Available online at www.sciencedirect.com

ScienceDirect

Journal of Interactive Marketing 31 (2015) 63 – 78

JOURNAL OF INTERACTIVE MARKETING

www.elsevier.com/locate/intmar

Buying Groceries in Brick and Click Stores: Category Allocation Decisions and the Moderating Effect of Online Buying Experience

Katia Campo * & Els Breugelmans

KU Leuven, Faculty of Economics and Business, Korte Nieuwstraat 33, 2000 Antwerp, Belgium

Available online 27 August 2015

Abstract

The large majority of online grocery shoppers are multichannel shoppers who keep visiting offline grocery stores to combine convenience advantages of online shopping with self-service advantages of offline stores. An important retail management question, therefore, is how these consumers divide grocery purchases across the retailer's online and offline channel. We provide a comprehensive analysis of the impact of category characteristics on the allocation pattern of multichannel grocery shoppers and find that category allocation decisions are affected not only by marketing mix differences between the online and offline channel, but also by intrinsic category characteristics like perceived purchase risk and shopping convenience. In addition, we examine the effect of online buying experience. In line with expectations, we find that it can affect allocation patterns in different ways: (i) it attenuates the perceived risk of buying sensory categories online, thereby reducing differences in online category share, (ii) it reinforces marketing mix (assortment) effects, thereby making online category share differences more pronounced, and (iii) it has no effect for factors such as promotions that are easy to evaluate without experience, thereby leaving the online category share stable. In addition to different experience effects across allocation factors, we also observe variations in experience effects across consumer segments.

Keywords: Multichannel shopping; Online grocery shopping; Category allocation decision; Buying experience

Introduction

While lagging behind in comparison with many other consumer markets, online shopping for groceries has increased dramatically over the last few years, and now tops the agenda of all major grocery retailers (Warschun 2012). "[Grocery] retailers are increasingly finding they must innovate in ways that make it easier and more convenient for their customers to get what they need without missing a beat," according to Nielsen's *Continuous Innovation* report, which found that "convenience itself may be the most creative and energetic example of retail innovation" (Nielsen 2014). Of these convenience-oriented retail innovations, the shift towards multichannel offline-online retailing is one of the most important and successful practices. Several of the large grocery retail chains (such as Walmart, Tesco and Ahold) now operate an online store next to their offline supermarket outlets ('brick and click' grocery retailers). By increasing their service levels, multichannel retailers aim to retain existing customers and gain new customers in the increasingly competitive retail environment (Chintagunta, Chu, and Cebollada 2012; Kabadayi, Eyuboglu, and Thomas 2007; Neslin and Shankar 2009; Zhang et al. 2010).

Customers clearly appreciate and take advantage of this extended service. The large majority of online grocery shoppers are multichannel shoppers who visit both the online and offline channel, thereby combining convenience advantages of online shopping with self-service advantages of offline stores (Alba et al. 1997; Chu, Chintagunta, and Cebollada 2008; Chu et al. 2010; Konuş, Verhoef, and Neslin 2008; Venkatesan, Kumar, and Ravishanker 2007). Although multichannel shoppers visit both channels, their purchase behavior tends to differ across the online and offline channel, both in the tendency to buy certain categories and in the sensitivity to marketing mix instruments. For instance, a product's online intangibility can result in low(er)

* Corresponding author.
E-mail addresses: katia.campo@kuleuven.be (K. Campo), els.breugelmans@kuleuven.be (E. Breugelmans).

http://dx.doi.org/10.1016/j.intmar.2015.04.001
1094-9968/

online purchase shares, especially for sensory categories that consumers prefer to physically examine before purchasing them (Degeratu, Rangaswamy, and Jianan 2000). Bulky and heavy categories, in contrast, tend to be top-selling categories in online stores because of the high online shopping convenience benefits (Chintagunta, Chu, and Cebollada 2012). Prior research has also shown that households tend to be more brand loyal and size loyal, but less price sensitive in the online channel than in the offline channel (Chu et al. 2010). Because channel differences in assortment and price can vary across categories, this may also influence consumers' allocation patterns over the online and offline channel. As a result, the multichannel shopping context clearly adds to the complexity of retailers' management decisions, and multichannel grocery retailers need more insight into how shoppers allocate their purchases across their online and offline stores (cf. Dholakia et al. 2010; McPartlin and Dugal 2012; Shankar and Yadav 2010).

The purpose of this study is to improve the understanding of multichannel shopping behavior and to provide a better insight into the underlying mechanisms and factors that determine how multichannel shoppers allocate their category purchases across the online and offline channel. Building on the multiple store and online shopping literature, we analyze the impact on purchase allocation patterns at the category level, and take 'traditional' marketing mix based factors as well as 'intrinsic' category characteristics into account. Given that online grocery shopping is still in the 'innovation stage' (small, but rapidly increasing number of consumers who start buying groceries online), our model explicitly accounts for dynamic adjustments of allocation patterns as consumers gain more experience with buying groceries online. We also account for the possibility that managers adjust category assortment and pricing decisions to anticipated channel differences in buying behavior, and correct for potential endogeneity biases in marketing mix effects.

Our research provides important contributions to the marketing and retailing literature. First, we extend insights from the multiple store shopping literature by examining category allocation decisions in a substantially different multichannel retail context, with fundamental differences in the factors driving purchase allocation decisions. Second, we add to the multichannel literature by providing a comprehensive analysis of the factors that can cause differences in online purchase tendency across grocery categories. As indicated in previous (offline) purchase behavior studies (Hoyer and MacInnis 2010), grocery shopping differs substantially from other purchase contexts. As the same products are purchased repeatedly, purchase involvement tends to be low, and consumers are not prepared to spend much time and effort to search for the 'best' product. Findings of previous multichannel studies – which mainly focused on durable goods – are therefore not directly transferrable to, and provide little insight into, what drives purchase allocation decisions in a multichannel grocery shopping context. The limited number of studies on multichannel purchases of groceries focused on specific issues such as channel differences in sensitivity to specific marketing mix instruments (e.g., price sensitivity: Chu, Chintagunta, and Cebollada 2008; Chu et al. 2010), the degree of brand exploration across both channels (Chu et al. 2010; Pozzi 2012) or the impact of transaction costs on channel choice (Chintagunta, Chu, and Cebollada 2012). While useful to develop expectations on the impact of specific factors, they do not provide insights into the overall purchase patterns of multichannel shoppers. Third, we refine and extend previous research on online buying experience effects (Ansari, Mela, and Neslin 2008; Frambach, Roest, and Krishnan 2007; Kim, Ferrin, and Raghav Rao 2008) by examining experience effects on category level purchase decisions and by taking different possible effects of experience into account.

