

# OPPORTUNITIES FOR ACTIVE STOCK-OUT MANAGEMENT IN ONLINE STORES: THE IMPACT OF THE STOCK-OUT POLICY ON ONLINE STOCK-OUT REACTIONS

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# **OPPORTUNITIES FOR ACTIVE STOCK-OUT MANAGEMENT IN ONLINE STORES: THE IMPACT OF THE STOCK-OUT POLICY ON ONLINE STOCK-OUT REACTIONS**

## **ABSTRACT**

This paper investigates the impact of an online retailer's stock-out policy on purchase incidence and choice. We make a distinction between three policies: (1) stock-outs are immediately *visible* and there are *no suggestions*, (2) stock-outs are only *visible after clicking* and (3) a *replacement item* is *suggested* for each stock-out product. Results from an extensive and realistic online grocery shopping experiment reveal that the adopted stock-out policy has a significant impact on both decisions. First, making stock-outs not immediately visible creates confusion and intensifies the consumer's loss experience, thereby reducing the tendency to buy in the category. Second, while suggesting a replacement item normally leads to a substantial increase in the item's choice probability, this effect is canceled out when higher-priced – suspicious – items are suggested. Overall, these results indicate that retailers have an interest in pursuing open and convenience-oriented stock-out policies.

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## **INTRODUCTION**

Product unavailability is a commonly occurring problem for grocery shoppers. Traditional out-of-stock research has shown that stock-outs have a negative impact for retailers, both directly, i.e. on category sales and profit (e.g. Campo, Gijsbrechts and Nisol 2003; Schary and Christopher 1979) and indirectly, i.e. via satisfaction, store loyalty and retail image (e.g. Bell and Fitzsimons 1999; Fitzsimons 2000; McGoldrick 2002; Zinn and Liu 2001). Recent evidence suggests that stock-out problems are not limited to traditional supermarkets (e.g. Anderson Consulting 1996; Corsten and Gruen 2003; PWC Consulting 2002), but constitute a far more daunting problem for virtual e-grocers (e.g. Danaher, Wilson and Davis 2003; Melany Smith – ClickZ-today 2004; see also online grocery sites like Netgrocer, Caddyhome). These online stores experience more severe forecasting problems and strongly fluctuating demand (e.g. Fitzsimons 2000; Anton van Elburg – Emerce 2001). What's more, especially online retailers are vulnerable to stock-out losses in the long term, as they are still struggling for a bite of the market ('Online grocery slowly gets back on its feet'; Regan 07/01/'02). Recent research has shown that product unavailability rates second in the top 3 of irritations with online shopping (Marketing online 9/11/2004).

Despite their importance, stock-outs have not yet been investigated systematically in an online (grocery) context. Yet, such research could be insightful for at least two reasons. First, online stock-out reactions might differ from those in brick-and-mortar settings because of, e.g., the lack of sensory attributes (Degeratu, Rangaswamy and Wu 2000) or the convenience-driven motivation to use online grocery shopping services (e.g. Morganosky and Cude 2002) (Alba et al. 1997; Danaher et al. 2003). More importantly, the online environment offers opportunities to deal with the negative effects of stock-outs (which we will refer to as '**stock-out policies**' hereafter) that are not or difficult to implement in a traditional grocery store. *First*, an online grocer has the possibility to not 'mention' out-of-stock occurrences. While an out-of-stock in a traditional store is visible for all clients, an online retailer may choose to notify only buyers of that particular product (i.e. apologizing for the out-of-stock occurrence after clicking). *Second*, online retailers are in an ideal position to 'replenish the empty shelf space' (cf. the traditional practice; Borin and Farris 1995; Campo and Gijsbrechts 2004; Urban 1998) through the suggestion of a substitution product (cf. online product recommendations: Bell and Fitzsimons 1999; Fitzsimons and Lehmann 2004; Senecal and

Nantel 2004). As soon as the online retailer has listed the replacement items (or specified a procedure to automate this), a technical process will make sure that suggestions are made immediately each time an out-of-stock occurs (cf. Senecal and Nantel 2004). In contrast, offline retailers have to physically reorganize the shelves when an out-of-stock is noticed, resulting in a more difficult and costly implementation of the replacement policy (Corsten and Gruen 2003).

Our research will contribute to the literature in two ways. First, it improves our understanding of online out-of-stock reactions. Our second, and main, contribution is to highlight the consequences for online retailers of actively pursuing alternative stock-out policies. Specifically, we investigate the category purchase incidence and choice effects of (1) a ‘visible, no-replacement’ stock-out policy (stock-outs visible for everyone and not suggesting a replacement item), (2) a ‘non-visible’ stock-out policy (stock-outs visible only for the buyer) and (3) a ‘replacement’ stock-out policy (suggesting a replacement product for each out-of-stock product). In the next section, we propose a conceptual framework and derive hypotheses regarding the stock-out policy effects. Next, we describe the methodology and the data set used to test our hypotheses. We then discuss the results of an online shopping experiment (for two categories: margarine and cereals) and indicate directions for future research.

## **CONCEPTUAL FRAMEWORK AND HYPOTHESES**

In this section, we present a literature-based framework for consumers’ response to alternative stock-out policies. To this end, we proceed in two steps. First, we briefly review decision process characteristics in ‘regular’ low-involvement choice settings and indicate how ‘disruptions’ in the choice context, such as stock-outs, affect consumers’ routine purchase behavior. Next, we describe how retailer actions aimed at recovering some of the stock-out losses, are evaluated by consumers and how they affect their ultimate purchase decisions. Based on these insights, we then formulate expectations on how a retailer’s out-of-stock policy influences stock-out reactions.

### *2.1 Conceptual framework*

#### *2.1.1 Consumer reactions to online stock-outs*

When making a purchase decision in a familiar fmcg context, consumers do not engage in extensive cognitive processing but employ task-simplifying decision rules. These simple rules

of thumb allow consumers to reach a satisfactory decision while minimizing cognitive effort (Hoyer 1984; Leong 1993). Disruptions in the choice environment may cause changes in the application and outcomes of these stabilized choice tactics, and thereby change routine purchase decisions (Andrews and Srinivasan 1995; Dickson and Sawyer 1990; Wu and Rangaswamy 2003). Stock-outs are a typical example of such disruptions. Yet, they differ from other disrupting events – such as promotions – in that they are essentially negative in nature and may *force* consumers to change their planned/habitual purchase decisions (Campo, Gijsbrechts and Nisol 2004). Below, we briefly characterize consumers' routine purchase decisions and indicate how stock-outs are expected to affect them.

Previous research has shown that the **incidence decision** (buy or do not buy) depends on the perceived attractiveness of the product category, together with household-specific variables (such as usage rates and in-home inventory levels) (e.g. Bucklin and Gupta 1992; Bucklin and Lattin 1991). Out-of-stocks reduce the attractiveness of the product category, as previously available alternatives can no longer be chosen. This reduction may turn a buy-decision into a non-buy-decision depending on the 'severeness' of the decline. The latter is largely governed by the consumers' preference for the missing items (e.g. Campo, Gijsbrechts and Nisol 2000; Sloot, Verhoef and Franses 2004) and the availability of suitable replacement items (e.g. Boatwright and Nunes 2000; Broniarczyk, Hoyer and McAlister 1998; Campo et al. 2000). In addition, purchase incidence effects will depend on the overall consequences of not making any purchase in the category (buying urgency, risk of running out of stock at home, see e.g. Campo et al. 2000; Sloot et al. 2004; Zinn and Liu 2001) and on preference uncertainty. When the consumer finds it difficult to make a decision, s/he may become confused and therefore reluctant to buy (Dhar 1997).

Next, when making repeat purchase decisions in a regular choice context, consumers have been found to simplify their **choice decisions** in several ways.

First, there is ample support that consumers do not take the universal set of alternatives into account each time they choose a low-involvement product. Instead, they simplify the decision process by using a more restricted subset of alternatives, called the consideration set, from which they make their final choice (e.g. Andrews and Srinivasan 1995; Bronnenberg and Vanhonacker 1996; Roberts and Lattin 1991; Shocker et al. 1991; Wu and Rangaswamy 2003). This screening process need not be binary: some alternatives may be considered to a

greater or lesser extent than others (Bronnenberg and Vanhonacker 1996; Fortheringham 1988; Wu and Rangaswamy 2003).

