

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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Abstract

This paper investigates the impact of an online retailer's stock-out policy on consumers' category purchase and choice decisions. We investigate three different policies: (1) stock-outs are immediately *visible* and there are *no replacement suggestions*, (2) stock-outs are only *visible after purchase attempts* and (3) stock-outs are immediately *visible* but a *replacement item is suggested*. Results from an online grocery shopping experiment reveal that the adopted stock-out policy has a significant impact on both decisions. Making stock-outs not immediately visible creates confusion and intensifies the consumer's loss experience, thereby reducing the tendency to buy in the category. Suggesting a replacement item, in contrast, facilitates the substitution decision and slightly reduces the purchase cancellation rate. It also substantially increases the suggested item's choice probability. Yet, this effect disappears when higher-priced – suspicious – items are suggested. Overall, these results indicate that online grocery retailers have an interest in pursuing open and convenience-oriented stock-out policies.

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Introduction

Product unavailability is a common problem for grocery shoppers. Traditional research has shown that stock-outs have a negative impact for retailers, both directly (on category sales and profit) and indirectly (on customer satisfaction, store loyalty and retail image) (Campo et al. 2003; Fitzsimons 2000; Sloot et al. 2005). Recent evidence suggests that out-of-stock (OOS) problems are not limited to traditional supermarkets, but may constitute a far more daunting problem for e-grocers—who experience more severe forecasting problems and strongly fluctuating demand (Fitzsimons 2000).

According to a recent survey, product unavailability also rates second in the top 3 of online shopping irritations (Marketing online 2004).

Despite their importance, OOS have not been investigated systematically in an online context. Yet, such research could be insightful for at least two reasons. First, online OOS reactions might differ from those in brick-and-mortar settings because of differences in store environment (e.g. the lack of sensory attributes) and shopping behavior (convenience being the major motivation to use online grocery shopping services) (see e.g. Degeratu et al. 2000; Morganosky and Cude 2002). Second, given the constraints of traditional stores, little attention has been paid before to the effect of different OOS policies, most stores just leaving the OOS item's shelf space empty (Verhoef and Sloot 2005). The more flexible online environment, however, offers unique opportunities to alleviate the negative effects of stock-outs.

Based on these observations, our paper contributes to the literature in two ways. Using a realistic virtual store experi-

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ment, we provide insights into how consumers react to online stock-outs. Our main objective, though, is to compare the effectiveness of the traditional OOS approach (empty shelf space) with two OOS policies made feasible by the greater flexibility of online stores: (i) a ‘non-visible’ policy (stock-outs are only announced after purchase attempts) and (ii) a ‘replacement’ policy (a substitute is suggested and takes up the OOS item’s shelf space).

In the next section, we propose a conceptual framework of online OOS reactions and derive hypotheses on the effect of different OOS policies. Next, we describe the methodology and data set. We then discuss the results of an online shopping experiment and indicate directions for future research.

Conceptual framework and hypotheses

In this section, we present a framework describing (i) the effect of stock-outs on consumers’ routine purchase behavior and (ii) the policies available to online retailers to alleviate stock-out consequences. Based on these insights, we formulate hypotheses on the effect of alternative stock-out policies on category purchase incidence and choice.

Conceptual framework

Consumer reactions to online stock-outs

When making low involvement purchase decisions, consumers tend to adopt task-simplifying decision rules (Hoyer 1984), which are especially useful in a disrupted choice environment. Below, we briefly characterize how OOS disruptions can affect consumers’ routine purchase decisions. Given the limited impact stock-outs appear to have on quantity decisions (Campo et al. 2003), we concentrate on purchase incidence and choice effects.

Previous research has shown that purchase *incidence decisions* not only depend on household product needs but also on the perceived attractiveness of the product category (Bucklin and Gupta 1992). Stock-outs reduce the appeal of the product category and may make consumers uncertain as to which item to select. This is especially true when highly preferred items are missing and when few appropriate substitutes are available (Boatwright and Nunes 2001; Broniarczyk et al. 1998; Campo et al. 2000; Sloot et al. 2005). As a result, consumers may decide to defer or cancel planned category purchases.

For grocery *choice decisions*, consumers tend to follow a sequential process. They first use simple tactics or cues to form a reduced set of choice alternatives (the consideration set, see e.g. Roberts and Lattin 1991; Shocker et al. 1991), which are then evaluated more thoroughly to make a final choice. While only a limited number of attributes and rough screening rules are used in the first stage, the second stage involves a more detailed analysis in which the intrinsic value of the retained alternatives is assessed based on all relevant attributes (Bronnenberg and Vanhonacker 1996; Wu and Rangaswamy 2003).

Since stock-outs do not change the intrinsic value of alternatives, they will predominantly affect choice decisions through the first screening stage. Depending on the choice heuristic used, stock-outs may disproportionately increase attention for alternatives that (1) share important attributes with the OOS item (Bell and Fitzsimons 1999; Campo et al. 2003), (2) have an acceptable price level (Jedidi and Zhang 2002; Xia et al. 2004), (3) are highlighted by in-store elements (e.g. shelf position: Drèze et al. 1994), and/or (4) have been purchased very recently (Bronnenberg and Vanhonacker 1996).

Online retailer stock-out policies

A consumer’s response to an OOS situation also depends on how retailers are perceived to deal with this service failure. Online retailers can adopt various OOS/service recovery policies, which differ in (i) when and how stock-outs are announced to customers (Verhoef and Sloot 2005), (ii) whether and how online shelves are adjusted when stock-outs occur and (iii) whether financial compensations are offered.

Stock-out announcement. Online stores – displaying product pictures or descriptions rather than real products – offer the opportunity of ‘masking’ stock-outs. In this case, store shelves can contain available as well as ‘phantom’ products. Customers are only informed about the product’s unavailability when they try to purchase it – or even worse – at the time of order delivery. By not communicating stock-outs right away, retailers hope to enhance consumers’ assortment perceptions (greater perceived variety: see e.g. Hoch et al. 1999; Van Ryzin and Mahajan 1999). Alternatively, online retailers can inform customers of a product’s unavailability from the start, for example, by adding an OOS-label to the product’s picture. In order to reduce customer dissatisfaction, online retailers can also easily provide extra information (e.g. indicate why the OOS occurred and/or when the product will be available again: see e.g. Beuk 2001; Verhoef and Sloot 2005).

Shelf adjustment. Online stores also provide greater flexibility for shelf rearrangements. Instead of physical replacements of actual products, automated reconfigurations of the computer screen can be used to accommodate stock-outs. Such shelf rearrangements may consist of (i) filling the ‘empty’ shelf space of OOS products with appropriate replacement items or (ii) shifting the position of available items to fill the blanks and mask stock-outs.

