf area containing the most salient (e.g. preferred) product. In addition to these attention-steering effects, shelf organization may provide cues signaling *product attractiveness*. Items that receive more shelf space and/or a more prominent placement (e.g. eye-level) are often thought to be more successful and hence, more attractive.

### *1.2 Online shelf effects*

A key question is *whether* and *how* these traditional shelf effects translate into online settings. Based on the differences between virtual and physical store shelves, we expect that shelf space and vertical shelf position (eye-level) will play no or only a minor role in online settings. First, in contrast to traditional stores, online stores typically allocate only one ‘facing’ to each item, making the number of facings a non-issue. Second, the convenient arrangement of products on a small computer screen eliminates the need for consumers to physically move to examine or compare products. When standing in front of a specific shelf area (screen in case of online stores), scanning the much larger physical shelves from top to bottom requires substantially more effort than browsing a computer screen. In addition, since all products are practically placed at eye-level, no on-screen position may be uniquely more attention-catching. Results from the communication literature seem to confirm this: advertisements published in comparable – small and 2-D – media do not appear to attract substantially more attention when placed on specific on-page positions (e.g. Hanssens and Weitz 1988). This is especially true in media used for product selection, such as catalogues

and store flyers (Nagelkerke 2004). Because of the quick and easy overview these media provide, consumers not always start their search from the middle (eye-level) position, but use many different starting points and scanning procedures (see e.g. Monk 1984).

In contrast, we expect sequence effects – triggered in traditional stores by horizontal shelf positions – to remain relevant in virtual stores. The order in which items are displayed online may continue to affect choice decisions for the following reasons. First, while virtual shelf space is endless, screen space is not: the number of products per screen remaining limited. Moreover, because of the absence of physical space constraints, online assortments are often quite large (Verhoef and Langerak 2001) and require more than one screen to display all items. Second, while browsing online shelves entails less effort than searching physical store shelves, this does not imply that online customers are oblivious to search costs. Being typically convenience-oriented, online shoppers, also, may be reluctant to engage in a complete category search, even if they only have to scroll between different screens to view all items (Wu and Rangaswamy 2003). Hence, they may be equally susceptible to the sequence in which category items are displayed.

Based on the traditional store shelf literature, we expect products encountered earlier in the search process to have a higher choice probability (primacy effect). An important difference with traditional outlets, though, is that online stores have a fixed shelf entrance point (i.e. the first screen). In addition, whereas more distantly displayed items are less visible in traditional stores, they are completely invisible in virtual stores as long as the consumer does not scroll to the following screen. In the same line as cover page positions enhance ad visibility (Gijbrecchts, Campo and Goossens 2003), we therefore expect placement on the first screen to entail substantially higher customer attention and, hence, choice probabilities. We thus hypothesize that:

**H<sub>1</sub>: Items that are displayed on the first screen of an online store have a higher probability of being chosen.**

As indicated above, previous research has shown that consumers, once they fixed their attention on a part of the shelf, tend to focus on the subset of items that are displayed on that particular shelf section (Hoch, Bradlow and Wansink 1999; Simonson and Winer 1992). This search behavior may be driven by a desire to simplify the choice process (see above) as well as by the perception that more closely positioned items are more similar (cf. Morales et al. 2005). We therefore expect that online shoppers will also confine their search process to the subsection of the shelf containing their focal item and hypothesize that:

**H<sub>2</sub>: Items located next to a consumer's focal item have a higher probability of being chosen.**

These primacy (H<sub>1</sub>) and proximity (H<sub>2</sub>) effects are a direct result of consumers' pursuit of satisfying and effortless solutions, which trigger the need for simplifying choice heuristics. As indicated above, recourse to such heuristics becomes more likely in the face of comprehensive (yet low-involvement) shopping tasks, such as having to select an item out of a large grocery product assortment (Campo and Gijbrecchts 2005). Apart from increasing the number of candidates for evaluation, large assortments may complicate the selection process as the assortment and shelf layout become more difficult to grasp (Broniarczyk, Hoyer and McAlister 1996). Hence, we expect that:

**H<sub>3</sub>: The online shelf sequence effect is stronger for a large than for a small assortment.**

**H<sub>4</sub>: The online proximity effect is stronger for a large than for a small assortment.**

## **2. Methodology**

### *2.1 Experimental data*

Data were collected by means of a realistic online store experiment. This approach allows to manipulate treatment variables like shelf placement and assortment, while controlling for extraneous influences such as promotions (Campo and Gijbrecchts 2005). Also, there is growing evidence that computer simulated shopping experiments provide highly realistic buying behavior data (Burke et al. 1992). This particularly holds in our study, where we were able to use the site of an existing online grocery store<sup>1</sup>.