Second, previous research has proposed that different decision rules are used for the two stages. In the first stage, consumers use simple tactics or cues to identify alternatives warranting greater consideration (i.e. a non-compensatory or hierarchical approach) (e.g. Andrews and Srinivasan 1995; Bronnenberg and Vanhonacker 1996; Gensch 1987; Gilbride and Allenby 2004; Laroche, Kim and Matsui 2003; Shocker et al. 1991). Specifically, consideration set formation in low-involvement categories is found to be driven by four main indicators: (1) preferred product characteristics (focal attributes; Bell and Fitzsimons 1999; Kamakura, Kim and Lee 1996), (2) acceptable price level (below the reservation price; Jedidi and Zhang 2002), (3) in-store elements that highlight products (e.g. displays and shelf position; Hoch, Drèze, & Purk 1994; Bronnenberg & Vanhonacker 1996; Nedungadi 1990) and (4) recency of purchase (preference reinforcement or variety-seeking effects; Bronnenberg and Vanhonacker 1996; McAlister 1982; Roberts and Lattin 1991). The second decision stage involves a more detailed analysis of the reduced set (i.e. a compensatory or simultaneous approach) (e.g. Andrews and Srinivasan 1995; Bronnenberg and Vanhonacker 1996; Gensch 1987; Laroche et al. 2003; Shocker et al. 1991). In this stage, other (non-focal) attributes will gain importance. So, while consideration set formation is more strongly rooted in differences in salience (prominence) between alternatives, the final choice is influenced by the intrinsic value of the alternative on all attributes (e.g. Bronnenberg and Vanhonacker 1996; Shocker et al. 1991; Wu and Rangaswamy 2003).

We expect that stock-outs, being a disruption in the normal choice environment, mostly influence the choice process through their impact on the consideration set. Obviously, out-of-stock alternatives cannot be selected, reducing their degree of consideration to 0% (cf. Campo et al., 2003). In addition, while out-of-stocks do not affect the intrinsic value of the remaining alternatives, they do enhance the degree of consideration of those alternatives, which can act as a replacement. The extent to which a stock-out increases another item's degree of consideration will depend on (1) shared attributes with the stock-out item (especially focal attributes, see e.g. Campo et al. 2003), (2) the difference in price level, (3) in-store elements that highlight the item (see next section), and (4) whether and how long ago the alternative item has been purchased before. Hence, it follows that stock-outs influence choice probabilities (of the remaining items) through their impact on the items' degree of consideration, rather than on the choice utility.

### 2.1.2 Consumer reactions to service recovery policies

Consumers' response to disruptions in the choice environment (in casu: stock-outs) also depends on how retailers are perceived to deal with these disruptions. Retailers can adopt various policies to alleviate the consequences of service failures like stock-outs: they can make these failures less prominent or attempt to compensate for the inconvenience they cause. Based on the service failure/recovery literature as well as equity literature (Clemmer and Schneider 1993; Fitzsimons and Lehmann 2004; Palmer, Beggs and Keown-McMullan 2000; Smith, Bolton and Wagner 1999), we expect consumers to judge such retailer policies on two criteria: outcome and procedure. First, the appreciation of the retailer's policy depends on the perceived fairness of the outcome, captured by the benefits (or lack thereof) consumers receive as a result of this policy. Second, the consumers' appreciation of the retailers' policy depends on the perceived fairness of the procedures or norms used. Prior research on attribution theory suggests that consumers make causal inferences about the behavior of others (in our case: the policy of retailers), which, in turn, affect their own subsequent behavior (in our case: choice and incidence) (Folkes 1988; Mizerski, Golden and Kernan 1979). Consumers can attribute the policy of the retailer either to 'altruistic' or customer-serving motives, or to 'egoistic' or self-serving motives (Kelley 1973; Ellen, Mohr and Webb 2000). The discounting principle of the attribution theory (Kelley 1973) dictates that the consumer will believe in the retailers' genuine willingness to serve consumers, unless policy benefits to the firm are salient (cf. Forehand and Grier 2004). If the retailer's policy is thought to be guided by firm-serving (retailer-enriching) motives, it will produce backlash behavior (cf. Fitzsimons and Lehmann 2004, Forehand and Grier 2004).

Based on the insights above, the next section presents hypotheses on how a retailer's out-of-stock policy influences stock-out reactions. Specifically, we consider three alternatives: (1) a visible, no-replacement policy, (2) a non-visible policy and (3) a replacement policy. For the latter policy, we explore the moderating impact of whether higher priced or same/lower priced substitutes are suggested (see figure 1).

## **INSERT FIGURE 1**

### *2.2 Hypotheses*

In traditional (brick-and-mortar) grocery stores, stock-outs are typically visible (as empty spaces on the shelf), and no replacement items are suggested. We use this approach as the

benchmark case in our paper. Below, we subsequently hypothesize how the introduction of a non-visible and a replacement stock-out policy affect consumer category purchase incidence and choice. We hypothesize that the non-visible policy influences the incidence decision while the replacement policy has an impact on both choice and incidence.

### 2.2.1 The impact of a non-visible out-of-stock policy

Instead of marking all out-of-stock items on the screen, online retailers may opt for a non-visible policy. With such a policy, product unavailability is only announced to potential buyers of the stock-out product at the time they click on the item to activate their purchase.

This practice produces the following effects. On the positive side, as long as consumers do not hit a stock-out item, they perceive the assortment as complete. This may lead to a more positive evaluation (for instance, higher perceived freedom of choice, cf. Reibstein, Youngblood and Fromkin 1975) compared to the visible policy, where the reduction in category attraction due to stock-outs is immediately observable. However, this positive effect should not be exaggerated. For one, even in a visible policy setting, consumers may fail to notice stock-outs (e.g. Beuk 2001). Moreover, while the assortment in a non-visible policy setting is perceived more positively at the outset, this situation may rapidly change as the consumer – in an attempt to purchase from the category – clicks on a stock-out item and discovers that the product s/he is interested in is in fact a non-available, phantom product (Farquhar and Pratkanis 1993). The more stock-out items the consumer clicks on in vein, the more likely it becomes that s/he will reach ‘a point of frustration’, i.e. a point where the category attractiveness in a non-visible policy becomes lower than the category attractiveness in a visible out-of-stock policy (see figure 2). At this point, s/he is less likely to make a purchase in the non-visible than in the visible policy.

### **INSERT FIGURE 2**

We conjecture that this point of frustration is reached very quickly (even after only one or a few clicks), each stock-out encounter in the non-visible policy producing particularly strong backlash effects. For one, the *outcome* of the non-visible policy may quickly become unappealing to the consumer for at least three reasons. First, upon clicking, the consumer is confronted with unavailability of a preferred item. The disappointment and/or frustration arising from clicking on a stock-out item strengthens the loss experience resulting from the out-of-stock situation. Second, not only does the consumer observe the stock-out in a stage

where s/he is already set on buying the product, s/he also becomes aware of the uncertainty about the true availability of other alternatives. The anticipation of a complex ‘trial and error’ purchase sequence may make him refrain from purchasing (Dhar 1997). Third, subsequent hits on unavailable items constitute segregated losses, which may quickly loom larger than the aggregated reduction in assortment attractiveness observed in the visible policy (Thaler 1985).

Moreover, consumer reactions with respect to the non-visible stock-out policy are also influenced by the evaluation of the *procedures* that guide this policy. Consumers are likely to attribute the non-visible policy to ‘self-serving’ motives – retailers hiding their stock-out problems. This is likely to further reduce their willingness to purchase.

In brief, we expect the positive effects of a non-visible policy to be more than counterbalanced by the negative effects:

**H<sub>1</sub>: When confronted with out-of-stocks, consumers are less likely to make a purchase in the category when the retailer follows a non-visible policy (where stock-outs are visible only after clicking) than when stock-outs are visible to all consumers.**

### 2.2.2 The impact of a replacement out-of-stock policy

With a replacement out-of-stock policy, the retailer accompanies notification of a stock-out by the suggestion of a replacement item (already present in the category). Such practice is bound to produce a number of positive effects. First, it diverts attention from the out-of-stock item (or the delivery failure) to the suggested item. Second, the recommendation can act as an uncertainty-reducing, decision-simplifying heuristic that helps consumers in making an easy and effortless decision when confronted with a stock-out (cf. Fitzsimons 2000; Huffman and Kahn 1998). This is likely to enhance their propensity to purchase from the category (Fitzsimons and Lehmann 2004).

Moreover, the replacement policy highlights a specific alternative as a choice option. Because suggested items ‘stand out’ on the shelf, their consideration and hence choice probability is likely to increase (cf. Bronnenberg and Vanhonacker 1996; Fader and McAlister 1996; Gupta 1988; Siddarth, Bucklin and Morrison 1995). As such, a replacement policy is also bound to produce a choice shift towards the suggested items.

The size of the increase in incidence and choice probability depends – again – on the perceived policy outcome and procedure. Specifically, to what extent highlighting a

replacement item will actually produce choice shifts and enhance perceived category value/facilitate decision making, is shaped by the intrinsic utility of this item. Second, the appreciation also depends on the consumers' faith in the retailer's good intentions. When consumers trust the retailer's suggestion as being the best (closest) replacement item, they are more likely to consider it helpful, and take the suggested alternative into consideration (and hence make a purchase in the category). Conversely, when the retailer is suspected of 'bait and switch' practices (cf. Hess and Gerstner 1998; Wilkie, Mela and Gundlach 1998), opposite effects may occur. One of the core issues when adopting a replacement policy, therefore, is how to select an appropriate substitution product.