Financial compensation. A third policy option is to offer consumers a financial incentive to backorder the unavailable item (Anderson et al. 2006; Verhoef and Sloot 2005). Customers could, for instance, receive a coupon with a price reduction for the next purchase.

Concerning OOS announcements, providing extra information appears to work well for non-grocery catalog retailers

OUT-OF-STOCK POLICY
(visible, no-replacement as benchmark)

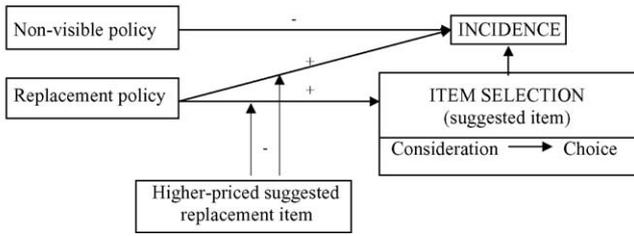


Fig. 1. Visual representation of the conceptual framework (hypotheses).

(Anderson et al. 2006). Yet, it hardly affects consumer reactions for groceries (Beuk 2001), which explains the limited use by online grocers. As for shelf organization, completely rearranging shelves to remove blank positions may well increase consumers' variety perceptions. Yet, it also distorts the perceived assortment structure and increases search costs for all consumers. Finally, while offering financial compensations is widespread among catalog retailers, it is uncommon for online grocery stores and its effectiveness appears limited (Anderson et al. 2006). Based on these observations, we focus on the following OOS policies hereafter: (i) announcing stock-outs but not adjusting shelves ('visible—no replacement' policy), (ii) not announcing stock-outs ('non-visible' policy) and (iii) announcing stock-outs and presenting a replacement item ('replacement' policy).

Hypotheses on the impact of stock-out policies

In traditional grocery stores, stock-outs are typically visible as empty spaces on the shelf and no replacement item is suggested. Using this approach as the benchmark, we derive hypotheses on how a 'non-visible' and 'replacement' OOS policy elicit different purchase incidence and choice decisions (see Fig. 1). Based on the service failure/recovery as well as equity literature, we expect consumers to judge a retailer's OOS policy on (i) the benefits it generates for them (perceived fairness of the outcome) and (ii) whether it is thought to be guided by customer-serving versus self-serving motives (perceived fairness of the procedure) (Palmer et al. 2000). If the policy is thought to stem from self-serving (retailer-enriching) motives, it may produce backlash behavior (Fitzsimons and Lehmann 2004).

Non-visible policy

Instead of immediately announcing stock-outs, online retailers may inform customers of a product's unavailability only when they click on the item to buy it. Hence, the assortment in a non-visible policy setting may appear more complete and may be perceived more positively at the outset. However, this situation may rapidly change when the consumer has to click several times before finding a product s/he can buy. The more stock-out items the consumer clicks on in vain, the more likely that s/he will reach 'a point of frustration', i.e. a point where the category attractiveness in a non-visible policy – and hence the probability of making a purchase – becomes lower than the category attractiveness in a visible policy (see Fig. 2).

We conjecture that this point of frustration is reached very fast, even after only one or a few clicks. The outcome of the non-visible policy may quickly become unappealing for at least two reasons. First, the disappointment and/or frustration from clicking on an OOS item may strengthen the loss experience from not being able to buy the preferred product. Second, once consumers have clicked on an OOS item, they know that the availability of other alternatives is also uncertain. The anticipation of a complex 'trial and error' purchase sequence may make them refrain from purchasing (Dhar 1997). Moreover, consumers are likely to attribute the non-visible policy to 'self-serving' motives—retailers hiding their OOS problems (unfair procedure). This may 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:

H1. When confronted with stock-outs, consumers are less likely to make a purchase in the category when the retailer follows a non-visible policy (where OOS are visible only after clicking) than when OOS are visible to all consumers.

Replacement policy

Suggesting another item from the assortment as a replacement may limit the decrease in category attractiveness and, consequently, the consumers' tendency to drop a category purchase. For one, suggesting a substitute may divert the customer's attention away from the OOS item (the service failure). In addition, it may reduce preference uncertainty, the recommendation providing a simplifying choice heuristic that helps consumers to select a substitute (cf. Fitzsimons

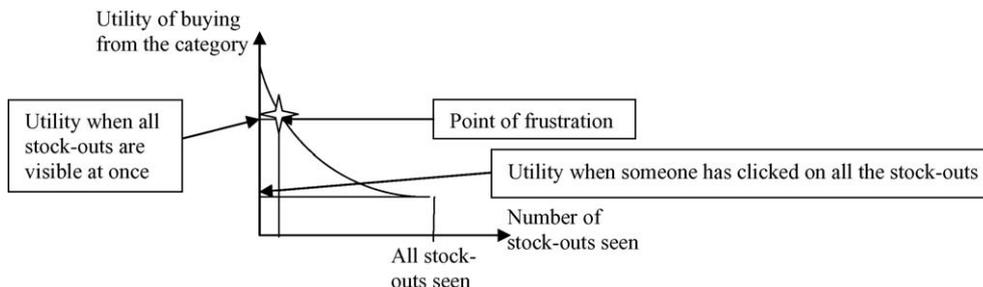


Fig. 2. The impact of the non-visible stock-out policy on the incidence decision.

and Lehmann 2004; Senecal and Nantel 2004). The replacement policy may also affect *choice* decisions, by directing attention towards the suggested – highlighted – item (cf. Bronnenberg and Vanhonacker 1996; Fader and McAlister 1990). We therefore hypothesize that, in general:

H2. When confronted with an OOS, consumers are less likely to refrain from a category purchase when the retailer suggests a substitute item than when no replacement item is suggested.

H3. Suggesting an item as a substitute for an OOS item increases the probability that the consumer will consider this item for selection.

It is important to note, however, that this effect only occurs when consumers *accept* the suggestion as a simplifying choice heuristic. This, in turn, depends on the perceived fairness of the policy outcome and procedure. When consumers trust the retailer's suggestion as being the best replacement item, they are more likely to consider it. Conversely, when the retailer is suspected of 'bait and switch' practices, opposite effects may occur: consumers may switch away from the suggested item or not buy anything from the category at all (Fitzsimons and Lehmann 2004).

Price may play an important role in this evaluation procedure. As consumers typically have an acceptable/fair price in mind (Jedidi and Zhang 2002; Xia et al. 2004), replacement items of a higher price may be valued less (lower expected *outcome*). Moreover, when the suggestion is of a higher price, consumers may suspect the retailer of deliberately setting alternatives unavailable to sell more profitable items (self-serving *procedure*). The price of the suggested items may for this reason have a moderating effect:

H4. Suggesting a higher-priced replacement item negatively moderates the (positive) effect of the suggestion.