From a managerial point of view, our results help multichannel retailers to improve the mix of customer services and enhance their overall value proposition for multichannel shoppers (Zhang et al. 2010). Our results can guide online category management and promotional decisions of multichannel retailers to stimulate online purchases. Striving for larger online shopping baskets can be beneficial and generate additional revenue that may cover the high fixed costs that online retailers face (e.g., storing and delivery costs). Next, by obtaining a better insight into the effects of experience on different types of factors that influence consumers' category purchase allocation decisions, multichannel retailers can better assess the importance of stimulating trial and repeat purchases (to generate positive experience effects) vs. taking corrective actions (e.g., adjust channel differences in assortment and/or price).

Conceptual Framework

In this section, we provide a conceptual framework on how multichannel shoppers allocate category purchases across the online and offline channel operated by a single retailer. We take the overall allocation of grocery purchases across channels (channel choice and visit frequency) as given and examine whether and how category-specific allocation factors lead to deviations from the overall allocation scheme (i.e., result in disproportionately low or high channel shares in category purchases). Building on the multiple store and multichannel shopping literature, we explain category allocation decisions as the outcome of a shopping utility maximization process that accounts for (i) acquisition utility, i.e., the benefits that consumers receive (e.g., product quality and promotions) and the costs they need to give up (e.g., price) when *acquiring* the product, and (ii) transaction utility, i.e., the benefits consumers receive (e.g., time-saving home delivery systems) and the cost they need to bear (e.g., perceived risk of online ordering) when *transferring* the products from the store to home (Baltas, Argouslidis, and Skarmeas 2010; Chintagunta, Chu, and Cebollada 2012; Gupta and Kim 2010; Vroegrijk, Gijsbrechts, and Campo 2013). Below, we identify the major acquisition and transaction utility related factors and discuss how they are expected to influence category allocation patterns over the online and offline channel. Next, we discuss how online buying experience in the category plays a moderating role (see also Fig. 1).

Acquisition Utility: The Impact of Marketing Mix Instruments

Studies on multiple store shopping behavior in an offline context have demonstrated that marketing mix based differences

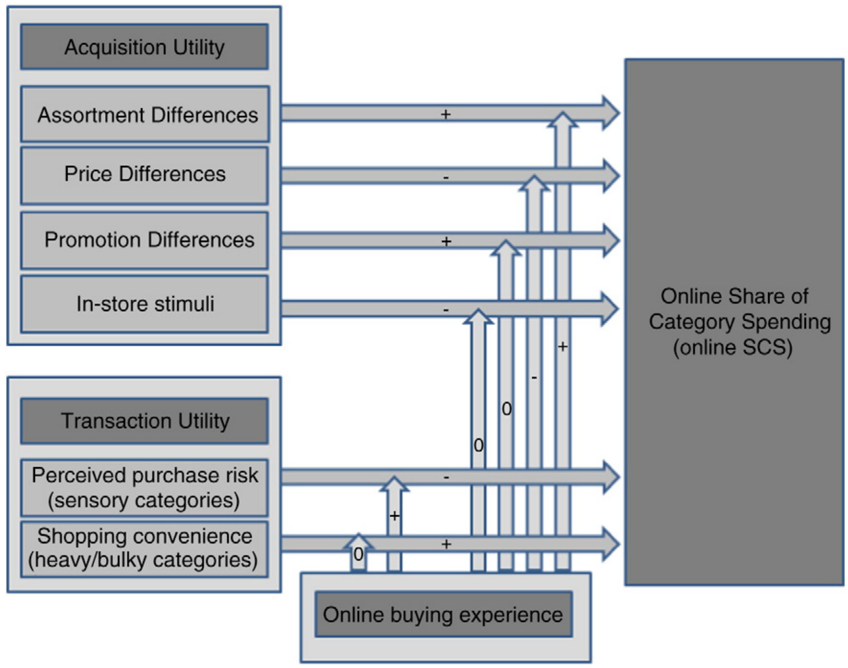

Fig. 1. Conceptual framework & expected effects.

in acquisition utility – such as assortment and price differences – are important drivers of category allocation decisions across stores (Gijsbrechts, Campo, and Nisol 2008; Vroegrijk, Gijsbrechts, and Campo 2013). As explained in more detail below, even though online and offline stores that belong to the same chain have a similar price/quality positioning, marketing mix instruments can still differ across channels for several reasons (Neslin et al. 2006; Wolk and Ebling 2010). In the following, we discuss the impact of channel differences in assortment, price and promotion intensity (Fox and Hoch 2005) and examine the differential effect of in-store incentives aimed at stimulating unplanned purchases on allocation decisions (Breugelmans and Campo 2011).

Assortment Differences

Online and offline assortments can differ in size for several reasons. On the one hand, online stores provide the opportunity to carry a larger assortment as a result of the online store's limitless shelves. On the other hand, cost and demand constraints, and the need to respect very short delivery times, can be reasons to restrict online assortments for some categories (such as groceries). The literature on assortment effects suggests that larger assortments tend to be preferred over smaller ones because they offer more choice flexibility and enhance feelings of autonomy (Oppewal and Koelemeijer 2005; Sloot, Fok, and Verhoef 2006)[1]. We expect that channel differences in assortment size can influence channel allocation decisions, such that consumers are more inclined to buy the category in the channel that offers the largest assortment.

Price Differences

Multichannel retailers can charge different prices in their online and offline channel in view of cost and demand considerations (Neslin and Shankar 2009; Wolk and Ebling 2010). For one, the online channel may entail higher operational costs, including additional ICT, picking, handling and delivery costs. At the same time, the online channel may experience cost savings as the result of lower store layout, display and shelf replenishment costs, and because price adjustments can literally be executed by pressing a button. In addition, several studies provided evidence of channel differences in price sensitivity (Chu, Chintagunta, and Cebollada 2008; Wolk and Ebling 2010). Multichannel grocery retailers can incorporate these cost and price sensitivity differences in product prices to safeguard profit margins (compensate for higher online operational costs) or to stimulate online purchases (let consumers benefit from lower online operational costs or use different price levels to exploit price sensitivity differences). Similar to assortment differences, we assume that multichannel shoppers will incorporate price differences in their category allocation decisions, and allocate a lower share of category purchases to the channel where the category is least attractive in price (cf. multiple store shopping literature; Gijsbrechts, Campo, and Nisol 2008; Vroegrijk, Gijsbrechts, and Campo 2013).