As indicated in the previous section, consumers typically consider items that have an acceptable or "fair" price (Jedidi and Zhang 2002; Xia, Monroe and Cox 2004). Replacement items of a higher price, therefore, will be valued less (implying a lower expected *outcome* of the replacement policy). Moreover, when the suggestion is of a higher price, consumers may suspect the retailer of deliberately setting alternatives unavailable with the aim of selling more profitable items (a firm-serving *procedure*). In that case, consumers might show reactance-style responses (Brehm 1966) and punish the retailer by switching away from the suggested item or not buying anything in the category (cf. backlash behavior: Fitzsimons and Lehmann 2004; Simonson, Carmon and O'Curry 1994). As a result, the price of the suggested replacement items moderates the main effect of the replacement out-of-stock policy. Hence:

**H<sub>2</sub>: When confronted with out-of-stocks, consumers are more likely to make a purchase in the category when the retailer suggests a substitute item than when no replacement item is suggested.**

**H<sub>3</sub>: Suggesting an item as a potential substitute for an out-of-stock item increases the probability that the consumer will consider this item for selection.**

**H<sub>4</sub>: Suggesting a higher-priced replacement item negatively moderates the (positive) effect of the suggestion.**

## MODEL DESCRIPTION

In this section we present the model used to test our hypotheses. We subsequently discuss the choice and incidence models.

### 3.1 Two-stage choice model

To test the impact of stock-outs and stock-out policies on item selection, we take the model of Bronnenberg and Vanhonacker (1996) as a starting point. This model – while parsimonious – allows to distinguish the consideration from the choice stage as follows:

$$p_{it}^h = \frac{\pi_{it}^h \exp(u_i^h)}{\sum_j \pi_{jt}^h \exp(u_j^h)} \text{ for } i = 1, \dots, I \quad (1)$$

with  $p_{it}^h$  = the choice probability of alternative  $i$  for consumer  $h$  at time  $t$

$u_i^h$  = the choice utility of consumer  $h$  for alternative  $i$

$\pi_{it}^h$  = the degree of consideration (inclusion probability) of consumer  $h$  for item  $i$  at time  $t$

In Bronnenberg and Vanhonacker (1996)'s model, consideration set formation ( $\pi_{it}^h$ ) depends on differences in salience across alternatives. For a given consumer, the consideration utility for an alternative  $i$  must exceed a minimum threshold level (i.e. minimum needs) to be included in the consideration set. From a modeler's perspective, the consideration utility ( $S_{it}^h$ ) and the cut-off value<sup>2</sup> ( $\Theta_t^h$ ) are observed indirectly with some error  $\xi_{it}^h$ . These errors are iid draws from the Type I extreme value distribution. Under these distributional assumptions, the probability that consumer  $h$  includes an alternative in the consideration set is given by:

$$\pi_{it}^h = \frac{1}{1 + \exp(\theta_t^h - s_{it}^h)} \text{ for } i = 1, \dots, I \quad (2)$$

with  $s_{it}^h$  = the deterministic part of the consideration utility of alternative  $i$  for consumer  $h$  at time  $t$

$\theta_t^h$  = the deterministic part of the threshold for consumer  $h$  at time  $t$

Our first modification of Bronnenberg and Vanhonacker's model ensures that items not available in the virtual store cannot be considered (or chosen). To this end, in line with

Campo et al. (2003), we modify the degree of consideration (equation 2) with an item stock-out dummy variable ( $OOS_{it}$ ) that equals 1 when item  $i$  is not available at time  $t$  and 0 otherwise.

$$\pi_{it}^h = \frac{1}{1 + \exp(\theta_t^h - s_{it}^h)} * (1 - OOS_{it}) \quad (3)$$

Note that the structure of the choice probability (equation 1) guarantees that alternatives that are not on the shelves (i.e. have a degree of consideration equal to 0), cannot be chosen (i.e. have choice probabilities equal to 0).

Second, the *consideration utility*  $s_{it}^h$  is based on differences in prominence across alternatives:

$$s_{it}^h = \omega_{lp} LP_{it}^h + \sum_A \omega_A OOS_{A,it} + \omega_{Sugg} SUGG_{it}^h + \omega_{Hpsugg} HPSUGG_{it}^h \quad (4)$$

where  $LP_{it}^h$  = last purchase dummy variable (equal to 1 when alternative  $i$  was last purchased by consumer  $h$  at the previous purchase occasion, 0 otherwise)

$A$  = set of attributes relevant to the product category

$OOS_{A,it}$  = stock-out asymmetry dummy variable for attribute  $A$  (equal to the number of items similar to  $i$  on attribute  $A$  that are OOS in  $t$ )

$SUGG_{it}^h$  = suggestion dummy variable (equal to 1 when alternative  $i$  is suggested as a replacement item to consumer  $h$  at time  $t$ , 0 otherwise)

$HPSUGG_{it}^h$  = higher price suggestion dummy variable (equal to 1 when alternative  $i$  is suggested as a replacement item to consumer  $h$  at time  $t$  and alternative  $i$  is of a higher package-equivalent price than the stock-out alternative, 0 otherwise)

$\omega_{lp}$ ,  $\omega_A$ ,  $\omega_{Sugg}$ ,  $\omega_{Hpsugg}$  = coefficients to be estimated

The salience or prominence of alternatives is not only influenced by the recency of purchase (Bronnenberg and Vanhonacker 1996), it should also incorporate several out-of-stock-affected heuristics. First, we postulated that the prominence of an available alternative is a function of how similar that item is to out-of-stock items (measured by the similarity on attributes such as brand, flavor, type and/or package size). A positive (negative) coefficient would point to an increase (decrease) in the degree of consideration of alternatives that have

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<sup>2</sup> The cut-off value or threshold is common across alternatives for a given consumer at a given occasion (see Bronnenberg and Vanhonacker 1996).

attribute levels similar to the out-of-stock alternative (cf. Campo et al. 2003). Second, the increase in consideration probability for items that are suggested in the context of a replacement policy must be incorporated. The size of this increase is moderated by whether the replacement item has a higher price or not: recommending a higher-priced replacement item makes the retailer look suspicious and causes a reactance-style response (i.e. switching away from the recommendations). Hence, we expect a positive coefficient for the suggestion (hypothesis H<sub>3</sub>) but a negative one when suggestions are higher-priced (hypothesis H<sub>4</sub>).

Finally, the *choice utility*  $u_i^h$  is a function of time-invariant or long-term preference components that represent the base preference toward alternative i (Bucklin and Gupta 1992; Bucklin et al. 1998; Wu and Rangaswamy 2003). Rather than using product-specific intercept terms, we model consumer preferences over the attributes that represent the SKUs in a product category (and therefore only indirectly model preferences for SKUs themselves)<sup>3</sup> (cf. Fader and Hardie 1996; Ho and Chong 2003). We also include a consumer-specific (long-term) preference measure (Bronnenberg and Vanhonacker 1996).

$$u_i^h = \sum_A \sum_{l \in L_A} \alpha_{A,l} * D_{A,l,i} + \alpha_{loy} Loy_i^h \quad (5)$$

where  $L_A$  = index set of levels relevant for attribute A

$D_{A,l,i}$  = attribute-level dummy variable (equal to 1 if alternative i is characterized by level l on attribute A, 0 otherwise)

$Loy_i^h$  = loyalty (equal to the initial preference share of consumer h for alternative i)

$\alpha_{A,l}, \alpha_{loy}$  = parameters to be estimated

### 3.2 Incidence model

Purchase incidence or the probability that consumer h will purchase in a category on a given purchase occasion t ( $PI_t^h$ ) is modeled as a binary logit model (see e.g. Bucklin, Gupta and Siddarth 1998; Bucklin and Lattin 1991):

$$PI_t^h = \frac{\exp(W_t^h)}{1 + \exp(W_t^h)} \quad (6)$$

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<sup>3</sup> Because price did not change in our experiment and is largely captured by the attributes that describe an SKU, we did not incorporate any price variable in the choice utility function. Estimation of a model incorporating both SKU attribute constants and price indeed led to serious estimation problems caused by extreme collinearity between both sets of variables.