The computer experiment consisted of: (1) a pre-purchase questionnaire to collect consumer background data, (2) a purchase simulation module and (3) a post-purchase questionnaire on the virtual store experiences and decision making process. Respondents were asked to make purchases in an online store during six fictitious weeks for two product categories (margarine and cereals). While the time compression of six shopping weeks into one experimental session might appear artificial, it has been shown to realistically capture dynamic purchase patterns (e.g. Burke et al. 1992). To further ensure the realism of purchase decisions, consumers were informed about their weekly home inventory levels, computed on the basis of previous purchases and reported consumption rates. Respondents were also explicitly told they were not obliged to buy every week.

*Shelf placement* was manipulated through changes in shelf arrangement: by brand or by flavor/type (in practice, the most commonly used shelf arrangements). Depending on the shelf arrangement, on-screen positions, order of appearance and product adjacencies differed. Consumers were randomly assigned to one of both shelf arrangements. To enhance the



realism of the online shopping task, consumers could change the default arrangement (although few did).

To test *proximity* effects ( $H_2$ ,  $H_4$ ), we used stock-outs as ‘natural’ indicators of consumers’ focal items<sup>2</sup>. Previous research has shown that most consumers switch to another item when the product they planned to buy (their focal item) is out-of-stock. In online stores, stock-out products typically remain visible on the screen, but a ‘flag’ is added to signal unavailability. Proximity to preferred stock-out items can therefore be used to examine whether consumers fix their attention on – and evaluate items within – a specific shelf area. The occurrence of stock-outs was uniformly distributed over weeks, low and high share items and attribute levels (brands, flavors, types and/or sizes) and set at a realistic average of about 8% of the products in the category (see e.g. Sloot, Verhoef and Franses 2005).

*Assortment size* manipulations were guided by retailer practices, brand and flavor being the predominant attributes along which assortments can be extended (Boatwright and Nunes 2001). Subjects were randomly assigned to one of three different assortments: (1) a limited assortment, (2) an assortment extended with flavors and (3) an assortment extended with brands. Table 1 gives an overview – for each category and assortment – of the number of products, respondents and purchase occasions. Table 1 also indicates whether or not more than one screen was needed to present all products.

<insert table 1>

To get a representative sample, we used e-mail addresses from 2 mailing lists. One was obtained from a list broker with addresses selected on the basis of demographic and purchase behavior information. The second list contained addresses from the full staff of the university – including technical and administrative staff. 17% of the respondents completed the purchase

simulation, a response rate that compares favorably to other online studies with e-mail based interception (e.g. Verhoef and Langerak 2001). The socio-demographic characteristics of our sample matched the online grocery sample profiles in other studies (see e.g. Degeratu et al. 2000; Rohm and Swaminathan 2002). For each mailing address, participation was requested of the household member typically in charge of grocery shopping. To stimulate participation without endangering the representativeness of the sample, participants were made eligible for some small rewards on a lottery basis.

## 2.2 Model structure

To test the hypotheses, we introduced shelf placement variables in a traditional multinomial logit (MNL) model. Specifically, our choice utilities take the following form:

$$u_{it|a}^h = \sum_{k=1}^K \alpha_{k|a} X_{k,it|a}^h + \beta_{seq|a} Seq_{it|a}^h + \beta_{prox|a} Prox_{it|a}^h \quad (1)$$

where  $u_{it|a}^h$  = choice utility of item  $i$  for household  $h$  facing assortment  $a$  at time  $t$ ,  $X_{k,it|a}^h$  ( $k=1,\dots,K$ ) = set of ‘traditional’ household and/or item variables (see below) and the last two terms capture shelf placement effects.