Model description

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:

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

where p_{it}^h is the choice probability of item i for household h at time t , u_i^h is the choice utility of item i for household h ,

and π_{it}^h is the degree of consideration (inclusion probability) of item i for household h at time t :

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

where s_{it}^h is the consideration utility of item i for household h at time t and θ is the threshold or minimum consideration utility an item has to exceed in order to be considered for choice.

Like Bronnenberg and Vanhonacker (1996), we assume that the *choice utility* u_i^h is a function of the intrinsic attractiveness of the items, captured by attribute-specific intercept terms ($D_{A,l,i}$)³ (Fader and Hardie 1996) and household preferences for specific items (Pref_i^h) (Ailawadi et al. 1999). An overview of the symbols is given in Table 1:

$$u_i^h = \sum_A \sum_{l \in L_A} \alpha_{A,l} D_{A,l,i} + \alpha_{\text{Pref}} \text{Pref}_i^h \quad (3)$$

The *consideration utility* (s_{it}^h) reflects the salience of an alternative for a household—irrespective of its intrinsic appeal. It is higher for recently purchased items, an effect captured through the last purchase variable (LP_{it}^h) in Eq. (4):

$$s_{it}^h = \omega_{\text{lp}} \text{LP}_{it}^h + \sum_A \omega_A \text{OOS}_{A,it} + \omega_{\text{sugg}} \text{SUGG}_{it}^h + \omega_{\text{Hpsugg}} \text{HPSUGG}_{it}^h \quad (4)$$

Moreover, as argued in the previous section, an item's consideration utility (s_{it}^h) and degree of consideration (π_{it}^h) may be influenced by stock-outs. First, we use stock-out dummy variables (OOS_{it}) to remove unavailable items from the consideration set:

$$\pi_{it}^h = \frac{1}{1 + \exp(\theta - s_{it}^h)} (1 - \text{OOS}_{it}) \quad (5)$$

Second, we have to account for the fact that remaining items that resemble OOS products on important attributes, may gain extra attention. Such disproportionate shifts in attention arise because consumers – especially habitual buyers who normally do not switch – may rely on specific product attributes as cues to facilitate the forced replacement decision and keep substitution risks low. For instance, consumers may expect items of the same brand to be of similar quality, or products of the same flavor to provide similar consumption experiences as the unavailable item. To account for these effects, we incorporate attribute-based stock-out asymmetry variables ($\text{OOS}_{A,it}$, where A can be brand, flavor, etc.) in Eq. (4). A positive (negative) coefficient of a stock-out asymmetry variable indicates

³ Traditionally, price would also be included in the utility function, as it determines a product's intrinsic attractiveness. 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.

Table 1
Variables in the incidence and two-stage choice models

Variable	Description	Model
PI_t^h	is the category purchase probability of household h at time t	
CR^h	Rate of category consumption for household h (as reported in the pre-purchase questionnaire)	Incidence
INV_t^h	In-home inventory level (mean-centered) for household h at time t : $INV_t^h = INV_{t-1}^h + N_{t-1}^h - CR^h$, where INV_0^h is the in-home inventory level at the start of the purchase simulations (as reported in the pre-purchase questionnaire) and N_{t-1}^h is the number of units bought by consumer h in $t - 1$	Incidence
CV_t^h	Category value for household h at time t (based on the parameters of the two-stage choice model): $CV_t^h = \ln(\sum_j \pi_{jt}^h \exp(u_j^h))$	Incidence
$NVPOL_t^h$	Non-visible OOS policy dummy variable (equal to 1 when household h has been exposed to an OOS policy where stock-outs are not visible at first sight and when there were OOS at time t , 0 otherwise)	Incidence
p_{it}^h	is the choice probability of item i for household h at time t	
OOS_{it}	Stock-out dummy variable (equal to 1 if item i is OOS, 0 otherwise)	Two-stage choice ^a
u_i^h	is the choice utility of item i for household h	
A	Set of attributes relevant to the product category (for instance: brand, flavor, type and/or package size)	Two-stage choice (CH)
L_A	Index set of levels relevant for attribute A	Two-stage choice (CH)
$D_{A,l,i}$	Attribute-level dummy variable (equal to 1 if item i is characterized by level l on attribute A , 0 otherwise)	Two-stage choice (CH)
$Pref_t^h$	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)	Two-stage choice (CH)
π_{it}^h	is the degree of consideration of item i for household h at time t	
θ	Deterministic part of the threshold (minimum needs)	
s_{it}^h	Deterministic part of the consideration utility of item i for household h at time t	
LP_{it}^h	Last purchase dummy variable (equal to 1 when item i was last purchased by household 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 OOS at time t)	Two-stage choice (CO)
$SUGG_{it}^h$	Suggestion dummy variable (equal to 1 when item i is suggested as a replacement item to household h at time t)	Two-stage choice (CO)
$HPSUGG_{it}^h$	Higher price suggestion dummy variable (equal to 1 when item i is suggested as a replacement item to household h at time t and when the item is of a higher package-equivalent price than the OOS item, 0 otherwise)	Two-stage choice (CO)

^a CO: consideration stage, CH: choice stage.

a tendency to consider (switch away from) alternatives with the same attribute (see also Campo et al. 2003).⁴

Last but not least, to test our hypotheses, we add two variables capturing the effect of the replacement policy: (i) a dummy variable ($SUGG_{it}^h$) for the main effect (which is expected to be positive, H3: $\omega_{sugg} > 0$) and (ii) an interaction variable with price ($HPSUGG_{it}^h$). The latter is introduced to test whether the suggestion effect decreases (or even becomes negative) when a higher-priced item is suggested (H4: $\omega_{Hpsugg} < 0$).⁵ Using models (1)–(4), the increase in choice probability when an item is suggested amounts to (see Appendix A for derivations):

$$\begin{aligned} \Delta p_i | sugg &= \frac{p_i | sugg - p_i | 0}{p_i | 0} \\ &= \frac{1}{[\pi_i | sugg + (1 - \pi_i | sugg) \exp(\omega_{sugg}^{net})]^{-1} (1 - p_i | 0) + p_i | 0} - 1 \end{aligned} \tag{6}$$

where $p_i | 0$ and $p_i | sugg$ are choice propensities of item i when it is not suggested and when it is highlighted as an OOS replacement, respectively. The component ω_{sugg}^{net} in expression (6) equals either $\omega_{sugg} + \omega_{Hpsugg}$ or ω_{sugg} , depending on whether the suggested item is or is not more expensive than the OOS product. Note that the consideration probability (π) and the choice probability (p) enter the expression separately, each exerting their own influence on the suggestion effect.