The category purchase utility for consumer  $h$  at time  $t$ ,  $W_t^h$ , is written as:

$$W_t^h = \gamma_0 + \sum_k \gamma_k Z_{k,t}^h + \gamma_{CV} CV_t^h + \gamma_{nv} NVPOL_{nv,t}^h \quad (7)$$

where  $Z_{k,t}^h$  = traditional household variables

$k = 1, \dots, K$  (number of traditional household variables)

$CV_t^h$  = category value for household  $h$  at time  $t$

$NVPOL_{nv,t}^h$  = non-visible out-of-stock policy dummy variable (equal to 1 when consumer  $h$  has been exposed to an out-of-stock policy where stock-outs are not visible at first sight and when there were stock-outs at time  $t$ , 0 otherwise)

$\gamma_0, \gamma_k, \gamma_{CV}, \gamma_{nv}$  = coefficients to be estimated

The purchase utility  $W_t^h$  is a function of traditional consumer characteristics affecting incidence, such as category consumption and inventory level, and of the attractiveness of the product category. The latter, category value, varies between purchase occasions as a result of marketing and other stimuli (cf. Bucklin and Gupta 1992; Bucklin et al. 1998). In the literature, the category value is defined as the expected highest utility available to consumer  $h$  from buying a brand in the category at time  $t$  (e.g. Bucklin and Gupta 1992). Mathematically, the category value is given by the log of the denominator of the choice probability (equation 1) (Ben-Akiva and Lerman 1985; see for applications: Bucklin and Gupta 1992; Bucklin et al. 1998):

$$CV_t^h = \ln \left( \sum_j \pi_{jt}^h \exp(u_j^h) \right) \quad (8)$$

This category value concept integrates choice model information in the incidence model, making purchase incidence probabilities dependent on expected choice utilities (cf. Bucklin et al. 1998).

In our case, category value captures the effect of stock-outs on the likelihood of a category purchase. The purchase incidence decision will be more severely affected (i) when more products are unavailable and (ii) when more favorable products are unavailable (see e.g. Broniarczyk et al. 1998; Campo et al. 2000). Second, the category value allows us to (indirectly) assess the impact of the replacement stock-out policy on the buy/no buy decision. To the extent that the replacement policy increases the suggested alternative's consideration utility, the attractiveness of the category also increases. This increase in category value may

further enhance purchase incidence (hypothesis H<sub>2</sub>). Yet, the positive suggestion effects on incidence are neutralized or counterbalanced in the case of higher-priced replacement items (hypothesis H<sub>4</sub>). Third, in order to find out how the non-visible policy affects the incidence decision, we incorporate a non-visible stock-out policy dummy variable in the equation. The coefficient of this dummy variable is expected to be negative, pointing to a reduced likelihood of a category purchase when customers are confronted with a non-visible stock-out policy (hypothesis H<sub>1</sub>).

### 3.3 Estimation approach

We use maximum likelihood procedures to jointly estimate the model parameters of the incidence and two-stage choice model. In order to incorporate heterogeneity in out-of-stock (policy) and other reactions, we use a latent class approach (cf. Bronnenberg and Vanhonacker 1996; Campo et al. 2003; Wu and Rangaswamy 2003). We specify the parameters of the incidence model ( $\gamma$ 's in (7)) and of the two-stage choice model ( $\theta$ 's in (2),  $\omega$ 's in (4) and  $\alpha$ 's in (5)) at the segment level. Let  $\psi(s)$  denote the relative size of segment  $s$  and  $W(s)$  the purchase utility (see equation 6),  $\pi(s)$  the degree of consideration (see equation 2) and  $u(s)$  the choice utility (see equation 5) of segment  $s$ . Segment-level parameters of the incidence and two-stage choice model can be estimated using the following likelihood function:

$$LL = \sum_h \ln \sum_s \Psi(s) \prod_t \left\{ (PI_{t|s}^h)^{y_t^h} * (1 - PI_{t|s}^h)^{(1-y_t^h)} * \prod_i [p_{t|s}^h(i|inc)]^{y_{it}^h} \right\} \quad (9)$$

where  $PI_{t|s}^h$  is given by equation 6,  $p_{t|s}^h(i|inc)$  is given by equation 1,  $y_t^h$  is equal to 1 if consumer  $h$  has made a purchase in the category at time  $t$  and 0 otherwise and  $y_{it}^h$  is equal to 1 if consumer  $h$  chooses alternative  $i$  at time  $t$  and 0 otherwise.

## EMPIRICAL STUDY

In this section, we first describe the experimental design that was used to gather data. Next, we discuss the overall estimation results. We end by specifically testing and interpreting the stock-out policy effects.

### 4.1 Experimental data

To investigate online stock-out (policy) effects, most scanner panel data (whether registering on- or offline sales) are not appropriate because of the lack of a systematic and

sufficiently detailed registration of out-of-stock occurrences. In the absence of systematic records of stock-outs, previous studies have typically relied on paper and pencil surveys (e.g. Campo et al. 2000; Sloot et al. 2004). Such an approach, however, is not suitable for our purposes. Not only does it fail to realistically represent the online shopping environment, it does not allow to mimic our focal treatments: alternative stock-out policies. In this research, we therefore collected data through a realistic online store experiment which was based on the site of an existing online shopping service and was adjusted to fit our experimental design<sup>4</sup>. Using an experimental design allows us to manipulate the stock-out policy, to control extraneous influences (like price, promotion,...) and to collect additional perceptual data (Burke et al. 1992; Campo and Gijsbrechts 2004; Swait and Andrews 2003).

Our computer experiment consists of three modules: (1) a short pre-purchase questionnaire to collect some general information, (2) a purchase simulation module and (3) a post-purchase questionnaire to survey the experiences with the virtual store. Subjects are randomly assigned to one of the three different out-of-stock policies: (1) *no-replacement* with out-of-stocks *visible* on the screen, (2) no-replacement with out-of-stocks *not visible* on the screen (only after clicking), (3) *replacement* with variations of the suggested substitution products according to different attributes. The dataset contained 17 SKUs for margarine and 46 SKUs for cereals. On average, in every experimental week, 8% of the products in the category were unavailable. This figure is in line with previously reported stock-out rates (Anderson Consulting 1996; Gruen, Corsten and Bharadwaj 2002; Sloot et al. 2004). The occurrence of out-of-stocks was uniformly distributed over low and high share items and over attribute levels (brands, flavors, types and/or sizes).

In order to get a representative sample, we used e-mail addresses coming from 2 mailing lists. Our sampling frame consisted of addresses from a list broker (addresses selected based on demographic and purchase behavior information), complemented with addresses from the staff members of the university (including technical and administrative as well as academic staff). Socio-demographic characteristics of our sample match with online grocery sample characteristics in other research (e.g. Degeratu et al. 2000; Morganosky and Cude 2002; Raijas and Tuunainen 2001). For each mailing address, participation was requested of the household member typically in charge of grocery shopping. Respondents were invited to

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<sup>4</sup> The software and the experimental site were developed by Hypervision, the software company responsible for the e-grocery site.

participate in the research by an e-mail that included a link to the online experimental site. They were asked to make purchases in an online store for two product categories (margarine and cereals) during six successive, fictitious weeks. While such time compression might appear artificial, it has been shown to realistically capture dynamic purchase patterns (Burke et al. 1992; Campo, Gijsbrechts and Guerra 1999). Only respondents regularly consuming from a category were confronted with questions/shopping trips for that category. Respondents were not obliged to buy every week and they were permitted to buy more than one package. For our analyses, the net sample is equal to 584 respondents. 473 (414) respondents completed the purchase simulation for margarine (cereals), leading to 2493 (2443) purchase occasions for margarine (cereals). The first week is used as an initialization week. Therefore, model estimation is based on weeks 2 to 6.

#### *4.2 Estimation results*

Table 1 gives an overview of the variables included in the models. Models are estimated for a varying number of classes and re-estimated using different sets of starting values<sup>5</sup>. Both the BIC and CAIC measures (Leeflang, Wittink, Wedel and Naert 2000) indicate that a two-segment model better fits the data than a single-segment and a three-segment model, for margarine as well as cereals (see table 2). The criteria also reveal that the two-stage model outperforms a simple (one-stage) MNL model (that includes the same variables as the two-stage model) in both categories. Separating out the consideration decision (affected by stock-outs and stock-out policy) from the final choice decision improves the models' descriptive validity<sup>6</sup>. We therefore retain the two-segment, (simultaneous incidence and) two-stage choice models for both categories.

### **INSERT TABLES 1 & 2**

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<sup>5</sup> Due to the conditioning of the dataset and the large number of SKU's in the cereals category, we used a two-step approach for this category. In a first step, we estimate the model with a given threshold (the value of the threshold was determined on the basis of prior research (Bronnenberg and Vanhonacker 1996) and the results of margarine). In a second step, we re-estimate the value of the threshold, given the parameter estimates. We repeated this procedure using the parameters of the previous iteration as starting values until the change in log-likelihood value was smaller than 0.01%.

<sup>6</sup> As an additional check, we also re-estimated the one-stage (simple MNL) and the two-stage (consideration and choice) models on a smaller estimation sample comprising (1) only the first five weeks of the data set (except the first, initialization, week) and (2) a subset (approximately 85%) of (randomly selected) households. We then compared the models' performance on a holdout sample containing respectively (1) observations from week six and (2) the subset (approximately 15%) of the remaining households. For both checks, the two-stage model is found to substantially outperform the one-stage model in terms of predictive validity, for cereals as well as margarine.