Promotion Differences

The intensity of promotional actions can differ between the online and offline channel of the same retailer to account for differences in price/promotion sensitivity across channels (Wolk and Ebling 2010) or for more pragmatic reasons such as

[1] While larger assortments may also come at the cost of more difficult evaluation processes because of information overload, choice conflict or regret (Dhar 1997; Huffman and Kahn 1998), the general expectation appears to be that the advantages of larger assortments tend to cancel out potential disadvantages (cf. negative effects of assortment reductions on category sales; Borle et al. 2005; Sloot, Fok, and Verhoef 2006).

different account managers being in charge of the promotion planning in each channel (Avery et al. 2012). Consumers can react by temporarily adjusting their allocation patterns to take advantage of more attractive promotional actions in one of both channels.

In-store Stimuli

In-store stimuli may trigger a forgotten need or new idea. Compared to the offline channel, online shoppers tend to be less sensitive to these in-store stimuli for several reasons: they can more easily control their shopping route and immediately navigate to the needed category by clicking the category's page; they do not have to wait at fresh meat/fish counters or at the cash register (locations that are often used to store impulse products) and the more 'functional' online shopping environment can evoke a more goal-oriented shopping attitude making consumers more reluctant to deviate from their purchase plans and give in to impulse purchases (Babin and Darden 1995). We therefore expect that the online store will obtain a lower share of purchases for impulse categories that consumers do not usually plan in advance to buy and for which they tend to be very sensitive towards in-store stimuli.

Transaction Utility: The Impact of Perceived Purchase Risk and Shopping Convenience

Multichannel studies have indicated that channel differences in transaction costs can depend on the categories that need to be purchased and are mainly based on two components: (i) perceived purchase risk and (ii) shopping convenience (Chintagunta, Chu, and Cebollada 2012; Gupta and Kim 2010). Online purchases can be associated with a higher perceived purchase risk as a result of the products' intangibility, i.e., the lack of sensory decision cues (Degeratu, Rangaswamy, and Jianan 2000; Laroche et al. 2005). On the other hand, online shopping provides convenience advantages through the possibility of having products picked up by online grocery staff and having them delivered at home (Chu et al. 2010; Gupta and Kim 2010).

Perceived Purchase Risk

The lack of sensory information in the online store can constitute an important disadvantage for sensory categories – such as fresh meat, vegetables and fruit – that tend to be evaluated prior to purchase based on sensory information cues (Degeratu, Rangaswamy, and Jianan 2000; Hoch 2002; Laroche et al. 2005; Peck and Childers 2003). Not being able to see or touch products can complicate the evaluation process and lead to greater uncertainty and a higher perceived risk of online purchases (Laroche et al. 2005; Pauwels et al. 2011; Weathers, Sharma, and Wood 2007). This may increase the transaction costs of buying sensory products in the online store (Gupta and Kim 2010) and result in relatively lower online purchase shares of sensory categories compared to other categories (Chintagunta, Chu, and Cebollada 2012).

Shopping Convenience

The shopping convenience advantage of online stores may especially benefit bulky and heavy categories since online shopping eliminates the burden of physically handling these products, e.g., putting them into the basket and carrying them home. The resulting increase in transaction utility can lead to disproportionately higher online category purchase shares of bulky and heavy categories (Chintagunta, Chu, and Cebollada 2012).

Moderating Impact of Online Buying Experience

Because online shopping for groceries is lagging behind compared to other categories (McPartlin and Dugal 2012), many consumers are still relatively new to and unfamiliar with the online grocery store environment and shopping process. Consequently, they may adjust their purchase behavior as they gain more experience with buying groceries online. For this reason, and given that the online purchase tendency can differ across grocery categories, we include category-specific online buying experience as a moderator of category allocation decisions. Based on the previous discussion and consumer behavior literature, we postulate that experience can work in different ways: (i) reduce the uncertainty and perceived risk of online purchases (Frambach, Roest, and Krishnan 2007; Iyengar, Ansari, and Gupta 2007; Kim, Ferrin, and Rao 2008), (ii) help to gain additional factual and choice-related knowledge (Alba and Hutchinson 1987; Iyengar, Ansari, and Gupta 2007) and (iii) involve a learning process in which consumers adjust their evaluation and decision processes to the new store environment (Degeratu, Rangaswamy, and Jianan 2000; Hamilton and Thompson 2007; Hoch 2002). Experience can thus attenuate as well as reinforce category differences in online purchase share, or it may not affect the allocation pattern at all when no risk is involved or no learning process is needed.

We expect that experience has a mitigating effect on the reluctance to buy sensory categories online. First, conditional upon a positive and satisfying outcome, experience can enhance confidence in the online purchase outcome and increase trust in the retailer's selection and delivery process (cf. Kim, Ferrin, and Raghav Rao 2008; Urban, Amyx, and Lorenzon 2009). Second, experience helps with 'learning' to infer missing information from other – verbal and visual – cues that can be easily accessed in the online store and that are diagnostic of the product's quality (e.g., quality labels, product characteristics that act as a quality cue such as brand names and expiration dates) (Degeratu, Rangaswamy, and Jianan 2000; Laroche et al. 2005; Peck and Childers 2003).

On the other hand, we expect that consumers may not be able to accurately assess assortment size and price differences between the online and offline channel from the start. For low involvement, multi-category purchases such as groceries, consumers may not be able or motivated to go through a complete evaluation of the entire assortment, and hence, may not be fully aware of actual assortment or price differences. After some online purchases in the category, they may gradually become aware that some items are missing or only available in the online assortment, or that some items are higher or lower priced online (Alba and Hutchinson 1987; Hoyer and MacInnis 2010). As a result, consumers may adjust their channel preferences and purchase allocation pattern, and these experience-based corrections in assortment and price perceptions may thus reinforce initial assortment and price effects.

Finally, we expect that sales promotions, in-store stimuli and the convenience of buying bulky/heavy categories are easy to evaluate without much online shopping experience. Hence, there is no incentive to learn and adjust the shopping process, and the reaction to these factors is expected to be immediate and independent of a consumer's online shopping experience.