Incidence model

The probability of purchasing in the category (PI_t^h) is modeled as a binary logit model (Bucklin et al. 1998; Bucklin and Gupta 1992):

$$PI_t^h = \frac{\exp(W_t^h)}{1 + \exp(W_t^h)} \tag{7}$$

⁴ As a robustness check, we tested several alternative stock-out asymmetry definitions: (i) using weighted stock-outs instead of counts and/or (ii) ‘normalizing’ the asymmetry variables with respect to the number of stock-outs to values between zero and one. These alternative variable definitions did not change the substantive results and did not provide a significant increase in model fit.

⁵ Note that, in contrast to the absolute price variable (see Footnote 3), the higher-price suggestion variable does not cause severe correlation problems for two reasons. First, the variable has only two levels (higher priced or not). Second, the variable reflects an item’s relative rather than absolute price position. It follows that – for the same suggestion item – the variable may have different values depending on which item it is compared to (1 if the OOS item it replaces is cheaper and 0 when the OOS item has a higher price).

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

$$W_t^h = \gamma_0 + \gamma_{CR} CR_t^h + \gamma_{INV} INV_t^h + \gamma_{CV} CV_t^h + \gamma_{nv} NVPOL_t^h \quad (8)$$

We include traditional household consumption rate (CR^h) and home inventory (INV_t^h) variables to characterize category needs and a category value (CV_t^h) variable to capture ‘category attractiveness’. CV_t^h is measured as the expected maximum utility of making a purchase in the category (see Table 1) and provides a link between incidence and choice decisions (see e.g. Ben-Akiva and Lerman 1985; Bucklin et al. 1998). Note that in our case, changes in category attractiveness (ΔCV) are driven by stock-outs because other category characteristics like price and promotion are held constant throughout the experiment. More specifically, as can be seen from Eqs. (2)–(5) and the specification of the CV variable in Table 1, CV will be lower when *more* – or *more preferred* products – are unavailable. Conversely, proper suggestions for replacement items may limit this decrease in CV. A *positive* CV-coefficient in the incidence equation would thus imply that stock-outs – especially of preferred products – reduce the probability that a consumer purchases from the category.⁶ Favorable effects of suggestions will carry through to the purchase incidence level via this positive CV coefficient as well (H2: $\gamma_{CV} > 0$). The total increase in category purchase propensity triggered by the replacement policy amounts to (see appendix A for derivations):

$$\begin{aligned} \Delta PI|repl &= \frac{PI|0 - PI|repl}{PI|0} \\ &= 1 - \frac{1}{e^{-\gamma_{CV} \Delta CV} (1 - PI|0) + PI|0} \end{aligned} \quad (9)$$

where $PI|0$ ($PI|repl$) is the purchase incidence probability in the benchmark (replacement) policy and the expression reduces to zero if either γ_{CV} or ΔCV become zero.

Finally, we hypothesized that a non-visible stock-out policy, by creating uncertainty and frustration, reinforces the negative impact of stock-outs on purchase incidence. To test this effect, we include a dummy variable ($NVPOL_t^h$) in the purchase utility equation (8), the coefficient of which is expected to be negative (H1: $\gamma_{nv} < 0$). Based on models (7) and (8), a non-visible policy changes category purchase incidence by (see Appendix A for derivations):

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

⁶ To check whether the CV variable can fully capture the negative effects of stock-outs on purchase incidence, we also estimated a model with a CV and an aggregated stock-out variable. The latter could capture additional psychological effects of the service failure, over and above the decrease in category attractiveness. Yet, inclusion of the aggregate stock-out variable did not significantly improve model fit.

where $PI|0$ and $PI|nv$ are purchase incidence propensities under the benchmark and non-visible policies, respectively. Note that both expressions (9) and (10) decrease in $PI|0$. This makes intuitive sense: consumers with strong initial purchase intentions (high usage rates, low inventories) are less likely to be affected by the adopted OOS policy.

Estimation approach

Incidence and choice models are estimated simultaneously. To incorporate household heterogeneity, we use a latent class approach, leading to the following likelihood function:

$$\begin{aligned} LL &= \sum_h \ln \sum_s \Psi(s) \prod_t \{ (PI_{t|s}^h)^{y_{it}^h} (1 - PI_{t|s}^h)^{1 - y_{it}^h} \\ &\quad \times \prod_i [p_{t|s}^h(i|inc)]^{y_{it}^h} \} \end{aligned} \quad (11)$$

where $PI_{t|s}^h$ and $p_{t|s}^h(i|inc)$ are given by Eqs. (1) and (7), y_{it}^h is equal to 1 if consumer h has made a purchase in the category at time t and 0 otherwise, y_{it}^h is equal to 1 if consumer h chooses item i at time t and 0 otherwise and $\Psi(s)$ denotes the relative size of segment s .

Empirical study

Experimental data

Data were collected by means of a realistic online store experiment. This approach offers several advantages over scanner panel data and traditional paper and pencil stock-out surveys (e.g. greater flexibility and control at relatively low cost; Burke 1996). Concerning external validity, there is growing evidence that computer simulated shopping experiments provide highly realistic buying behavior data (Burke et al. 1992; Campo et al. 1999). This particularly holds in our study, where both the real and experimental choice setting were online. The fact that we could use the site of an existing online grocery store further adds to this realism.⁷

The computer experiment consisted of three modules: (1) a short pre-purchase questionnaire to collect general information, (2) a purchase simulation module and (3) a post-purchase questionnaire on the virtual store experiences. Subjects were randomly assigned to one of the three different OOS policies. With the exception of the first week (which served as an initialization period), stock-outs occurred in each experimental week (weeks 2–6). Rather than manipulating OOS rates from week to week

⁷ 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).

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

	Margarine			Cereals				
	Simultaneous with two-stage choice			Simultaneous with one-stage choice	Simultaneous with two-stage choice			Simultaneous with one-stage choice
	Segmenten: 1	2	3	2	1	2	3	2
LL	−0.08162	−0.07596	−0.07358	−0.07961	−0.04625	−0.04546	−0.04467	−0.0462505
BIC	7175	6961	7026	7296	11011	10857	10971	10989
CAIC	7199	7010	7100	7249	11064	10913	11051	10942

(and/or across respondent groups), we kept the OOS rate constant, at a realistic level of about 8% of the products in the category (Anderson Consulting 1996; Corsten and Gruen 2003; Sloot et al. 2005). The occurrence of stock-outs was uniformly distributed over weeks, low and high share items and attribute levels (brands, flavors, types and/or sizes).

To get a representative sample, we used e-mail addresses from two 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. The socio-demographic characteristics of our sample matched the online grocery sample profiles in other studies (e.g. Degeertu et al. 2000; Rohm and Swaminathan 2004). For each mailing address, participation was requested of the household member typically in charge of grocery shopping. Respondents were invited to participate by an e-mail that included a link to the online experimental site. To stimulate participation without endangering the representativeness of the sample, participants were made eligible for some small rewards on a lottery basis.