Table 3 presents the parameter estimates for the two-segment models, for margarine as well as for cereals.

### **INSERT TABLE 3**

For both categories, the coefficients of category consumption, inventory, last purchase and loyalty are all strongly significant and in the expected directions. The last purchase variable has a positive effect on consideration utility when behavior is of the reinforcing type (cf. enduring set; Roberts and Lattin 1991) and a negative one when behavior is of the variety-seeking type (cf. McAlister 1982) (Bronnenberg and Vanhonacker 1996). Whereas the margarine category is typically characterized as a category with brand-loyal respondents, the cereals category is more likely to be characterized as a category with variety-seeking respondents (Campo et al. 2003; Roberts and Lattin 1991). Our results reflect these category differences: we found 2 segments with a positive last purchase coefficient in the category of margarine and 1 segment with a negative (i.e. variety-seeking segment) and 1 segment with a positive (i.e. brand-loyal segment) last purchase coefficient in the category of cereals. The results also show that short-term preferences in the consideration stage are different from long-term preferences in the choice stage. Although respondents of the first segment of cereals tend to switch away from the previously purchased item (negative effect of last purchase), they have stable (long-term) preferences within a set of alternatives (positive effect of loyalty) (Bronnenberg and Vanhonacker 1996). The constants for each attribute (brand, flavor, type or size) reflect the difference in attractiveness with respect to a reference item.

Concentrating on stock-out effects, we find that, for the two categories under consideration, switching to one of the remaining alternatives is the predominant reaction. This result is in line with observed stock-out responses in offline stores (e.g. Campo et al. 2003). Moreover, we find significant out-of-stock asymmetry effects in one of the two segments for both categories. For margarine, consumers of segment 1 are more likely to consider alternatives of the same brand. For cereals, consumers of segment 2 are more likely to consider alternatives of the same brand and/or flavor. These results are comparable to findings for the same categories in a traditional store setting (Campo et al. 2003). Only for one segment (segment 1 of margarine), we find a significant negative effect of stock-outs on purchase utility (captured by the significant effect of the category value parameter). As stock-outs reduce the category value, consumers are significantly less likely to make a purchase in the category. Research in a bricks-and-mortar setting has shown similar findings: the number of consumers that canceled or switched stores in these categories being rather low (Campo et

al. 2000). In the next paragraphs, we will first discuss the formal (hypotheses) test of the stock-out policy effects and then look at the consequences of actively pursuing a stock-out policy.

#### *4.3 Test of the stock-out policy hypotheses*

*Impact of the non-visible policy.* With respect to the non-visible policy, we find that, for the two categories, not showing stock-outs has a significant and negative influence on the incidence decision in one of the two segments (segment 1 for margarine and segment 2 for cereals)<sup>7</sup>. As hypothesized in H<sub>1</sub>, consumers in these segments are less likely to purchase in a category when they have to click on an alternative before knowing whether or not it is available. This negative effect occurs in the segments that have a strong tendency to repurchase the same item (segments with a strong positive impact of the last purchase variable). For these highly loyal consumers, the false expectations of being able to buy their favorite products – created by the non-visible policy – intensifies the loss they experience when they find out that their preferred item is unavailable after clicking.

*Impact of the replacement policy: main effect.* To assess the significance of the main and moderating effect of the replacement policy on choice, we use the approach outlined in Jaccard, Turrisi and Wan (1990). Starting with the main effect of the replacement stock-out policy, we find that the suggestion has a significant and positive impact on the consideration utility of that alternative, for one of the two segments in both categories. As hypothesized in H<sub>3</sub>, consumers in this segment are significantly more likely to consider an alternative when it was suggested than when it was not. These effects do (segment 1, margarine) or do not (segment 2, margarine and segment 1 & 2, cereals) carry through to incidence, via the category value. The purchase probability is significantly, yet only marginally affected in the margarine category and not affected at all in the cereals category (partial support for hypothesis H<sub>2</sub>)<sup>8</sup>. In sum, while the replacement policy does guide the choice decision of an important segment of consumers, its impact on category purchases remains small to non-existent.

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<sup>7</sup> We also considered testing whether the inclusion of the number of clicks had a significant moderating impact on the non-visible policy. However, such a test did not reveal very meaningful because most consumers typically clicked on at most one stock-out item per week. Only a minority of consumers had to click on more than two items to find a suitable and available alternative.

<sup>8</sup> As a robustness check, we ran a model where a replacement policy dummy was added at the incidence level. Such a dummy could capture influences of the replacement policy ‘as such’ on the consumers’ propensity to buy – apart from its impact on suggested items’ utility. In neither category/segment did the replacement policy dummy reveal significant.

*Impact of the replacement policy: moderating effect of a higher-priced suggestion.* Based on the results in Table 3 (Jaccard et al. 1990), we find that the positive impact of the replacement policy on consideration is no longer significant when the suggestion is a higher-priced item<sup>9</sup>. Hence, in both categories, the positive consideration (and choice) effect of the suggestion is neutralized when a replacement item with a higher price is suggested. It follows that, in the margarine category where the replacement policy has a significant main effect on incidence, this positive effect is nullified when higher-priced replacement items are suggested (support of hypothesis H<sub>4</sub>).

#### 4.4 Consequences of the stock-out policy

In order to assess the overall consequences of the adopted stock-out policy, we use the actual purchase data as a simulation basis. We start by calculating the choice and incidence probabilities for a base scenario, i.e. a scenario where all the stock-out products are visible and no suggestions are made. Next, we change the setting by introducing (1) a non-visible dummy variable (non-visible stock-out policy) and (2) suggestion dummy variables for (non-suspicious) replacement items (replacement stock-out policy) and recalculate the incidence and choice probabilities in these new settings. Table 4 reports the average changes in incidence and choice probability in the new settings compared to the base setting, for margarine as well as for cereals.

#### INSERT TABLE 4

In addition, to obtain better insights into the mechanisms underlying the changes in category and item purchase decisions, we derive analytical expressions for the stock-out effects under different policies.

*Impact of the non-visible policy.* Compared to the visible/no-replacement policy, a non-visible stock-out policy was expected and found to reduce the consumers' tendency to buy in the category (see H<sub>1</sub> and section 4.3). The results reported in table 4 indicate that the non-visible policy leads to a non-negligible decrease in category purchase incidence in both categories. The purchase probability drops by 10.48% and 8.21% for margarine and cereals,

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<sup>9</sup> In the model presented here, the suggestion is considered as 'higher priced' as soon as its price per volume-unit (say, ounce) exceeds that of the stock-out item. We also considered alternative operationalizations, where (i) the price difference was required to exceed a (10% and 15%) threshold, or where (ii) the comparison was between package (instead of volume-unit) prices. The substantive results remained unaltered: significant and negative moderating effects nullifying the positive impact of the suggestion.

respectively, in the segments where a significant response is noted. These figures represent a 5.04% and 4.74% decrease for the market as a whole.

As can be seen from equation 10 (see appendix A for more details on the derivation of this expression), the decrease in incidence probability ( $\Delta PI$ ) strongly depends on the parameter  $\gamma_{NV}$ :

$$\Delta PI = \frac{PI|0 - PI|\Delta pol}{PI|0} = 1 - \frac{1}{e^{-\gamma_{NV}} * (1 - PI|0) + PI|0} \quad (10)$$

where  $PI|0$  is the purchase incidence probability when consumers are exposed to the benchmark policy (visible, no-replacement) and  $PI|\Delta pol$  is the purchase incidence probability when the policy changes to a non-visible policy. Larger values of  $\gamma_{NV}$  (in absolute terms) will lead to stronger reductions in purchase rates, and hence to larger retailer losses. In other words, the more clicking on phantom items in vein frustrates consumers, the larger the reduction in category purchases will be, compared to the visible stock-out policy. From the estimation results reported above, we know that this will especially be the case when consumers are strongly attached to their favorite item.

*Impact of the replacement policy.* Based on the estimation results, suggesting a replacement item may affect incidence as well as choice decisions. The simulation results reported in table 4 show that, on average, the choice probability of the suggested alternative, within the segments where the replacement policy is significant, increases dramatically. The likelihood that a suggested item is chosen, increases on average with 64.03% (margarine, segment 1) and 42.93% (cereals, segment 1) as compared to the visible/no-replacement policy. Looking at the implications at the market level (both segments), the average increase in choice probability of the suggested item still amounts to 45.59% (margarine) and 15.83% (cereals). Despite the large effects on the choice probability, the incidence probability is only marginally affected in the margarine category (increase of 0.7% for segment 1; increase of 0.38% for the whole market) and not affected at all in the cereals category.