Model

To examine multichannel category allocation decisions, we focus on the online channel's share in category spending (SCS), taking overall spending at the chain as given. Using a relative instead of absolute measure of online category expenditures has the advantage of removing the effect of customer and category differences in total spending. In line with multiple store shopping literature (Gijsbrechts, Campo, and Nisol 2008; Vroegrijk, Gijsbrechts, and Campo 2013), we concentrate on allocation patterns over a longer period of time (i.e., bi-weekly periods, t), rather than category purchase decisions on a visit-by-visit basis. In addition, because consumers only have to decide how to allocate their purchases within this two-week period when they plan to buy the category and when they visit both channels, we focus on observations with (i) a category need (i.e., an online and/or offline purchase in the category) and (ii) an online and offline store visit (i.e., a multichannel shopping period where consumers are in the opportunity to buy the product online and/or offline and allocation is not pre-defined to 0% or 100%). This allows us to eliminate both the effect of a consumer's general online buying tendency (decision to visit the online store) and the effect of category purchase decisions on observed category allocations.

The online channel's share in spending for category c in period t for household i (SCS_{it}^{c}) is defined and estimated over all categories simultaneously (pooled estimation)[2]:

$$SCS_{it}^{c} = \frac{e^{U_{it}^{c}}}{1 + e^{U_{it}^{c}}}. \tag{1}$$

By using a logistic model in Eq. (1), we ensure that the values of the outcome variable are restricted within the zero–one range. To linearize the model, we use the method of log-centering (Cooper and Nakanishi 1996; Lesaffre, Rizopulos, and Tsonaka 2007), that has been applied in many other studies (see e.g., Cleeren, van Heerde, and Dekimpe 2013; Leenheer et al. 2007):

$$\ln\left[\frac{SCS_{it}^{c}}{1-SCS_{it}^{c}}\right] = V_{it}^{c} + \mu_{it}^{c}. \tag{2}$$

To avoid that the dependent variable in Eq. (2) is equal to the log of zero (SCS_{it}^{c} equal to zero) or an undefined value (division by zero, SCS_{it}^{c} equal to one), we add a small amount to the numerator and denominator of Eq. (2) (cf. Bass et al. 2009; Cleeren, van Heerde, and Dekimpe 2013), such that:

$$\ln\left[\frac{SCS_{it}^{c} + 0.001}{1-SCS_{it}^{c} + 0.001}\right] = V_{it}^{c} + \mu_{it}^{c}. \tag{2'}$$

We use consumer, marketing mix and experience as explanatory variables:

$$\begin{aligned} V_{it}^{c} + \mu_{it}^{c} = {} & \left[\gamma_{0i} + \gamma_1 * STS_{it} + \gamma_2 * Exp_{it}^{c} + \gamma_3 * Usage_i^{c}\right] \\ & + \left[\delta_1 * Ass^{c} + \delta_2 * Price^{c} + \delta_3 * Promo^{c} + \delta_4 * ISS^{c}\right] \\ & + \left[\delta_5 * Sens^{c} + \delta_6 * Bulky\_Heavy^{c}\right] + \mu_{it}^{c}. \end{aligned} \tag{3}$$

The first square brackets in Eq. (3) capture consumer characteristics that account for individual differences in the tendency to allocate purchases in category c to the online channel, including a consumer-, category- and time-specific online buying experience variable (Exp_{it}^{c}), and a usage variable capturing the consumer's overall experience with the category ($Usage_i^{c}$). In addition, we include the online store's share in total spending in period t for consumer i (STS_{it}), defined as the overall percentage of online purchases in total grocery expenditures of consumer i at the chain in period t. Including this variable allows capturing category-specific deviations from the overall online/offline allocation pattern that result from channel differences in acquisition and transaction utility. The second square brackets include variables that may entail channel differences in acquisition utility, i.e., category-specific channel differences in assortment size (Ass^{c}), price ($Price^{c}$), promotion ($Promo_t^{c}$), and in-store stimuli (ISS^{c}). The third square brackets capture the effect of transaction cost related characteristics, including whether the category is a sensory ($Sens^{c}$), or bulky/heavy ($Bulky\_Heavy^{c}$) category. We describe the operationalization of these variables in the Data section. μ_{it}^{c} is a normally-distributed error term.

To incorporate the effect of category-specific online buying experience, we use a model with varying coefficients (Foekens, Leeflang, and Wittink 1999; Kopalle, Mela, and Marsh 1999). The parameters of the category-specific variables are a function of experience, allowing the effect to increase or decrease with higher levels of online buying experience in the category:

$$\delta_q = \delta_{q0} + \delta_{q1} * Exp_{it}^{c}, (q = 1\text{–}6). \tag{4}$$

Next, because channel differences in assortment and price variables can be inspired by management expectations on multichannel purchase behavior, we control for potential

[2] To simplify the discussion, we use an overall index t and c for time periods and categories respectively. As we only include multichannel purchase occasions (periods where household i visited both channels), and categories for which the household made a purchase within this period, the time index is actually household-specific while the category index is household- plus time-specific.

endogeneity of these variables using a control function approach (Luan and Sudhir 2010; Petrin and Train 2010)[3]. Web appendix A provides more detailed information. Our final model includes the residuals of the control function models of assortment (Res_Ass^c) and price (Res_Price^c) as additional variables:

$$\begin{aligned} V_{it}^c = & \left[\gamma_{0i} + \gamma_1 * STS_{it} + \gamma_2 * Exp_{it}^c + \gamma_3 * Usage_i^c\right] \\ & + \left[\delta_1 * Ass^c + \delta_2 * Price^c + \delta_3 * Promo^c + \delta_4 * ISS^c\right] \\ & + \left[\delta_5 * Sens^c + \delta_6 * Bulky\_Heavy^c\right] \\ & + \left[\theta_1 * Res\_Ass^c + \theta_2 * Res\_Price^c\right]. \end{aligned} \quad (3')$$

Finally, to capture unobserved heterogeneity, we use (i) latent-class estimation, allowing the parameters of explanatory variables to vary across latent segments (Andrews, Ainslie, and Currim 2002; Kamakura and Russell 1989), and (ii) a random coefficient approach by introducing a standard normally distributed latent factor (F_i), allowing intercepts to vary across households (Vermunt and Magidson 2013). We formulate the household-specific intercept in Eq. (3′) as:

$$\gamma_{0i} = \gamma_{01} + \gamma_{02} * F_i. \quad (5)$$

We use Latent GOLD® software to compute the latent factor and estimate the coefficient γ_{02} (while fixing the value of the standard deviation of the latent factor to 1; see Vermunt and Magidson 2013, p 100–101). Latent GOLD® uses a factor-analytic parameterization of the random-intercept model. The parameter γ_{02} can be interpreted as the standard deviation of the random intercept. The significance of the parameter gives an indication of the importance of household differences in the share they allocate to the online store. A non-significant parameter, corresponding to a zero standard deviation of the intercept, points to homogeneous online purchase tendencies.