The first variable ( $Seq$ ) is a dummy variable indicating whether or not item  $i$  is displayed on the first screen presented to household  $h$  at time  $t$ . This variable tests the sequence effect, which is expected to be positive ( $H_1: \beta_{seq} > 0$ ). Relative shelf placement effects are captured by the proximity variable ( $Prox$ ). This variable determines whether an alternative is positioned next to focal (highly-preferred) stock-out items (for details, see table 2). Since respondents do not pay equal attention to all stock-out items (Beuk 2001), we use the attractiveness (initial preference share) for a stock-out item as weights. Because consumers in a stock-out situation focus on a small part of the shelf, they are more likely to select an adjacent item rather than a

distant one. Items would thus benefit from being placed next to out-of-stock items, implying a positive coefficient for *Prox* ( $H_2: \beta_{prox} > 0$ ).

<insert table 2>

Table 2 summarizes the other explanatory variables in our model: i.e. attribute-specific intercept terms<sup>3</sup> ( $D_{A,I,i}$ ), long-term preference measures ( $Pr ef_i^h$ ), purchase event feedback variables ( $LP_{it}^h$ ) and attribute-specific stock-out asymmetry variables ( $OOS_{A,it}$ ). The latter capture possible non-IIA choice shifts triggered by stock-outs (see Campo, Gijsbrechts and Nisol 2003). A positive (negative) coefficient indicates a tendency to switch to (away from) alternatives with the same attribute (e.g. brand) in case of a stock-out.

### 2.3 Estimation

In each category, we estimate the choice model across the three assortments:

$$p_{it|a}^h = \frac{\exp[\mu_a(u_{it|a}^h)]}{\sum_{j \in C_a^h} \exp[\mu_a(u_{jt|a}^h)]} \text{ for } i \in C_a^h \quad (2)$$

with  $p_{it|a}^h$  = the probability that household h chooses item i at time t, facing assortment a at time t,  $u_{it|a}^h$  = the choice utility of item i for household h facing assortment a at time t,  $C_a^h$  = set of category items available to household h within assortment a and  $\mu_a$  = Gumbel scale factor.

As suggested by Swait and Andrews (2003), we allow the scale factors  $\mu_a$  and key utility parameters – including shelf effects – to differ between assortments<sup>4</sup>. For identification purposes, the scale factor of the first (limited) assortment is normalized to one ( $\mu_1 = 1$ ) (cf. Andrews and Currim 2002; Swait and Louvière 1993). To accommodate household heterogeneity, we opt for a continuous mixture approach with normally distributed parameters across households (McFadden and Train 2000). As suggested by Train (2001), we do not

introduce random effects for attribute-specific constants<sup>5</sup> or for variables that themselves already capture preference heterogeneity such as the LT preference measure and proximity variable. We estimate the mixed MNL (MMNL) model through simulated maximum likelihood using the quasi-random Monte Carlo (or Halton) method (Bhat 2001).

### 3. Estimation results

Table 3 presents the estimation results for margarine and cereals. Coefficients of the *non-shelf-related* variables (attribute constants, item preference, last purchase, stock-out asymmetry) are significant in the majority of cases and have the expected sign.

<insert table 3>

*Main shelf effects.* The *sequence* variable has a positive and significant impact in assortment 3 ( $\beta_{seq}=.619$ ,  $p<.01$ ) for cereals and assortment 2 ( $\beta_{seq}=.367$ ,  $p<.05$ ) for margarine. In both categories, we thus find evidence of a primacy effect, supporting hypothesis 1. Note that for margarine in assortment 1, all items are visible on one screen, eliminating possible first screen effects. Within the assortments where this parameter is significant, first-screen alternatives experience an important increase in choice probability: on average 11.30% for margarine (assortment 2) and 20.75% for cereals (assortment 3).

Interestingly, a similar pattern is observed for the *proximity* variable. Items adjacent to stock-outs are more likely to be chosen in assortment 2 for margarine ( $\beta_{prom}=1.03$ ,  $p<.01$ ) and in assortment 1 ( $\beta_{prom}=2.01$ ,  $p<.01$ ) and 3 ( $\beta_{prom}=4.11$ ,  $p<.01$ ) for cereals. As hypothesized in H<sub>2</sub>, consumers tend to fix their attention to the shelf area containing their focal (out-of-stock) item and are more likely to select a proximate item rather than a distant one. When significant, this proximity effect is substantial, items close to stock-outs having, on average, 9.30% (margarine, assortment 2) and 21.96% and 41.15% (cereals, assortments 1 and 3) higher propensities of being selected.