Equation 11 provides more detailed insights into the underlying mechanisms (see appendix A for derivations). The change in **choice probability** when item  $i$  is suggested ( $p_i|S$ ) compared to when it is not suggested ( $p_i|NS$ ) is equal to:

$$\frac{p_i|S - p_i|NS}{p_i|NS} = \frac{1}{[\pi_i|S + (1 - \pi_i|S) * \exp(\omega_{Sugg})]^{-1} * (1 - p_i|NS) + p_i|NS} - 1 \quad (11)$$

A first important conclusion that can be derived from equation 11 is that the increase in choice probability for suggested items will be smaller for items that already received a high degree of consideration. Second, the increased attention for suggested items will only translate into substantial increases in choice probability when the items' intrinsic value is sufficiently high. Note that these insights would not be revealed if a one-stage choice model would be used, which could lead to an overestimation of the suggestion effect (as explained in appendix A). To illustrate these implications, we use a hypothetical example described in table 5.

### INSERT TABLE 5

Consider an assortment of 4 items (A, B, C and D) with 'regular' choice probabilities (no disruptions) as defined in panel a. Note that alternatives A and B have the same choice probability but differ in their degree of consideration and choice utility. In comparison with B, A has a high degree of consideration and a low choice utility. Alternatives B and C, in contrast, have the same choice utility, but different degrees of consideration (C has a higher degree of consideration than B). To isolate the effects of the out-of-stock policy, we assume that there are no differences between the items in asymmetric switching effects.

Suppose alternative D is out-of-stock. Panel b of table 5 shows the change in choice probabilities for the remaining alternatives if no suggestions are made. Items with the same prior choice probability (A and B) lever up to the same point. Yet, this is no longer true with a replacement policy. Panel c reports the choice probability for each item when it is the suggested alternative for item D. Comparing the change in choice probability for items B and C indicates that the suggestion works better for alternatives with a low degree of consideration (item B). In line with this, among items with the same prior propensity of being chosen (A and B), the effect of the suggestion is far more pronounced for the low consideration, high utility item (B)<sup>10</sup>.

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<sup>10</sup> Compared to a two-stage model, the one-stage model would lead to an overestimation of the suggestion effect for highly salient but intrinsically unappealing items. Indeed, in the one-stage model, items with the same prior choice probability (A and B) would obtain the same gain from being suggested irrespective of the underlying consideration and intrinsic choice utility (see appendix A for derivations).

Purchase incidence effects of the replacement policy ( $PI|\Delta pol$ ) – compared to the benchmark (visible, no-replacement) policy ( $PI|0$ ) – are given by the following expression (see appendix A for derivations):

$$\Delta PI = \frac{PI|0 - PI|\Delta pol}{PI|0} = 1 - \frac{1}{e^{-(\gamma_{CV}\Delta CV)} * (1 - PI|0) + PI|0} \quad (12)$$

Equation 12 demonstrates that a replacement policy will reduce the negative effect of stock-outs on purchase incidence decisions when (i) suggesting a substitute leads to a lower decrease in category attractiveness ( $\Delta CV$ ; see appendix A), and (ii) decisions to make a purchase in the category more strongly depend on category attractiveness ( $\gamma_{CV}$ ). The estimation results discussed in section 4.2 indicate that the second condition is not satisfied for the categories under study. Only for one segment of the margarine category, a significant yet small effect of CV on incidence probabilities is observed. This explains why the replacement policy has no (cereals) or only a very limited (margarine) effect on purchase incidence decisions.

## **DISCUSSION AND LIMITATIONS**

The main purpose of this research was to investigate how online purchase incidence and choice decisions are affected by the retailer’s stock-out policy. The results of the incidence and two-stage choice models indicate that the adopted stock-out policy has a significant impact on whether consumers make a purchase in the category or not, and if so, what they buy. Our findings have important policy implications for retailers.

First, we find that a non-visible policy, where consumers only become aware of a stock-out when they click on the product to purchase it, reduces the probability of purchasing in a category for the majority of consumers. Consumers clearly prefer to know ‘what they are up to’ upfront. A retailer who masks his stock-out problems evokes negative consumer reactions, resulting in reduced purchase rates. An interesting observation is that, in both product categories, especially consumers who tend to repurchase the same item react negatively to the non-visible policy. These consumers, in fact, face a ‘double-jeopardy’ effect. First, given their stronger preference to stay with the same item, unavailability of this favorite item creates confusion and intensifies the reduction of the assortment’s appeal. Second, because they typically repurchase the same product and hence, have little experience with other alternatives, identifying a suitable replacement item is a more difficult and risky task for these

consumers. Our results suggest that adopting a non-visible policy is likely to make these consumers refrain from purchasing, and maybe even renege from buying in the online store altogether.

Second, we find that suggesting a replacement item dramatically increases the consideration and choice probability of the suggested item for a large number of consumers. These consumers are more likely to consider – and hence select – the suggested item (cf. Senecal & Nantel, 2004). An important implication of this finding is that manufacturers – in their role of category captains – or retailers can re-direct choices in case of stock-outs, by suggesting appropriate replacement items. Yet, there are limits to what can be achieved. For one, the results also indicate that consumers cannot be lured into purchasing more expensive items. When consumers become suspicious of the retailer's fairness, the positive effects of the suggestion cancel out. Second, suggesting a replacement item affects its choice probability through an increase in consideration utility rather than a change in intrinsic utility. It follows that suggesting an item as replacement will have little effect if that item does not really appeal to consumers. Third, the change in choice probability also depends on the item's initial consideration utility. More specifically, items that would otherwise have a low probability of being considered as a substitute have more to gain from being suggested than items that are already highly salient without the suggestion.

A somewhat surprising finding is that stock-out-related changes in the assortment's appeal, as captured in the 'category value' variable, have only a limited to no effect on the consumers' propensity to buy from the category. No effects are found for cereals and only small effects are found for margarine. This also implies that the replacement policy does not significantly improve purchase incidence. This might be linked to the categories under consideration. Previous research has shown that the number of consumers that cancel or switch stores is rather low in these categories (Campo et al. 2000). What's more, finding no results for the category of cereals might be caused by the large assortment and the variety-seeking tendency in this category. Consumers are more likely to find and select an acceptable available alternative in the category, thereby limiting the impact of stock-outs and the stock-out policy on the incidence decision.

In sum, our results thus demonstrate (1) that online retailers may reduce stock-out losses by adopting a replacement policy but that they should be careful in the selection of the

suggested replacement item and (2) that the stock-out reaction may be more negative when customers become skeptical about the retailer's stock-out policy (hiding stock-outs or suggesting higher-priced options as a retailer-enriching strategy). Taken together, the findings clearly reveal that consumers value and reward an open and honest retailer, i.e. a retailer who puts all his cards on the table and truly helps the consumer in making an easy and effortless decision. These observations are consistent with other research findings. Fitzsimons and Lehmann (2004), for instance, found that recommendations aimed at facilitating the online search process are generally highly appreciated, except when dubious recommendations are made. In line with customer relationship marketing principles, this confirms that a customer-oriented stock-out approach will benefit both the retailer and consumer.

Obviously, our research has several limitations. Because of the experimental design, we only had a small number of observations per respondent and were not able to take dynamic effects into account. Yet, recent literature has shown that stock-outs might have an impact on the purchase incidence and choice decision in post-out-of-stock periods (cf. Campo et al. 2003). What's more, despite the advantages of a tightly controlled experimental setting, using an artificial setting might result in biases (e.g. lack of a realistic budget constraint or no real consumption) (Campo et al. 1999; Swait and Andrews 2003). Therefore, doing the research in a virtual store 'in real time' would be a valuable extension. Second, we do not investigate the impact of the offered assortment and of the shelf organization on stock-out (policy) effects. Previous studies suggest that stock-out reactions may depend on the assortment (size and composition), i.e. on the number of available, acceptable replacement items (cf. Campo et al. 2000) and on the organization of the shelf (Campo and Gijbrecchts 2004; Gruen, Corsten and Bharadwaj 2002). Investigating these moderating effects is an interesting question for future research. Third, although we find indications that online out-of-stock reactions are comparable with out-of-stock reactions in a brick-and-mortar setting, a more detailed and comparative analysis of the mechanisms underlying stock-out responses in an online and offline environment would be a useful extension. Finally, future studies could broaden the scope, by incorporating more categories, or investigating the effect of stock-out policies for the (online) store as a whole.