The log-likelihood function defined by Eq. (3) and Eqs. (2′), (3′), (4), and (5) is given by:

$$LL = \sum_i \ln\left\{\sum_s P_i(s) \prod_t \prod_c f\left(\ln\left(\frac{SCS_{it}^c + 0.001}{1 - SCS_{it}^c + 0.001}\right) \middle| V_{it,s}^c\right)\right\}, \quad (6)$$

where $V_{it,s}^c$ is the segment-specific version of Eq. (3′) that allows for differences between segments in their sensitivity to factors that affect channel allocation decisions, f is the joint density function of the normal distribution and $P_i(s)$ is the (a priori) probability that household i belongs to segment s, which is defined as:

$$P_i(s) = \frac{e^{\varphi_s}}{\sum_{r=1}^{R} e^{\varphi_r}}, \quad (7)$$

where φ_s reflects the size (importance) of segment s and R is the total number of segments. Eq. (7) indicates that segments are defined over a household's complete purchase history, i.e., over all time periods t and categories c.

Data

Our data come from a major European grocery chain which has a prominent presence throughout the country and is one of the leading offline and online grocery retailers. As we focus on online and offline stores of a single retail chain, online and offline assortments mainly differ in size and not in composition (the online assortment is a subset of the offline assortment), and category prices are directly comparable (price differences are not linked to quality differences). When an online order gets placed, professional shoppers (pickers) fill the order from an independent warehouse; the retailer then delivers the order to the place and at the time specified by the consumer. The online store operates independently and is given full control over merchandising decisions. As a consequence and notwithstanding the similarities in chain policy, there are differences between the online and offline channel in assortment size, product prices and promotional actions.

We used loyalty card information to link online and offline purchase data over a one-year period (2006). To get stable model estimations and a representative sample of multichannel shoppers, we focus on households that made (i) at least two online and two offline store visits during the estimation period (thereby excluding one-off online trial purchases), and (ii) at least two purchases in the category (irrespective of the channel, to include heavy as well as light buyers of the category). In the model estimations, we made a further selection and only focus on bi-weekly periods (of retained households) with a visit to both channels and a category purchase in at least one of the channels. During these periods, the household needs the category, but allocation is not predetermined as would be the case in online-only (100% online) or offline-only (0% online) periods. Table 1 gives an overview of the 25 frequently-purchased categories that were used, and indicates per category the number of households and observations retained.

As Table 1 indicates, most categories that we examined are purchased during multichannel shopping occasions on a regular basis: on average 32% of all transactions are multichannel transactions (min. 24% for vegetables and max. 40% for water). Online-only shopping occasions occur least often (on average 12%; min. 1% for fresh fish and max. 20% for water), while offline-only shopping occasions are most common (on average 57%; min. 40% for water and max. 70% fresh fish). In general, consumers are more likely to visit (and purchase categories in) the offline channel than the online channel: the average number

[3] We expect that the endogeneity problem is especially important for the assortment and price variables because these are typically long-term strategic decisions where the offline channel's price and assortment are taken into account. Promotions, on the other hand, are expected not to have an endogeneity problem because they are short-term decisions made independently from the decisions in the other channel. Estimation of a control function model for promotion intensity indeed provided extremely low explanatory value, and robustness checks confirmed that no improvements in fit or substantive results can be gained when controlling for endogeneity in the promotion variable.

Table 1
Descriptives across the 25 categories.

Category	# of HH retained that	# of bi-weekly periods with category purchase at (% of total transactions with category purchase)			Purchase frequency (average # of bi-weeks/ year with cat. purch.)		Online category share of spending	
	Purchase cat. ≥2 times and have ≥1 multichannel transaction	Both channels (multichannel transactions)	Online channel only	Offline channel only	Online	Offline	Across bi-weeks with cat. purch.	Across bi-weeks with cat. purch. & MC trans.
Fresh meat	421	1,215 (33.27%)	429 (11.75%)	2,008 (54.98%)	3.90	7.66	.27	.41
Charcuterie	572	2,147 (25.96%)	754 (9.12%)	5,371 (64.93%)	5.07	13.14	.20	.34
Fresh fish	385	1,102 (28.77%)	55 (1.44%)	2,673 (69.79%)	3.01	9.81	.05	.08
Fruit	567	2,020 (26.82%)	726 (9.64%)	4,786 (63.54%)	4.84	12.00	.23	.39
Vegetables	640	2,572 (24.42%)	879 (8.35%)	7,081 (67.23%)	5.39	15.08	.17	.27
Bakery pastry	581	2,112 (25.62%)	561 (6.81%)	5,569 (67.57%)	4.60	13.22	.12	.20
Fat	520	1,728 (30.62%)	718 (12.72%)	3,197 (56.65%)	4.70	9.47	.33	.54
Cheese	624	2,427 (26.14%)	1,076 (11.59%)	5,782 (62.27%)	5.61	13.16	.26	.42
Milk	580	2,169 (34.60%)	1,011 (16.13%)	3,088 (49.27%)	5.48	9.06	.37	.64
Yoghurt	590	2,299 (25.96%)	916 (10.34%)	5,641 (63.70%)	5.45	13.46	.23	.37
Canned fruit & veg.	525	1,716 (35.41%)	670 (13.83%)	2,460 (50.76%)	4.54	7.95	.41	.62
Condiments & sauces	484	1,411 (32.90%)	481 (11.21%)	2,397 (55.89%)	3.91	7.87	.30	.46
Breakfast cereals	362	1,064 (32.86%)	349 (10.78%)	1,825 (56.36%)	3.90	7.98	.37	.59
Biscuits	515	1,758 (29.42%)	634 (10.61%)	3,583 (59.97%)	4.64	10.37	.26	.43
Pastes & rice	495	1,443 (34.03%)	535 (12.62%)	2,262 (53.35%)	4.00	7.48	.37	.56
Chocolate	437	1,283 (29.86%)	398 (9.26%)	2,616 (60.88%)	3.85	8.92	.23	.37
Hot beverages	505	1,794 (32.90%)	759 (13.92%)	2,900 (53.18%)	5.06	9.30	.37	.55
Water	603	2,413 (39.80%)	1,231 (20.30%)	2,419 (39.90%)	6.04	8.01	.56	.84
Juice	408	1,258 (35.92%)	411 (11.74%)	1,833 (52.34%)	4.09	7.58	.42	.65
Soft drinks	504	1,768 (34.00%)	813 (15.63%)	2,619 (50.37%)	5.12	8.70	.49	.73
Pet food	237	900 (34.19%)	455 (17.29%)	1,277 (48.52%)	5.72	9.19	.47	.67
General body care	511	1,608 (31.63%)	535 (10.53%)	2,940 (57.84%)	4.19	8.90	.28	.48
Washing products	538	1,713 (39.13%)	687 (15.69%)	1,978 (45.18%)	4.46	6.86	.54	.77
Toilet paper	522	1,707 (38.00%)	627 (13.96%)	2,158 (48.04%)	4.47	7.40	.49	.73
Cleaning products	578	1,940 (30.56%)	686 (10.81%)	3,722 (58.63%)	4.54	9.80	.38	.60
Average (across 25 cat.)		31.71%	11.84%	56.45%	4.66	9.69	.33	.51

Table 2
Variable notation & description.