*Moderating assortment effects.* As expected (H<sub>3</sub>, H<sub>4</sub>), we find strong primacy and proximity effects for the largest assortments (assortment 2 for margarine and assortment 3 for cereals). Yet, this is not uniformly true for all extended assortments (like assortment 3 for margarine and 2 for cereals), suggesting that characteristics other than assortment size are also at play. To better understand what is driving the results, we use additional information from the post-purchase questionnaire, where consumers were asked to report how easy it was to find a suitable alternative (ease of processing or cognitive requirements: Gourville and Soman 2005; van Ketel et al. 2003). ANOVA-analyses reveal significant differences between assortments, for margarine as well as for cereals<sup>6</sup>. Combining tables 3 and 4, we note that primacy and proximity effects are especially important when extended assortments are difficult to evaluate.

<insert table 4>

This observation is in line with the intuition behind hypotheses 3 and 4: shelf-based heuristics being used more often in complex choice situations. However, the difficulty to find a suitable item does not simply increase with assortment size: larger assortments even *facilitate* choice decisions when they provide more variation on key attributes. In line with previous results, we find that the type of attribute guiding customer choices differs between categories (e.g. Campo et al. 2003). In the cereals category, 70% of the respondents indicate to place strong emphasis on flavor, while only 44% of the shoppers mention this criterion as important when selecting margarine. Margarine choices, in contrast, are strongly guided by brand cues: 49% of margarine-buyers mention this attribute as important while only 17% does so for cereals.

*Robustness checks.* To verify the validity of our findings, we conducted several robustness checks. First, we tested alternative operationalizations of the sequence effect. Replacing the first screen definition by a count variable (reflecting the serial order in which products are

encountered when consumers scroll on to subsequent screens) did not produce any improvement in model fit. We also added a last screen variable, which turned out to have a negative effect, confirming that primacy effects are more important than recency effects. Second, in addition to the sequence variable (capturing *across* screen placement), we inserted an on-shelf position variable ( $OS_{it}^h$ ), capturing the placement of products *on* the first screen. We tested several alternatives, checking whether products presented on (i) top rows, (ii) middle rows (the counterpart of eye-/hand-level) or (iii) top-left positions had higher choice propensities. As expected, none of these alternative on-screen variables improved model fit or face validity. Third, we tested another definition of the proximity variable, using last purchase as an alternative indicator for the consumers' focal item. This did not lead to any improvement in model fit either. Finally, to make sure that our proximity or sequence effects were not an artifact of the way the shelf was arranged (by brand or flavor), we added interactions between these shelf position variables and shelf arrangement<sup>7</sup>. No significant differences were found.

#### **4. Discussion**

Our results show that, despite debates about the ease of searching on the Internet, virtual shelf management remains an important issue for online stores. First, while the allocation of shelf facings to products is no longer important, we find that *across* screen placement may strongly affect consumer choices. First-screen alternatives are more likely to be selected, as consumers start to acquire and process information on that screen and tend to stop their search process as soon as they find a satisfactory product (primacy-effect). The fight for shelf space thus becomes a fight for 'first screen placement', manufacturers having an interest in procuring positions on the initial category screen. Online retailers can use the first screen as an in-store stimulus to highlight specific alternatives (e.g. higher-margin and/or private label items). A

possible caveat is that, on many e-grocery sites, consumers have the possibility to change the layout of the shelf themselves. Yet, consumers *do* see the default/start option first, and previous research (Wu and Rangaswamy 2003) as well as the current study reveal that they tend to stay with this option. As such, ‘default’ first screen effects remain important.

Second, even though the absolute placement of products *on* a screen is not influential, their placement *relative* to other items is. Once consumers focus on a particular section of the shelf – the area containing their favorite item – and find out that this item is out-of-stock, they are more likely to stay within that section, switching to items placed close to the focal product. Hence, shelf arrangement can be a useful and effective instrument to guide replacement decisions in the direction of specific (e.g. private label) items.

Third, while their potential impact is substantial, sequence and proximity effects are not always active. Our results indicate that consumers are more inclined to adopt shelf-based choice heuristics when they experience more difficulty in finding and choosing an item from the category assortment. This ‘difficulty of processing’ is found to depend not only on the number of alternatives offered – which can either be too small or too large – but also on assortment composition. In particular, variation on non-crucial attributes seems to complicate the decision process – an observation in line with previous findings (cf. Boatwright and Nunes 2001; van Herpen and Pieters 2002). Especially in such cluttered assortments will online shelf management guide consumer choices.