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Figure 1: Visual representation of the conceptual framework (hypotheses)

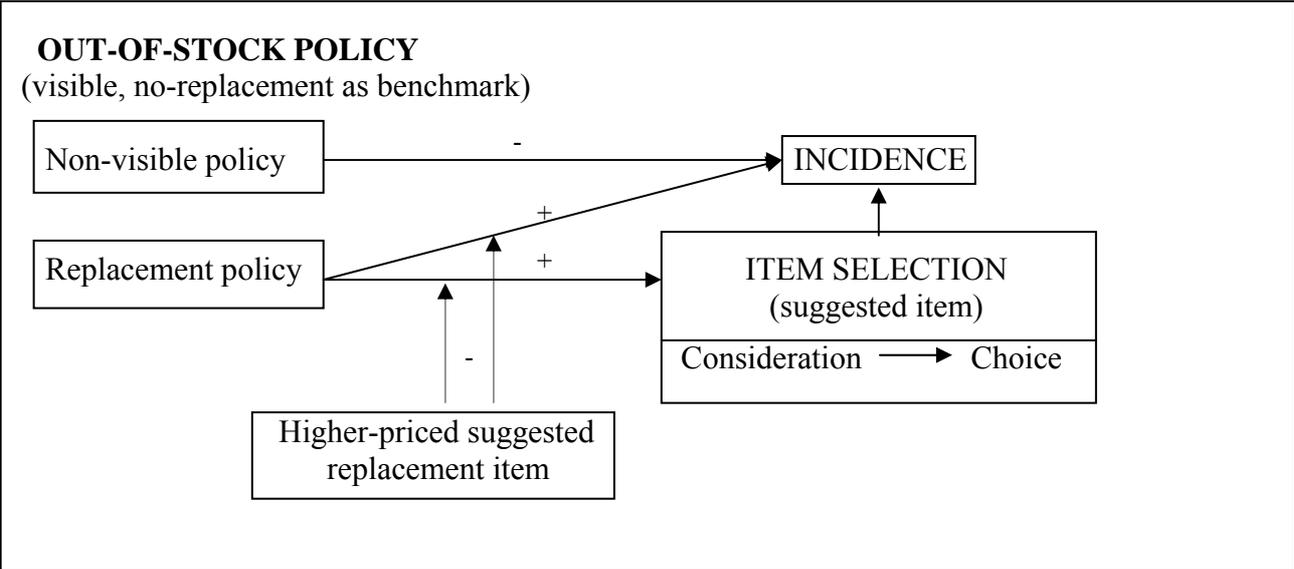


Figure 2: The impact of the non-visible stock-out policy on the incidence decision

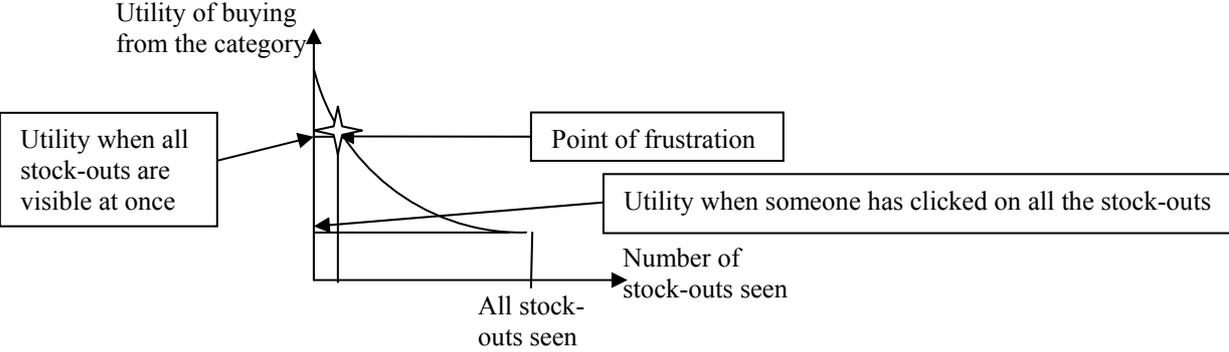


Table 1: Variables in the incidence and two-stage choice (consideration or choice stage) models

<u>Variable</u>	<u>Description</u>	<u>Model</u>
$CR^h$	Rate of category consumption for household h	Incidence
$INV_t^h$	Inventory (mean-centered) for household h at time t	Incidence
$NVPOL_t^h$	Non-visible out-of-stock policy dummy variable (equal to 1 when consumer h has been exposed to an out-of-stock policy where stock-outs are not visible at first sight and when there were stock-outs at time t, 0 otherwise)	Incidence
$CV_t^h$	Category value for household h at time t (based on the parameters of two-stage choice model)	Incidence
$OOS_{it}$	Stock-out dummy variable (equal to 1 if alternative i is out-of-stock, 0 otherwise)	Two-stage choice
$D_{A,l,i}$	Attribute-level dummy variable (equal to 1 if alternative i is characterized by level l on attribute A, 0 otherwise)	Two-stage choice (CH)
$LOY_i^h$	Loyalty or initial (LT) preference of consumer h for alternative i	Two-stage choice (CH)
$LP_{it}^h$	Last purchase dummy variable (equal to 1 when alternative i was last purchased by consumer h at time t, 0 otherwise)	Two-stage choice (CO)
$OOS_{A,it}$	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)	Two-stage choice (CO)
$SUGG_{it}^h$	Suggestion dummy variable (equal to 1 when alternative i is suggested as a replacement item to consumer h at time t)	Two-stage choice (CO)
$HPSUGG_{it}^h$	Higher price suggestion dummy variable (equal to 1 when alternative i is suggested as a replacement item to consumer h at time t and when the alternative is of a higher package-equivalent price than the stock-out alternative, 0 otherwise)	Two-stage choice (CO)

Table 2: Goodness-of-fit (BIC, CAIC-statistics) for simultaneous incidence and choice models (margarine and cereals)

Segm	Margarine				Cereals			
	Simultaneous with two-stage choice			Simultaneous with one-stage choice	Simultaneous with two-stage choice			Simultaneous with one-stage choice
	1	2	3	2	1	2	3	2
LL	-0.08162	<b>-0.07596</b>	-0.07358	-0.07961	-0.04625	<b>-0.04546</b>	-0.04467	-0.0462505
BIC	7174.77	<b>6960.742</b>	7025.514	7296.314	11011.45	<b>10857.12</b>	10971.19	10988.66
CAIC	7198.77	<b>7009.742</b>	7099.514	7249.314	11064.45	<b>10912.67</b>	11051.19	10941.66

Table 3: Estimation results for the simultaneous incidence and two-stage choice model

<u>Margarine</u>			<u>Cereals</u>		
<u>Variable</u>	<u>segment 1</u>	<u>Segment 2</u>	<u>Variable</u>	<u>segment 1</u>	<u>segment 2</u>
<b>CONSIDERATION SET FORMATION MODEL</b>					
<b>Stage 1: Consideration set formation</b>			<b>Stage 1: Consideration set formation</b>		
Brand asymmetry	1.0982***	0.4657*	Brand asymmetry	-0.1449	0.5742***
Size asymmetry	-0.0819	0.0536	Flavor asymmetry	0.0297	0.2029***
Suggestion	1.3789***	-0.0864	Type asymmetry	0.0987	0.0871
Suggestion (higher price)	-1.0449**	0.2404	Suggestion	0.5663**	0.4169
Last purchase	2.9992***	1.4677**	Suggestion (higher price)	-0.3645	-0.0200
Threshold	6.5874	4.3681	Last purchase	-0.7793***	5.0513***
			Threshold	3.9994***	3.1230***
<b>Stage 2: Item selection</b>			<b>Stage 2: Item selection</b>		
<u>Brand</u>			<u>Brand:</u>		
Alpro	0.0401	0.1059	Nestlé	-0.5482*	-0.0350
Belolive	-0.4608*	0.0502	Others	-1.4213***	-0.1869
Benecol	-1.0809***	-0.2695*	Private label	-0.7564***	-1.3670***
Bertolli	0.1344	0.1585	<u>Flavor:</u>		
Delhaize	0.3347	-0.5428*	Nature	0.3004	-0.1821
Derby	0.2182	-0.0193	Honey	0.4555*	0.3816**
Effi	-0.2363	-0.2499	Fruit	0.1924	0.4692***
Planta	-0.2634	-0.1657	Mixed	0.3117	-0.1041
Roda	-0.8718*	-1.1981**	<u>Type:</u>		
Solo	-0.7633**	-0.3191*	Corn	0.6428**	0.7944***
Vitelma	0.2149	0.0493	Wheat	0.4643*	-0.4210**
<u>Size:</u>			Filled	-0.0499	-2.2536***
Large size	-0.6637**	-0.5334***	Muesli	0.7959**	0.4631***
Loyalty	2.6845***	3.2386***	Crunchy	0.6679**	-0.4613***
			Mixed	0.2945	-0.2826
			Variety	-0.0073	-0.2033
			Loyalty	9.1276***	1.8783***
<b>PURCHASE INCIDENCE MODEL</b>					
Constant	-0.6695	0.7010	Constant	-1.2369***	-0.2465
Category consumption	0.6273***	0.9740***	Category consumption	1.6876***	0.3324***
Inventory	-2.2610***	-0.0979**	Inventory	-1.0835***	-0.1415***
Nv-policy	-0.2540**	-0.1798	Nv-policy	0.1320	-0.1972**
CV	0.1254**	0.0808	CV	-0.0501	0.0592
Heterogeneity, relative size	67.35%	32.65%	Heterogeneity, relative size	57.95%	42.04%