Notation	Name	Description	Formula
SCS_{it}^{c}	Share in category spending of consumer i for category c in period t	Online spending in category c by customer i in period t ($Spending_{it}^{online,c}$) divided by overall spending (online and offline: $Spending_{it}^{online,c} + Spending_{it}^{offline,c}$) in category c for consumer i in period t. (online and offline prices are measured in constant prices; period t are bi-weekly periods where the consumer visited the online and offline store and made a purchase in the category in the online and/or offline store).	$SCS_{it}^{c} = \frac{Spending_{it}^{online,c}}{\left(Spending_{it}^{online,c} + Spending_{it}^{offline,c}\right)}$
STS_{it}	Share in total spending of consumer i in period t	Online spending across all categories by customer i in period t ($Spending_{it}^{online}$) divided by the overall grocery spending (online and offline: $Spending_{it}^{online} + Spending_{it}^{offline}$) for consumer i in period t.	$STS_{it} = \frac{Spending_{it}^{online}}{\left(Spending_{it}^{online} + Spending_{it}^{offline}\right)}$
Ass^{c}	Assortment difference for category c	Assortment difference ratio (number of SKUs in category c in the online store divided by the number of SKUs in category c in the offline store).	$Ass^{c} = \frac{Ass^{online,c}}{Ass^{offline,c}}$
$Price^{c}$	Price difference for category c	The unit price difference (difference between online and offline average unit prices computed over a common set of category products, i.e., the set of products that are available in both channels).	$Price^{c} = Price^{online,c} - Price^{offline,c}$
$Promo_{t}^{c}$	Online share in promotion intensity for category c in period t	'Share-of-voice' based variable, measured as the share in overall category promotions of the online store (number of SKUs on promotion in category c in the online store in period t, divided by the number of SKUs on promotion in category c in the online and offline store combined in period t; equal to 0 in case there were no promotions in the category).	$Promo_{t}^{c} = \frac{NrPromo_{t}^{online,\,c}}{NrPromo_{t}^{online,\,c} + NrPromo_{t}^{offline,\,c}}$
ISS^{c}	In-store stimuli dummy variable for category c	Indicator variable equal to 1 if sensitivity towards in-store stimuli is high for category c, 0 elsewhere.	
$Sens^{c}$	Sensory dummy variable for category c	Indicator variable equal to 1 if category c is a sensory category, 0 elsewhere.	
$Bulky\_Heavy^{c}$	Bulky/heavy dummy variable for category c	Indicator variable equal to 1 if category c is a bulky or heavy item category, 0 elsewhere.	
Exp_{it}^{c}	Online buying experience of consumer i for category c in period t	Weighted sum of previous online purchases in category c for consumer i in period t ($b_{i,t-1}^{c}$), with weights equal to λ (between 0 and 1) and based on all the previous periods (s = 1,…, $t-1$) to capture fading effects, and Exp_{i1}^{c} as starting value based on an initialization period of 26 bi-weeks (we used λ = .7 and checked the results' sensitivity via robustness checks).	$Exp_{it}^{c} = \lambda * Exp_{i,t-1}^{c} + \lambda * b_{i,t-1}^{c} = \sum_{s=1}^{s=t-1} \lambda^{s} * b_{i,t-s}^{c} + \lambda^{t-1} * Exp_{i,1}^{c}$
$Usage_{i}^{c}$	Online usage level of consumer i for category c	Indicator variable of whether consumer i is a heavy user of category c based on the estimation period.	

of *bi-weeks* per year with a purchase in the category equals 4.66 for the online channel and 9.69 for the offline channel. The online category share of spending equals 33% (min. 5% for fresh fish and max. 56% for water) across all bi-weekly periods with a category purchase and increases to 51% (min. 8% for fresh fish and max. 84% for water) for the multichannel periods only.

Table 2 describes the details of the variable operationalization. The share in category spending is operationalized as the ratio of online purchases in category c by consumer i in period t, divided by the consumer's overall category purchases during that period in the online and offline channel combined. As we focus on multichannel shopping occasions, consumers may distribute purchases over both channels (share of online category spending between zero and one), but they can also decide to allocate the purchases to one of both channels (share of online category spending equal to zero or one).

Marketing mix information was obtained via the retailer. As a measure of channel differences in assortment size, we used the ratio of the assortment size (number of SKUs) of category c in the online store divided by the assortment size (number of SKUs) of category c in the offline store[4]. This ratio is comparable across categories, and is smaller (larger) than one when the online assortment is smaller (larger) than the offline assortment. To capture the category price variable, we compute the difference in average category prices between online and offline stores (average price for the set of category products that is available in both channels)[5]. To capture promotion effects, we use the share in overall category promotions of the online store, defined as the number of SKUs on promotion in category c at time t in the online store, divided by the number of SKUs

[4] We have detailed offline assortment and price information for one time period only and therefore had to use time-independent price and assortment variables. However, for the retailer under consideration, regular price and assortment within a category hardly changed during our observation period. In addition, we only have category-level data and are constrained in making marketing mix variables individual-specific (e.g., by using SKU-weights).

[5] We explicitly checked whether price differences between the online and offline channel were related to the online assortment reduction strategy (e.g., only the more expensive items in the online assortment) and found that this was not the case since the online assortment of all categories covers a range of items with different price levels.

on promotion in category c at time t in the online and offline store combined. This eliminates the effect of differences in assortment size and makes the variable comparable across product categories. The in-store stimuli variable is operationalized as a dummy variable that is equal to one when purchases of category c are often unplanned and strongly influenced by in-store stimuli. This classification was checked by survey data, where a representative convenience sample of respondents assessed on a 7-point Likert scale the extent to which a category is bought spontaneously when seeing it in the store ($t = -7.41$, $p < .01$). The categories that were classified as 'high in-store sensitive' match those where the majority of the respondents indicated they often buy these categories without having planned the purchase. Sensory and bulky/heavy characteristics are captured by dummy variables equal to one when the category is classified as sensory or bulky/heavy. Like for the in-store stimuli variable, we checked the sensory classification with survey data, where a representative convenience sample of respondents was asked to rate each category on the importance of physical inspection of sensory attributes prior to purchase ($t = -15.684$, $p < .001$). Bulky/heavy categories are categories for which more than 75% of online shoppers in our dataset buy package sizes that exceed a certain weight (e.g., multi-packs) or that are considered as bulky according to management.