Obviously, our research has a number of limitations and leaves several aspects of online shelf management uncovered. First, using an experiment may have entailed some biases because of, for instance, the lack of budget/time constraints and the relatively easy shopping task (only two categories). Despite these experimental conditions, our results already reveal that consumers rely on task-simplifying decision rules. In fact, our experiment constitutes a

conservative test: consumers' tendency to use heuristics probably increasing when they have a long shopping list and are really pressed for time. At the same time, it is clear that other issues remained uncovered. For instance, the impact of store familiarity was difficult to account for, given the limited number of shopping occasions. Future real-time longitudinal studies could shed more light on the use of shelf-based cues over time.

Second, we only studied two categories, manipulated two possible assortment extensions (by brand or by flavor) and considered assortments that remained modest in size. The fact that we do find evidence of shelf-based heuristics in such a setting is, again, encouraging. Even so, more extensive analysis is needed to examine whether and how assortment differences (e.g. more variation in assortment size, variation along different attributes), in a wider range of categories, affect perceived decision difficulty and the use of shelf-based heuristics.

Third, while our experiment provides interesting findings, it also raises new issues. For one, we cannot tell whether our first screen effect is due to consumers not scrolling to subsequent screens, or performing only cursory checks after having selected a first-screen alternative. Also, the absence of significant 'on screen' effects may stem from the fact that brand stimulus characteristics, that we do not control for (e.g. package color, see van der Lans, Pieters and Wedel 2005), dominate on-screen salience, and blur consumers' systematic search patterns. Experimental approaches that allow for closer analysis of consumers' decision processes (e.g. decision time, eye movements) may shed more light on these interesting issues.

Finally, the finding that online grocery shoppers are susceptible to shelf sequence and proximity effects opens up exciting new research possibilities: the influence of typical online instruments, such as display customization possibilities or the availability of previous shopping lists, being high on the research agenda.



## 5. Notes

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<sup>1</sup> The software and the experimental site were developed by Hypervision, the software company responsible for the e-grocery site. Some adjustments were made to fit our experimental design (e.g. absence of promotions).

<sup>2</sup> Last purchase variables could be used as an alternative indicator for the customers' focal item. Yet, they only provide a good indication of the item consumers focus on in categories with high item loyalty and low variety seeking tendency. In contrast, out-of-stocks allow for a more universal and direct indicator of focal items, as is confirmed by the robustness checks reported below.

<sup>3</sup> Traditionally, price would also be included in the utility function. However, due to our experimental setup, prices do not change over time and are – therefore – strongly linked to the set of attributes describing the SKU. Estimation of a model incorporating both SKU attribute constants and price would, under these circumstances, lead to serious estimation problems caused by collinearity between both sets of variables.

<sup>4</sup> As argued before, consumers are more likely to turn to task-simplifying tactics when they have to search a (replacement) product in a large compared to a small assortment. We expect differences with respect to the sequence, proximity and asymmetric switching variables between assortments: the effects being (more) significant in a large than in a small assortment ( $H_3$  and  $H_4$ ). Although we did not explicitly include hypotheses with respect to the moderating effect of assortment size on the tendency to asymmetrically switch towards items with specific attributes, it is not inconceivable that a similar logic holds for these asymmetry variables. The probability that consumers will focus on key product attributes as a heuristic to make easy and effortless decisions is more likely in a large than in a small assortment. Not only assortment size, also composition might affect the tendency to turn to specific asymmetric switching heuristics. For these reasons, we decided not to constrain asymmetric switching variables to be equal across assortments. In contrast, the tendency to have a LT preference or to repurchase the same item is a personality trait that is expected to be prevalent across assortments (cf. Andrews and Currim 2002). The validity of these choices was confirmed by robustness checks that explicitly tested whether variables should be pooled or not.