\*\*\* = sign. at 1% level; \*\* = sign. at 5% level; \* = sign. at 10% level (1-tailed significance test)

Table 4: Average changes in incidence and choice probabilities (relative to the base setting) from changes in the stock-out policy (actual data set)

	Margarine			Cereals		
	Segment 1	Segment 2	Total	Segment 1	Segment 2	Total
<b>Non-visible policy</b>						
- change in incidence probability	-10.48%	n.s.	-5.04%	n.s.	-8.20%	-4.74%
<b>(Non-suspicious) replacement policy</b>						
- change in choice probability of the suggested item	64.03%	n.s.	45.59%	42.93%	n.s.	15.83%
- change in incidence probability	0.79%	n.s.	0.38%	n.s.	n.s.	n.s.

n.s. = not significant

Table 5: Changes in incidence and choice probabilities when a replacement item is suggested (hypothetical example)<sup>11</sup>

	Item selection				Category purchase
	A	B	C	D	
<b>Panel (a) Regular choice environment</b>					
Degree of consideration	0.69	0.4	0.69	0.85	
Choice utility	0.18	0.74	0.74	0.6	
Choice probability	18%	18%	31%	33%	
Incidence probability					57%
<b>Panel (b) Disrupted choice environment (stock-out of D)</b>					
Choice probability	27%	27%	47%	0%	
Incidence probability					55%
<b>Panel (c) Suggesting replacement items for the out-of-stock item</b>					
Degree of consideration if item is suggested	0.90	0.72	0.90	0	
Choice utility	0.18	0.74	0.74	0.6	
Choice probability if item is suggested (others not)	32%	40%	53%	0%	
Incidence probability if item A is suggested					56%
<b>Panel (d) Effect of replacement policy</b>					
$\Delta$ in consideration probability if item is suggested (others not)	30.20%	81.72%	30.20%		
$\Delta$ in choice probability if item is suggested (others not)	20.52%	48.97%	14.16%		
$\Delta$ in incidence probability if item A is suggested (others not)					0.4%

<sup>11</sup> Based on expressions (11) and (12). In this example, we do not take the effects of asymmetric switching into account. As an example, we take the coefficient of the suggestion/category value variable of segment 1, margarine (see table 3): 1.3789 and 0.1254, respectively.

## Appendix A

### 1. The effect of the replacement stock-out policy on the choice probability

The choice probability for alternative  $i$  when no suggestions are made, is given by the following expression:

$$p_i|NS = \frac{A_i}{\sum_j A_j} \quad (A1)$$

with  $A_i = \exp(u'_i)$  for a one-stage (MNL) choice model

$A_i = \pi_i \exp(u_i)$  for a two-stage (B&V) choice model

When only alternative  $i$  is suggested (and other alternatives not), its attractiveness ( $A_i$ ) increases (with a suggestion factor  $SF_i > 1$ ) while the attractiveness of the remaining alternatives ( $A_j, j \neq i$ ) remains unaltered:

$$p_i|S = \frac{SF_i A_i}{\sum_{j \neq i} A_j + SF_i A_i} \quad (A2)$$

where the suggestion factor ( $SF_i$ ) captures the increase in attraction when an item is suggested compared to when it is not.

Therefore, the change in choice probability can be written as:

$$\begin{aligned} \frac{p_i|S}{p_i|NS} &= \frac{SF_i A_i}{\sum_{j \neq i} A_j + SF_i A_i} * \frac{\sum_j A_j}{A_i} = \frac{SF_i * \sum_j A_j}{\sum_j A_j - A_i(1 - SF_i)} = \frac{SF_i}{1 - \frac{A_i(1 - SF_i)}{\sum_j A_j}} = \frac{SF_i}{1 - p_i|NS * (1 - SF_i)} \\ &= \frac{1}{SF_i^{-1} * (1 - p_i|NS) + p_i|NS} \end{aligned} \quad (A3)$$

It is interesting to compare the increase in attractiveness of an alternative when it is suggested (the suggestion factor) between a one-stage and a two-stage choice model.

In a one-stage (MNL) choice model the increase in attractiveness can be captured by:

$$SF_i = \exp(\omega'_{sugg}) \quad (A4)$$

In a two-stage choice model, the increase in attractiveness depends on the impact of the suggestion on the consideration probability and is captured by the following expression:

$$SF_i = \frac{\pi_i|S}{\pi_i|NS} = \frac{1 + \exp(\theta - s_i)}{1 + \exp(\theta - s_i - \omega_{Sugg})} = \frac{1}{1 + \exp(\theta - s_i - \omega_{Sugg})} + \frac{\exp(\theta - s_i)}{1 + \exp(\theta - s_i - \omega_{Sugg})}$$

$$= \pi_i|S + (1 - \pi_i|S) * \exp(\omega_{Sugg}) \quad (A5)$$

Hence, incorporating (A4) and (A5) in expression (A3) equals:

$$\frac{p_i|S}{p_i|NS} = \frac{1}{[\exp(\omega_{Sugg})]^{-1} * (1 - p_i|NS) + p_i|NS} \quad (\text{one-stage model}) \quad (A6)$$

$$\text{and } \frac{p_i|S}{p_i|NS} = \frac{1}{[\pi_i|S + (1 - \pi_i|S) * \exp(\omega_{Sugg})]^{-1} * (1 - p_i|NS) + p_i|NS} \quad (\text{two-stage model}) \quad (A7)$$

## 2. The effect of the stock-out policy on the incidence probability

Changing the benchmark stock-out policy (visible, no replacement) ( $PI|0$ ) to a more active stock-out policy (non-visible or replacement) ( $PI|\Delta pol$ ) changes the purchase incidence probability with the following fraction:

$$\Delta PI = \frac{PI|0 - PI|\Delta pol}{PI|0} = \frac{\frac{e^W}{1 + e^W} - \frac{e^{W'}}{1 + e^{W'}}}{\frac{e^W}{1 + e^W}} = 1 - \frac{e^{W'}}{e^W} * \frac{1}{\frac{1}{1 + e^W} + \frac{e^{W'}}{1 + e^{W'}}} =$$

$$1 - \frac{e^{W'}}{e^W} * \frac{1}{(1 - PI|0) + PI|0 * \frac{e^{W'}}{e^W}} = 1 - \frac{1}{e^{-(W'-W)} * (1 - PI|0) + PI|0} \quad (A8)$$

a) The effect of the non-visible policy is captured by the coefficient of the non-visible policy:

$$W' - W = \gamma_{NV} \quad \rightarrow \quad \exp(W' - W) = \exp(\gamma_{NV}) \quad (A9)$$

b) The effect of the replacement policy is captured by the coefficient of the category value and by the difference in the category value:

$$W' - W = \gamma_{CV} \Delta CV \quad \rightarrow \quad \exp(W' - W) = \exp(\gamma_{CV} \Delta CV) \quad (A10)$$

The change in the category value can be expressed as:

$$\Delta CV = \ln \left( \sum_j \exp(u_j) * \pi_j|S \right) - \ln \left( \sum_j \exp(u_j) * \pi_j|NS \right) \quad (A11)$$

Using the denominator of (A2) and (A1), respectively and assuming that there is only a suggestion for alternative i gives:

$$\begin{aligned}\Delta CV &= \ln\left(\sum_{j \neq i} A_j + SF_i A_i\right) - \ln\left(\sum_j A_j\right) = \ln\left(\frac{\sum_j A_j - A_i + SF_i A_i}{\sum_j A_j}\right) = \ln\left(1 - \frac{A_i * (1 - SF_i)}{\sum_j A_j}\right) \\ &= \ln(1 - p_i | NS * (1 - SF_i))\end{aligned}\tag{A12}$$

Substituting in (A10) the change in category value with expression (A12) and the suggestion factor with expression (A5) gives:

$$\begin{aligned}\exp(W' - W) &= \exp(\gamma_{CV} \ln(1 - p_i | NS * (1 - SF_i))) = (1 - p_i | NS * (1 - SF_i))^{\gamma_{CV}} \\ &= (1 - p_i | NS * (1 - \pi_i | S - (1 - \pi_i | S) * \exp(\omega_{Sugg})))^{\gamma_{CV}} = (1 - p_i | NS * (1 - \pi_i | S) (1 - \exp(\omega_{Sugg})))^{\gamma_{CV}} \\ &= (1 + p_i | NS * (1 - \pi_i | S) (\exp(\omega_{Sugg}) - 1))^{\gamma_{CV}}\end{aligned}\tag{A13}$$