Respondents were asked to make purchases in an online store during six fictitious weeks for two product categories (margarine with 17 SKUs and cereals with 46 SKUs). The net sample comprised 584 respondents (response rate of 17%). For margarine (cereals), 473 (414) respondents completed the purchase simulation, leading to 2493 (2443) purchase occasions. 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 (Burke et al. 1992; Campo et al. 1999). Also, while purchases are fictitious and not restricted by real (financial, space/inventory) constraints, cues were provided to enhance realism. Respondents were informed about their weekly home inventory levels, computed on the basis of previous purchases and reported consumption rates. The purchase simulation instructions also explicitly indicated that respondents were not obliged to buy every week. In addition, when the adjusted household inventory – at the end of the shopping trip – was insufficient to satisfy average (weekly) consumption needs, they were asked whether they would visit another store to purchase the (missing) product.

Estimation results

Models are estimated for a varying number of classes and re-estimated using different sets of starting values.⁸ Based on BIC and CAIC measures (see Table 2), we retain a two-segment, two-stage choice model for both categories.⁹ Table 3 presents parameter estimates.

The effects for the *traditional* variables are significant and as expected. In the incidence model (panel b of Table 3), higher consumption rates and/or lower in-home inventory levels increase the propensity to buy from the category ($p < .01$). The choice model results (panel a of Table 3) show that most consumers tend to stay with the previously chosen item for margarine (positive last purchase coefficient in both segments, $p < .01$). For cereals, a subset of households switch between products (negative last purchase coefficient in segment 1, $p < .01$). This is not unexpected, cereals being a category in which many consumers seek variation. Still, as indicated by the attribute specific constants and item preference coefficients, these consumers seem to have clear long-term preferences for specific items and attributes. In other words, even variety seekers switch among a limited set of preferred alternatives (combination of a negative last purchase coefficient of -0.7793 and a positive item preference coefficient of 9.1276 in segment 1 of cereals—pointing to multi-item loyalty).

⁸ Due to the conditioning of the dataset and the large number of SKUs in the cereals category, we used a two-step approach for this category. In a first step, we estimated 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-estimated 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%.

⁹ The two-stage model provided a significant improvement in fit over a simple MNL model containing the same variables. 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 5 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 6 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 both categories.

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

Variable	Margarine		Variable	Cereals	
	Segment 1	Segment 2		Segment 1	Segment 2
Panel (a): Consideration set formation model			Panel (a): Consideration set formation model		
Stage 1: Consideration set formation			Stage 1: Consideration set formation		
Brand asymmetry			Brand asymmetry	-0.1449	0.5742***
Size asymmetry	1.0982***	0.4657*	Flavor asymmetry	0.0297	0.2029***
	-0.0819	0.0536	Type asymmetry	0.0987	0.0871
Suggestion	1.3789***	-0.0864	Suggestion	0.5663**	0.4169
Suggestion (higher price)	-1.0449 ^a	0.2404 ^a	Suggestion (higher price)	-0.3645 ^a	-0.0200 ^a
Last purchase	2.9992***	1.4677**	Last purchase	-0.7793***	5.0513***
Threshold	6.5874	4.3681	Threshold	3.9994***	3.1230***
Stage 2: Item selection			Stage 2: Item selection		
Brand			Brand		
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	Flavor		
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**	Type		
Solo	-0.7633**	-0.3191*	Corn	0.6428**	0.7944***
Vitelma	0.2149	0.0493	Wheat	0.4643*	-0.4210**
Size			Filled	-0.0499	-2.2536***
Large size	-0.6637**	-0.5334***	Muesli	0.7959**	0.4631***
Item preference			Crunchy	0.6679**	-0.4613***
	2.6845***	3.2386***	Mixed	0.2945	-0.2826
			Variety	-0.0073	-0.2033
			Item preference	9.1276***	1.8783***
Panel (b): Purchase incidence model			Panel (b): Purchase incidence model		
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***
Non-visible policy	-0.2540**	-0.1798	Non-visible policy	0.1320	-0.1972**
Category value	0.1254**	0.0808	Category value	-0.0501	0.0592
Heterogeneity, relative size	67.35%	32.64%	Heterogeneity, relative size	57.95%	42.04%

*Significant at 10% level, ** significant at 5% level, *** significant at 1% level (one-tailed significance test).

^a Because this is a moderating effect, the approach of Jaccard et al. (1990) must be adopted. Applying their rule indicates that higher-priced suggestion items have a significant moderating effect in the first segment of margarine and in the first segment of cereals. In both segments, the (main, positive) suggestion effect is no longer significant when higher-priced replacement items are suggested.

Concentrating on overall *stock-out* effects, we find that switching to a remaining alternative is the predominant reaction. Panel b of Table 3 shows that stock-out induced reductions in category value only lower purchase incidence probabilities for segment 1 of margarine (positive CV coefficient of 0.1254, $p < .05$).¹⁰ Research in a brick-and-mortar setting has shown similar findings (Campo and Gijbrecchts 2005;

Slout et al. 2005). In the choice model (panel a, consideration set formation), we find significant OOS 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 ($b = 1.0982$, $p < .01$). For cereals, consumers of segment 2 are more likely to consider alternatives of the same brand ($b = 0.5742$, $p < .01$) and flavor ($b = 0.2029$, $p < .01$). These results are comparable to findings for the same categories in a traditional store setting (Campo et al. 2003).

Test of stock-out policy hypotheses

In support of H1, we find that *not showing stock-outs* has a significant and negative impact on purchase incidence for the majority of margarine buyers ($\gamma_{NV} = -0.2540$, $p < .05$

¹⁰ Note that the absence of any significant effect in the other segments does not mean that purchase incidence decisions are in no way influenced by the attractiveness of the category at the time of purchase. Since in our application, changes in category value are predominantly a result of stock-outs (and, for example, not of price changes or promotions), the non-significant coefficients only imply that (a limited number of) stock-outs do not reduce the category's attractiveness enough to make respondents refrain from their planned purchases.

in segment 1, representing 67% of the sample) and almost half of the cereals buyers ($\gamma_{nv} = -0.1972$, $p < .05$ in segment 2, representing 42% of the households). Households in the remaining segments do not react negatively to the non-visible policy.¹¹ Comparison of segment characteristics learns that consumers who tend to stick to the same item (strong positive impact of the last purchase variable) are more likely to cancel their purchase under a non-visible policy.¹² For these habitual buyers, the false expectations of being able to buy their favorite products – created by the non-visible policy – may reinforce the perceived loss when they find out, after clicking, that their preferred item is unavailable.