<sup>5</sup> There are various reasons why we decided to keep attribute-specific coefficients constant. First, it is shown that mixed logit models have a tendency to be unstable when all coefficients are allowed to vary (Train 1999). Models where all coefficients varied did indeed not converge in any reasonable number of iterations. Fixing the attribute-specific coefficients resolved this instability. Second, Train (2001) has indicated that the mixture might be empirically unidentifiable in a model where, next to final idd extreme value terms, the item-specific dummy coefficients are assumed to be random. Including a similar distribution (which is the case for the normal and extreme value distribution) results in unstable estimations because the final idd extreme-value terms in a model with item-specific constants already constitute the random portion of these constants. Robustness checks explicitly testing whether or not variables should be fixed, confirmed the validity of our choices.

<sup>6</sup> The underlying structure was confirmed by a principal components analysis. Ease of processing had a Cronbach alpha of 0.814 (0.875) for margarine (cereals).

<sup>7</sup> Note that the stock-out asymmetry variables already account for the fact that, when facing stock-outs, consumers may more readily switch to items of the same size, brand and/or flavor. Proximity effects thus reflect the impact of product adjacencies *over and above these attribute-driven switches*. The robustness checks provide an additional guarantee that it is proximity, and not attribute-based shelf arrangement, that drives results.

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Table 1: Descriptives for each assortment (margarine and cereals)

<b>MARGARINE</b>			
<b>Attribute</b>	<b>Assortment 1 (limited)</b>	<b>Assortment 2 (add new flavors of existing brands)</b>	<b>Assortment 3 (add new brands of existing flavors)</b>
Brand	Common <sup>a</sup>	Common	Common Add new brands
Flavor	Common	Common Add new flavors	Common
# alternatives	11	19	17
# respondents	105	116	100
# purchase occasions	275	279	278
# screens needed	< 1	> 1	> 1
<b>CEREALS</b>			
<b>Attribute</b>	<b>Assortment 1 (limited)</b>	<b>Assortment 2 (add new flavors of existing brands)</b>	<b>Assortment 3 (add new brands of existing flavors)</b>
Brand	Common	Common	Common Add new brands
Flavor	Common	Common Add new flavors	Common
# alternatives	21	32	46
# respondents	81	97	87
# purchase occasions	271	261	281
# screens needed	> 1	> 1	> 1

<sup>a</sup> common refers to attribute levels that are present in all three assortments

Table 2: Variables in MNL choice model

<u>Variable</u>	<u>Description</u>
A	Set of attributes relevant to the product category (for instance: brand, flavor, type and/or package size)
L <sub>A</sub>	Index set of levels relevant for attribute A
D <sub>A,l,i</sub>	Attribute-level dummy variable (equal to 1 if item i is characterized by level l on attribute A, 0 otherwise)
$Pr ef_i^h$	Preference of household h for item i, measured as its ‘purchase share’ in the period prior to the experiment (as reported in the post-purchase questionnaire)
$LP_{it}^h$	Last purchase dummy variable (equal to 1 when item i was last purchased by household h at time t, 0 otherwise)
$OOS_{A,it}$	Stock-out asymmetry variable for attribute A (equal to the number of alternatives similar to i on attribute A that are out-of-stock in t)
$Seq_{it}^h$	Shelf sequence variable (equal to 1 if item i for household h is shown on the first screen at time t, 0 otherwise)
$Prox_{it}^h$	Proximity variable (equal to the weighted sum of the number of out-of-stock items ( $i_{oos}$ ) that are positioned next to item i at time t for household h, with weights equal to the preference of household h for the stock-out item ( $Pr ef_{i_{oos}}^h$ ))  $Prox_{it}^h = \sum_{i_{oos}} Pr ef_{i_{oos}}^h * Adj_{i-i_{oos},t}^h$ with $Adj_{i-i_{oos},t}^h =$ adjacent dummy variable (equal to 1 if item i is adjacent to stock-out item $i_{oos}$ for household h at time t, 0 otherwise)

Table 4: ANOVA-results for the impact of assortment (margarine and cereals)

Variable	Margarine			Cereals		
	<b>Ass 1 Limited</b>	<b>Ass 2 Ext flavors</b>	<b>Ass 3 Ext brands</b>	<b>Ass 1 Limited</b>	<b>Ass 2 Ext flavors</b>	<b>Ass 3 Ext brands</b>
# of items	11	19	17	21	32	46
<b>Ease of processing</b>	5.59	5.67	<b>5.89</b>	5.48	<b>5.85</b>	5.28
	Significant difference: 1 & 3, 2 & 3			Significant difference: 1 & 2, 2 & 3		