To capture online buying experience, we use the weighted sum of previous online purchases in the category (cf. Foekens, Leeflang, and Wittink 1999), and use an initialization period of 26 bi-weeks to compute the starting value[6]. The experience variable increases with the number of previous purchases (frequency effect), but each previous purchase receives a weight that becomes smaller when the purchase occurred longer ago (recency effect) (see Table 2). The resulting experience measure is larger when the customer has purchased the category more often and more recently in the online store, and varies substantially across households and over time (range = [0, 2.33], mean = .46, standard deviation = .58). Finally, category-specific usage is operationalized as the average spending of consumer i in category c divided by the global average for category c, to make the variable comparable across categories.

Table 3 classifies the categories according to marketing mix differences and sensory, heavy/bulky and impulse characteristics. The classification clearly shows that there is sufficient variation across the different characteristics. On average, online assortments tend to be smaller while online prices tend to be higher. Several other online grocery chains follow a similar strategy (Cheng 2010). The degree of assortment reduction and the size of the online price premium, however, substantially differ across categories.

Empirical Results

Estimation results of the control function models can be found in Web Appendix A. We estimated the endogeneity-corrected version of the SCS model with a varying number of latent classes. Although additional segments provide a further improvement in goodness-of-fit, there is a clear elbow (Fig. 2) in the graph of the Bayesian Information Criteria (BIC) statistic at four segments with additional segments providing only a minor improvement in fit. The BIC statistic also indicates that the correction for endogeneity improves the results (BIC of four-segment model without vs. with endogeneity correction: 253,836 vs. 253,828). Overall the model explains the differences in allocation pattern across categories and consumers very well (pseudo $R^2 = .48$). To investigate to what extent product category characteristics, experience effects and household characteristics contribute to the model's explanatory power, we examined the variance decomposition. Results of partial model estimations indicate that each of these explanatory variables significantly improves goodness-of-fit, both based on R^2_{adj} and likelihood ratio statistics. The increase in R^2_{adj} (LR statistic) for instance, amounts to .18 (LR = 10,574; $p < .005$) for product characteristics (compared to an intercepts-only model), to .04 (LR = 2,888, $p < .005$) for experience (compared to a model with intercepts and product characteristics) and to .08 (LR = 5,594, $p < .005$) for household characteristics other than experience (compared to a model with intercepts, product characteristics and experience effects). We also conducted several robustness checks to verify the validity of our model and the consistency of our findings. They are summarized in Web Appendix B. Table 4, Panel A reports the estimation results for the homogeneous model as well as for the four-segment model. As we will focus on the results of the four-segment model, we first describe the differences across segments, and next provide a general discussion of the main and interaction (experience) effects.

Overall, in terms of segment differences, we find that segment 1 customers (29% of all customers) are most sensitive to purchase allocation factors (assortment, promotion, in-store stimuli, sensory and bulky/heavy), and make the strongest (effect-reducing) adjustments when they gain more online buying experience. Segment 2 customers (22%) are sensitive to price differences, in-store stimuli, sensory and bulky/heavy allocation factors, but are less sensitive to experience effects than segment 1, which can be explained by the low overall increase in online buying experience (see below). Segments 3 and 4 (14% and 35% of the customers respectively) are both much less sensitive to the examined allocation factors than customers of the other segments (significant effects are limited to in-store stimuli and bulky/heavy), but differ between each other in online buying experience reactions. While higher levels of experience have almost no effect on segment 3 consumers, segment 4 customers adjust their reaction to channel price differences, in-store stimuli, sensory and bulky/heavy categories in a positive way.

We thus observe differences between consumer segments in online buying experience effects: (i) attenuating effects that reduce category differences in purchase allocation (segments 1 and 4), (ii) reinforcing effects that increase category differences in purchase allocations (segment 2), and (iii) no or limited adjustment effects (segment 3). Table 4, Panel B provides an overview of segment characteristics that can explain these differences in reactions. Segments 1 and 4 both allocate a large

[6] We have one year of data (2006) on online and offline category purchases that allows us to derive multichannel occasions. But, we have one additional year (2005) of online data that allows us to initialize the experience variable.

Table 3
Classification of 25 categories.

Category	Assortment reduction (low/high)[a]	Price difference (low/high)[b]	Impulse (yes/no)	Sensory (yes/no)	Bulky/heavy (yes/no)
Fresh meat	High	High	No	Yes	No
Charcuterie	High	High	No	Yes	No
Fresh fish	High	High	No	Yes	No
Fruit	Low	Low	No	Yes	No
Vegetables	High	Low	No	Yes	No
Bakery pastry	High	Low	Yes	Yes	No
Fat	Low	Low	No	No	No
Cheese	High	High	No	Yes	No
Milk	Low	Low	No	No	No
Yoghurt	High	Low	No	No	No
Canned fruit & vegetables	High	High	No	No	No
Condiments & sauces	Low	High	No	No	No
Breakfast cereals	Low	High	No	No	No
Biscuits	High	High	Yes	No	No
Pastes & rice	High	High	No	No	No
Chocolate	Low	High	Yes	No	No
Hot beverages	Low	High	No	No	No
Water	Low	Low	No	No	Yes
Juice	Low	Low	No	No	No
Soft drinks	Low	Low	No	No	Yes
Pet food	Low	High	No	No	No
General body care	High	High	No	No	No
Washing products	Low	Low	No	No	No
Toilet paper	High	Low	No	No	Yes
Cleaning products	Low	High	No	No	No

[a] The low and high assortment reduction cover the range of .461–.614 and .060–.459, respectively.
[b] The low and high price difference cover the range of .000–.289 and .320–2.000, respectively.

share of purchases to the online channel, and their level of online buying experience increases substantially over the estimation period. In addition, segment 4 already had a relatively high level of experience at the start, which can explain the smaller number of significant main effects (the experience-reducing effects have to some extent already taken place). We label segment 1 as ‘new online grocery fans’ and segment 4 as ‘experienced online grocery fans’. Compared to segments 1 and 4, segments 2 and 3 both allocate a low(er) share to the online channel in general, which may explain the absence of experience-reducing effects. In contrast to segment 3, segment 2 customers’ online experience level remains low, which may additionally signal a low interest in the online channel and thus could explain experience-reinforcing