To assess the significance of the main and moderating effect of the *replacement policy*, we use the approach outlined in Jaccard et al. (1990). Starting with the *main* effect on *choice* we find that, in support of H3, being suggested has a significant and positive impact on consideration in the first segment of margarine ($b = 1.3789$, 67% of households) and cereals ($b = 0.5668$, 58% of households). Especially consumers who find the product category less important¹³ (lower ratings on importance scales, $p < .05$ and lower consumption rates, $p < .05$) appreciate the retailer's guidance. For these segments, suggesting a substitute item also tempers the decrease in category attractiveness (CV) caused by stock-outs. Yet, these changes in category value only carry through to *incidence* in the first segment of margarine, where the coefficient of CV is significant (see Table 3). It follows that the replacement policy only has a limited effect on purchase incidence, providing partial support for hypothesis H2. A possible explanation is that Eq. (8) only allows for indirect effects of suggestions on category purchase, through the CV variable. As a robustness check, we therefore ran a model where a replacement policy dummy is added to Eq. (8) to capture the influence on incidence directly. However, in neither category/segment did this dummy reveal significant, leaving the conclusions unchanged.

Concerning the *moderating* effect of the recommended replacement item's price, we find – from Table 3 and using

¹¹ One possible reason is that these households, despite the random assignment of stock-outs, simply faced fewer OOS encounters. To check this, we computed (i) the average number of stock-outs (ii) seen by households in the non-visible policy condition (iii) that had an intention to buy from the category (clicked on at least one item), before they either successfully purchased or decided to cancel planned purchases. This number is not significantly different between segments that do and do not buy less under the non-visible policy, indicating that the difference in response is not an 'artifact' of the experimental setup.

¹² It is important in this respect to make a distinction between intrinsic item preference (measured by the long-term average purchase share Pref) and habit persistence (measured by the last purchase variable LP) (see e.g. Ailawadi et al. 1999). Consumers of segment 2 (margarine) and 1 (cereals) appear to be loyal to a *set* of items (strong effect of long-term preference), from which they make a selection that may vary by purchase occasion (low habit persistence or even a tendency to switch between different items over time in segment 1 of cereals).

¹³ As indicated in Experimental data section, additional questions were included in the computer experiment to collect general consumer information, such as product usage rates and involvement.

the approach of Jaccard et al. (1990) – that the impact of the replacement policy on consideration is no longer significant when the suggestion is a higher-priced item.¹⁴ Hence, in both categories, the positive consideration (and choice) effect disappears when a more expensive replacement item is suggested. Likewise, the positive main effect of the replacement policy on *incidence*, observed for margarine in segment 1, is nullified when higher-priced replacement items are suggested, confirming hypothesis H4.

Consequences of the stock-out policy

To further assess the consequences of OOS policies, we use the actual purchase data as a simulation basis. Choice and incidence probabilities are computed for each of the three policies. Table 4 reports the *average* changes in these probabilities when a non-visible or replacement policy is adopted instead of the benchmark (visible, no replacement) approach.

Compared to the visible/no replacement policy, a *non-visible* policy substantially reduces the consumers' tendency to buy in the category (see Table 4). In segments where a significant response is noted, the purchase probability drops by 10.48% for margarine and 8.21% for cereals. These figures represent a 5.04% and 4.74% sales decrease for the market as a whole.

Suggesting a *substitute* item substantially increases its choice probability and sales volume (see Table 4). Within the segments where the replacement policy is significant, the likelihood that a suggested item is chosen, increases on average with 64% (margarine, segment 1) and 43% (cereals, segment 1) as compared to the visible/no replacement policy. This represents an increase of about 46% (margarine) and 16% (cereals) at the market level (both segments taken together). Overall sales increases for the suggested items show comparable figures (see Table 4), as category purchase rates are only marginally affected for margarine (increase of 0.7% for segment 1; increase of 0.38% for the whole market) and not affected at all for cereals.

The extent to which suggesting a replacement item increases its choice probability mainly depends on two factors (see Eq. (6)). First, the effect will be smaller for substitutes that already had a high probability of being *considered*. Second, the increase in attention will only translate into substantial increases in choice probability, when the suggestion's *intrinsic value* is sufficiently high. A hypothetical example illustrates this.

Consider, in Table 5, an assortment of four items (A–D) with 'regular' choice probabilities (no disruptions) as defined in panel a. Alternatives A and B have the same

¹⁴ 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 OOS 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.

Table 4

Average changes in incidence and choice probabilities (relative to the base setting) from changes in the OOS policy (actual data set)

	Margarine			Cereals		
	Segment 1	Segment 2	Total	Segment 1	Segment 2	Total
Non-visible policy						
Change in incidence probability	−10.48%	n.s. ^a	−5.04%	n.s.	−8.21%	−4.74%
Expected volume (sum ^b of incidence probabilities) in base scenario	660.42678	608.20114	1268.94109	596.91032	759.61312	1356.52344
Expected volume (sum ^b of incidence probabilities) in non-visible policy	591.20114	608.20114	1199.71545	596.91032	697.30401	1294.235164
(Non-suspicious) replacement policy						
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.
Expected volume (sum ^b of purchase probability × choice probability) of items that were suggested in base scenario	53.979380	38.56588	92.54526	62.360761	92.054887	154.4155648
Expected volume (sum ^b of purchase probability × choice probability) of suggested items	91.341003	38.56588	129.906883	88.578737	92.054887	180.633724

^a n.s.: not significant.^b Over respondents and shopping trips.

Table 5

Changes in incidence and choice probabilities when a replacement item is suggested (hypothetical example)^a

	Item selection				Category purchase
	A	B	C	D	
Panel (a): Regular choice environment					
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					56.6%
Panel (b): Disrupted choice environment (stock-out of D)					
Choice probability	27%	27%	47%	0%	
Incidence probability					55.4%
Panel (c): Suggesting replacement items for the out-of-stock item					
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 is suggested	55.6%	56%	55.8%		
Panel (d): Effect of replacement policy					
Δ in consideration probability if item is suggested (others not)	30.20%	81.72%	30.20%		
Δ in choice probability if item is suggested (others not)	20.52%	48.97%	14.16%		
Δ in incidence probability if item is suggested (others not)	0.43%	1.10%	0.73%		

^a Based on expressions (6) and (9). 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.

choice probability, but alternative A has a higher degree of consideration and a lower choice utility.¹⁵ Alternatives B and C, in contrast, have the same choice utility but C has a higher degree of consideration than B. To isolate the effects

¹⁵ Although consideration and choice utility of alternatives will often be positively related, low consideration items may have high choice utilities. Habitual buyers may fail to consider high-utility items that have been added to a category, because they adhere to their purchase routine—except, e.g. when forced to do so because of stock-outs. For instance, while the cereals category is dominated by strong national brands (high consideration and high choice utility), private label entrants often constitute a valuable substitute as retailers practically duplicate the national brands' cereals assortment. Yet, though their choice utility is high, private labels' consideration utility may remain low until 'forced' into the consumers' consideration set.

of the OOS policy, we assume that there are no differences between the items in asymmetric switching effects.