Table 3: Model estimation results<sup>a</sup>

Margarine				Cereals			
Variable	Assortment 1	Assortment 2	Assortment 3	Variable	Assortment 1	Assortment 2	Assortment 3
Scale factor	[1.00] <sup>b</sup>	1.2498***	1.2627***	Scale factor	[1.00] <sup>b</sup>	1.0562***	0.7573***
<b>Mean</b>				<b>Mean</b>			
Last purchase	2.0675***	[2.5840***] <sup>c</sup>	[2.6106***] <sup>c</sup>	Last purchase	0.6441***	[0.6803***] <sup>c</sup>	[0.4888***] <sup>c</sup>
Item preference	2.8310***	[3.5382***] <sup>c</sup>	[3.5747***] <sup>c</sup>	Item preference	5.2011***	[5.4934***] <sup>c</sup>	[3.9109***] <sup>c</sup>
Brand asymmetry	0.2805	0.4228**	0.5400*	Brand asymmetry	0.0077	0.6130	0.0969
Size asymmetry	-0.0841	-0.0880	0.0169	Taste asymmetry	-0.0260	0.2938**	-0.1596
Sequence	- <sup>d</sup>	0.3672**	-0.1190	Type asymmetry	0.3119	-0.0614	0.3816**
Proximity	0.8332	1.0303***	0.6235	Sequence	-0.3311	-0.0695	0.6190***
				Proximity	2.0041***	0.7214	4.1140***
<b>Brand</b>				<b>Brand</b>			
Becel, control <sup>b</sup>	0.000	0.000	0.000	Kellogg's <sup>b</sup>	0.000	0.000	0.000
Benecol	-0.0945	-0.7846***	-1.2260**	Others	-0.8398**	0.0710	-1.2232***
Delhaize, margarine	0.0445	0.8489**	-0.3246	Private label	-	-	-1.7760***
Derby	-0.6000*	-0.3389	-0.2753	Nestlé	-	-	-1.1367***
Effi	-0.4256*	0.4075	0.0216	<b>Taste</b>			
Roda	-0.3640	0.0556	-1.4357*	Choco <sup>b</sup>	0.000	0.000	0.000
Solo	0.3068	0.0462	-0.9912***	Nature	-0.2962	-0.2474	-0.0597
Vitelma	0.3102	0.0163	-0.3268	Honey	-0.0838	0.4272	-0.4073
Becel, essential	-	-0.0521	-	Sugar	-	0.1679	-
Becel, pro-activ	-	-0.0988	-	Health	-	0.3459	-
Delhaize, minarine	-	-0.8314**	-	Fruit	-	-	0.3226
Alpro	-	-	-0.0484	<b>Type</b>			
Belolive	-	-	-0.4749*	Rice <sup>b</sup>	0.000	0.000	0.000
Bertolli	-	-	0.0417	Corn	0.2516	0.4012	0.9734***
Planta	-	-	-0.3425	Wheat	-0.8162 **	0.4189	0.3231
<b>Size</b>				Muesli	-0.4724	-0.0142	0.6461
Small size <sup>b</sup>	0.000	0.000	0.000	Crunchy	-0.4608	-0.2162	-0.5938
Large size	-0.4101	-0.9719***	-0.4353**	Mixed	-	-	0.6281
<b>Variances</b>				Variety	-0.9833**	-0.4384	0.0495
Last purchase	2.0153***	1.9935***	2.2995***	<b>Variances</b>			
Brand asymmetry	0.0605	0.0283	0.0532	Last purchase	3.3945***	0.8278***	2.6386***
Size asymmetry	0.0301	0.0179	0.0276	Brand asymmetry	0.4075*	0.4307	0.5193
Sequence	- <sup>d</sup>	0.0965	0.1341	Taste asymmetry	0.2134	0.1773	0.7050***
				Type asymmetry	0.1311	0.5058***	0.4332
				Sequence	0.5041	0.0863	0.8247**

a \*\*\* = sign. at 1% level; \*\* = sign. at 5% level; \* = sign. at 10% level; 2-tailed significance test, with exception of sequence and proximity variables, for which a 1-tailed test was applied.

b This constant is used as the reference.

c These coefficients are derived parameter estimates (found by multiplying the values for these variables by the relative scale parameter).

d In assortment 1 (margarine), all alternatives are shown on the first page, implying that no first-screen effect could be estimated for this assortment.