Suppose alternative D is OOS. 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. 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; see panel c). In line with this, among items with the same prior propensity of being chosen (items A and B), the effect of the suggestion is far more pronounced for the low consideration, high util-

ity item (item B).¹⁶ As indicated in the table (and already clear from Eq. (9)), these changes will carry through in the purchase incidence effects of the replacement policy—be it only marginally. More ‘effective’ suggestions (in the hypothetical example: suggesting item B) lead to a lower decrease in category attractiveness ΔCV and hence to slightly higher category purchase propensities.

Discussion and limitations

In spite of many differences between online and offline stores, OOS reactions in online grocery stores appear to be very similar to reactions observed in traditional stores. Most consumers prefer to buy another item, rather than dropping the category purchase or visiting another store. This may seem surprising at first, various sources suggesting that shopping around is much less of an imposition in an online setting (e.g. Alba et al., 1997). In hindsight, the fixed cost-per-delivery or the burden of having to familiarize themselves with another virtual store, combined with the fact that online shoppers are typically time-pressed and convenience-oriented (Morganosky and Cude 2002), may refrain these consumers from procuring OOS items in competing e-stores. Even though the consumers in our experiment did not actually experience these inconveniences, the fact that they were asked to mimic true purchase behavior may have been sufficient. Clearly, future studies of actual online purchases and/or motivations are needed to confirm these findings.

Our primary objective, however, was to assess the effect of alternative OOS policies that are easily implementable in online settings. We find that a non-visible policy (where consumers only become aware of an OOS when they click on the product to purchase it) reduces category purchases for the majority of consumers. Consumers clearly prefer to know the real assortment they can choose from upfront. This effect is especially strong for consumers who tend to repurchase the same item. In fact, these consumers face a ‘double-jeopardy’ effect. Given their preference to stay with the same item, they are more strongly disappointed when finding out that their favorite item is in fact unavailable. Also, because they tend to repurchase the same product, they typically have little experience with other alternatives and, consequently, face higher search costs. In contrast, consumers who divide their purchases over a set of items (multi-item loyals or variety seekers) react less negatively to the non-visible policy. Most of them simply select another product from their favorite set, rather than giving up the planned purchase. It follows that a non-visible OOS policy not necessarily evokes negative reactions for all consumers,

product categories and purchase situations. The effect of a non-visible policy may also depend on the number of OOS items and the frequency with which stock-outs occur. Even consumers with a high variety-seeking tendency may eventually become frustrated and cancel their purchase when the level or frequency of stock-outs becomes too high.

Second, suggesting a replacement item substantially increases the consideration and (hence) choice probability of the suggested item. An important implication is that retailers can re-direct choices in case of stock-outs, by suggesting appropriate substitutes. 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 a replacement item will have little effect if that item does not really appeal to consumers. Third, the change in choice probability depends on the item’s initial consideration utility. Items that would otherwise have a low consideration probability, have more to gain from being suggested than items that are already highly salient without the suggestion.

While the replacement policy strongly affects consumers’ choice decisions, it hardly influences the probability that consumers will cancel the store purchase. This is not too surprising, given the fact that stock-outs have no or only a limited effect on purchase incidence in general. No effects are found for cereals and only small effects for margarine. This might be linked to the categories under consideration. Previous OOS research has shown that purchase incidence effects may depend on category features like assortment size, the consumers’ variety seeking tendency and perceived differences within the category.

The absence of category purchase effects sheds further light on appropriate replacement practices and, in particular, on the use of price-matching recommendations—where a more expensive substitute is made available at the price of the OOS item. On the one hand, our choice-level results indicate that higher-priced suggestions will not be acted upon by consumers. In view of this, reducing the substitute’s price to that of the OOS product can be considered as ‘good practice’, if the e-tailers’ objective is to ‘re-direct’ choices. On the other hand, if – as our findings suggest – higher-priced suggestions hardly translate into reduced category losses, such price-matching would only lower per unit margins without any category gains. E-grocers, therefore, have a clear interest in critically assessing the implications of their replacement approach.

Taken together, our results demonstrate (1) that online retailers can guide a consumer’s choice in an OOS situation by adopting a replacement policy but that they should be careful in the selection of the suggested replacement item and (2) that the OOS reaction may be more negative when customers become skeptical about the retailer’s OOS policy

¹⁶ Compared to a two-stage model, the one-stage model would lead to serious biases of the suggestion effect. 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).

(hiding stock-outs or suggesting higher-priced options as a retailer-enriching strategy). Consumers clearly value an open and honest retailer who truly helps in finding an appropriate substitution item. This is 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 study leaves ample opportunities for future research. First, due to the small number of observations per respondent in our experiment, we were not able to take dynamic effects into account. Also, despite the advantages of a tightly controlled experiment, using a laboratory setting may have entailed some biases. While we stressed that respondents were not obliged to make a purchase in the category each week, we cannot rule out that the limited purchase incidence effect is partially due to the artificial setting. Future studies based on real purchase data from online stores could study the medium and long-term effect of OOS policies on category and even store purchases. Second, we only focused on a subset of OOS policies available to online retailers. Investigating and comparing additional policies (e.g. other shelf rearrangements) might be an interesting topic for future research. Third, we fixed the OOS rate to the 8% average reported in previous studies. While this figure is representative for most brick-and-mortar grocery stores, it constitutes a conservative estimate of online OOS rates. This might explain why half of the respondents do not react negatively to the non-visible OOS policy. Finally, our results are obtained for only two categories and not necessarily generalizable to other grocery products or other e-tailers. For instance, while we observed negative moderating effects of suggesting higher-priced items, up-selling might pay off for non-frequently purchased goods if consumers can be convinced of the substitute's higher intrinsic value. Also, while we found stock-outs to be harmful and OOS policies capable in alleviating negative consequences, there are settings where product scarcity may signal attractiveness and, hence, raise demand. Future studies could broaden the scope and investigate the impact of stock-outs and stock-out policies in other shopping environments.

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Appendix A

Effect of the replacement stock-out policy on choice probability

The choice probability when item i is *not* suggested as a substitute for the OOS item, is given by

$$p_i|0 = \frac{A_i}{\sum_j A_j} \quad (\text{A.1})$$

with $A_i = \exp(u_i)$ for the one-stage (MNL) choice model and $A_i = \pi_i \exp(u_i)$ for the two-stage (B&V) choice model.

When item i is suggested as a substitute for the OOS item, 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:

$$p_i|\text{sugg} = \frac{SF_i A_i}{\sum_{j \neq i} A_j + SF_i A_i} \quad (\text{A.2})$$

The change in choice probability can be written as

$$\begin{aligned} \frac{p_i|\text{sugg} - p_i|0}{p_i|0} &= \frac{SF_i A_i}{\sum_{j \neq i} A_j + SF_i A_i} \frac{\sum_j A_j}{A_i} - 1 \\ &= \frac{SF_i \sum_j A_j}{\sum_j A_j - A_i(1 - SF_i)} - 1 \\ &= \frac{1}{SF_i^{-1}(1 - p_i|0) + p_i|0} - 1 \end{aligned} \quad (\text{A.3})$$

In a *one-stage* (MNL) choice model, the increase in attractiveness is given by

$$SF_i = \exp(\omega'_{\text{sugg}}) \quad (\text{A.4})$$

with $\omega'_{\text{sugg}} = \omega'_{\text{sugg}} + \omega'_{\text{Hpsugg}}$ if the suggested item is more expensive than the OOS product and $\omega'_{\text{sugg}} = \omega'_{\text{sugg}}$ if the suggested item is not more expensive than the OOS product.

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:

$$\begin{aligned} SF_i &= \frac{\pi_i|\text{sugg}}{\pi_i|0} = \frac{1 + \exp(\theta - s_i)}{1 + \exp(\theta - s_i - \omega'_{\text{sugg}})} \\ &= \frac{1}{1 + \exp(\theta - s_i - \omega'_{\text{sugg}})} \\ &\quad + \frac{\exp(\theta - s_i)}{1 + \exp(\theta - s_i - \omega'_{\text{sugg}})} \\ &= \pi_i|\text{sugg} + (1 - \pi_i|\text{sugg}) \exp(\omega'_{\text{sugg}}) \end{aligned} \quad (\text{A.5})$$

with $\omega_{\text{sugg}}^{\text{net}} = \omega_{\text{sugg}} + \omega_{\text{Hpsugg}}$ if the suggested item is more expensive than the OOS product and $\omega_{\text{sugg}}^{\text{net}} = \omega_{\text{sugg}}$ if the suggested item is not more expensive than the OOS product.

Incorporating (A.4) and (A.5) in expression (A.3) leads to

$$\frac{p_i|\text{sugg} - p_i|0}{p_i|0} = \frac{1}{[\exp(\omega_{\text{sugg}}^{\text{net}})]^{-1}(1 - p_i|0) + p_i|0} - 1$$

for the one-stage model (A.6)

$$\frac{p_i|\text{sugg} - p_i|0}{p_i|0} = \frac{1}{[\pi_i|\text{sugg} + (1 - \pi_i|\text{sugg}) \exp(\omega_{\text{sugg}}^{\text{net}})]^{-1}(1 - p_i|0) + p_i|0}$$

for the two-stage model (A.7)

Effect of the non-visible and replacement stock-out policy on 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 | Δpol) changes the purchase incidence probability with the following fraction:

$$\begin{aligned} \Delta\text{PI} &= \frac{\text{PI}|0 - \text{PI}|\Delta\text{pol}}{\text{PI}|0} = \frac{\frac{e^W}{1+e^W} - \frac{e^{W'}}{1+e^{W'}}}{\frac{e^W}{1+e^W}} \\ &= 1 - \frac{e^{W'}}{e^W} \frac{1}{\frac{1}{1+e^W} + \frac{e^{W'}}{1+e^{W'}}} \\ &= 1 - \frac{e^{W'}}{e^W} \frac{1}{(1 - \text{PI}|0) + \text{PI}|0 \frac{e^{W'}}{e^W}} \\ &= 1 - \frac{1}{e^{-W'-W}(1 - \text{PI}|0) + \text{PI}|0} \end{aligned}$$

(A.8)

For the *non-visible policy*, we have

$$\exp(W' - W) = \exp(\gamma_{\text{nv}}) \tag{A.9}$$

and hence

$$\Delta\text{PI}|_{\text{nv}} = \frac{\text{PI}|0 - \text{PI}|_{\text{nv}}}{\text{PI}|0} = 1 - \frac{1}{e^{-\gamma_{\text{nv}}}(1 - \text{PI}|0) + \text{PI}|0} \tag{A.10}$$

For the *replacement policy*, the effect depends on the coefficient of category value and on the difference in the category value:

$$\exp(W' - W) = \exp(\gamma_{\text{CV}} \Delta\text{CV}) \tag{A.11}$$

and hence

$$\begin{aligned} \Delta\text{PI}|_{\text{repl}} &= \frac{\text{PI}|0 - \text{PI}|_{\text{repl}}}{\text{PI}|0} \\ &= 1 - \frac{1}{e^{-\gamma_{\text{CV}} \Delta\text{CV}}(1 - \text{PI}|0) + \text{PI}|0} \end{aligned} \tag{A.12}$$

where change in the category value can be expressed as

$$\Delta\text{CV} = \ln \left(\sum_j \exp(u_j) \pi_j | \text{sugg} \right) - \ln \left(\sum_j \exp(u_j) \pi_j | 0 \right) \tag{A.13}$$

Using the denominator of (A.2) and (A.1) gives

$$\begin{aligned} \Delta\text{CV} &= \ln \left(\sum_{j \neq i} A_j + \text{SF}_i A_i \right) - \ln \left(\sum_j A_j \right) \\ &= \ln \left(\frac{\sum_j A_j - A_i + \text{SF}_i A_i}{\sum_j A_j} \right) \\ &= \ln \left(1 - \frac{A_i(1 - \text{SF}_i)}{\sum_j A_j} \right) = \ln(1 - p_i|0(1 - \text{SF}_i)) \end{aligned} \tag{A.14}$$

Substituting (A.5) and (A.14) in (A.11) gives

$$\begin{aligned} \exp(W' - W) &= \exp(\gamma_{\text{CV}} \ln(1 - p_i|0(1 - \text{SF}_i))) = (1 - p_i|0(1 - \text{SF}_i))^{\gamma_{\text{CV}}} \\ &= (1 - p_i|0(1 - \pi_i|\text{sugg} - (1 - \pi_i|\text{sugg}) \exp(\omega_{\text{sugg}}^{\text{net}})))^{\gamma_{\text{CV}}} \\ &= (1 - p_i|0(1 - \pi_i|\text{sugg})(1 - \exp(\omega_{\text{sugg}}^{\text{net}})))^{\gamma_{\text{CV}}} \\ &= (1 + p_i|0(1 - \pi_i|\text{sugg})(\exp(\omega_{\text{sugg}}^{\text{net}}) - 1))^{\gamma_{\text{CV}}} \end{aligned} \tag{A.15}$$

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