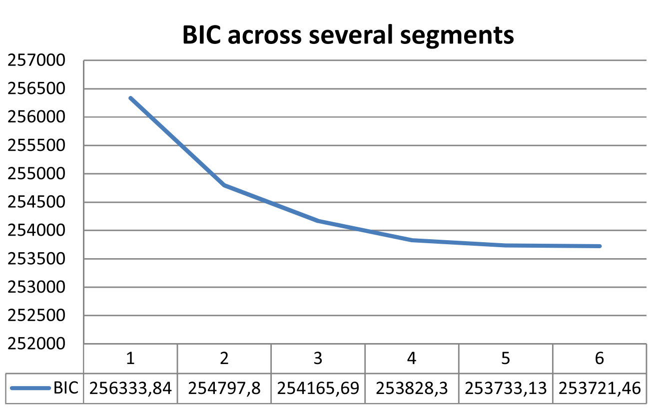

Fig. 2. Model goodness-of-fit.

effects. We label segment 2 as ‘online grocery skeptics’ and segment 3 as ‘occasional online grocery shoppers’.

In terms of model estimation results, we find that the latent factor coefficient is significant for all segments, indicating that there is still some ‘unobserved’ (unexplained) variation across households in the overall tendency to spend a larger SCS online. However, comparison of the magnitude of this coefficient (which captures the standard deviation of the intercept over households; see Model section) with that of the segment-specific intercept (i.e., the constant which captures the average effect) indicates that the model explains a large part of the (observed) household variation in online buying tendency. We further obtain significant and expected positive effects for the control variables, share in total spending (STS_{it}) and experience (Exp_{it}^{c}), across all four segments. The category usage level ($Usage_{t}^{c}$), on the other hand, is negative and significant for two out of four segments. A possible explanation for this negative effect could be that heavy users, who buy the category more frequently, buy a lower share online because they have more opportunities to buy the category in the offline store.

In terms of the impact of acquisition utility factors, we find that *assortment differences* have a weakly significant and positive main effect in one segment (segment 1, $\delta_{10,s1}$ = 6.710, p < .10), and a significant and positive experience interaction effect for two other segments (segment 2: $\delta_{11,s2}$ = 5.439, p < .10; segment 3: $\delta_{11,s3}$ = 1.729, p < .01). These results indicate that the online channel captures a larger share of category purchases in categories where the online assortment is more similar in size to the offline assortment for 3 out of the 4 segments (65% of the consumers), but for some customers (segments 2 and 3, 36%)

Table 4
Model estimation results.

Variables	Homog. model	Four-segment model			
		Seg. 1	Seg. 2	Seg. 3	Seg. 4
Panel A: Parameter coefficients					
Constant (γ_{01})	−5.654 ***	−5.518 ***	−3.877 **	−4.796 **	−6.914 ***
Latent factor (γ_{02})	−1.048 ***	.772 ***	.670 ***	−1.144 ***	.573 ***
Share in total spending (γ_1)	9.680 ***	7.901 ***	6.862 ***	10.316 ***	10.955 ***
Experience (γ_2)	2.232 ***	1.846 ***	10.535 ***	3.441 ***	.711 **
Usage level (γ_3)	−.239 ***	−.046	−.054	−.389 ***	−.298 ***
Acquisition utility (marketing mix)					
Assortment (δ_{10})	3.297 *	6.710 *	−.887	−3.136	5.782
Assortment * experience (δ_{11})	1.006 ***	.738	5.439 *	1.729 **	−.159
Price (δ_{20})	−.270 **	−.074	−1.564 ***	.084	−.087
Price * experience (δ_{21})	.463 ***	1.041 ***	−.953	−.247	1.050 ***
Promotion (δ_{30})	.270 *	.737 **	−.031	.306	.096
Promotion * experience (δ_{31})	−.365 **	−.635	.621	−.276	−.388
In-store stimuli (δ_{40})	−1.445 ***	−.606 **	−1.468 ***	−1.124 ***	−1.881 **
In-store stimuli * experience (δ_{41})	.155	−.650 *	−3.092 ***	−.078	.367 *
Transaction utility (category characteristics)					
Sensory (δ_{50})	−2.717 ***	−4.527 ***	−3.379 ***	−1.695 *	−.364
Sensory * experience (δ_{51})	.964 ***	2.054 ***	−1.253	−.519 **	.470 **
Bulky/heavy (δ_{60})	2.867 ***	2.118 ***	5.212 ***	4.156 ***	.681 **
Bulky/heavy * experience (δ_{61})	−.855 ***	−.848 ***	−9.724 ***	−.762 ***	.552 ***
Residual assortment (θ_1)	2.023	−.195	4.682	7.085 *	−.078
Residual price (θ_2)	−.326 **	−.194	1.569 ***	−.763 **	−1.316 ***
Segment membership (φ_s)		29%	22%	14%	35%
BIC	256,333.8	253,828.3			

Panel B: Segment characteristics

Variables	Four-segment model			
	Seg. 1	Seg. 2	Seg. 3	Seg. 4
Average online buying exp first 4 bi-weeks	.339	.128	.394	.451
Average online buying exp last 6 bi-weeks	.490	.191	.668	.837
Change in average online buying exp	.151	.063	.274	.386
Total online spending amount (€)	932.69	401.47	1,041.25	1,677.81
Total offline spending amount (€)	1,505.21	2,825.98	3,554.61	1,718.19
Average online purchase share (%)	72.64	46.01	42.16	78.83

* Significant at $p < .10$.
** Significant at $p < .05$.
*** Significant at $p < .01$.

only after they gain more online buying experience. To assess the overall effect of assortment differences, these results have to be evaluated in combination with the endogeneity correction effects. The coefficient of the assortment control function residuals is only significant at 10% for segment 3, indicating that there is no serious endogeneity problem for the assortment variable (Wooldridge 2013). Overall, these results indicate that consumers are sensitive to assortment differences (except for segment 4), and that actual differences in online and offline assortments are still mainly guided by other managerial considerations than expected customer reactions (no substantial endogeneity effect).

For *price differences*, we find a negative and significant effect for the online grocery skeptic segment 2 ($\delta_{20,s2} = -1.564$, $p < .01$), and no significant effect for the other three segments. Yet, in contrast to assortment, we obtain significant effects for the residual of the price correction function in all segments except segment 1. This indicates not only that the price variable is endogenous, but also that the online-offline price differences are in line with category differences in price sensitivity. This is confirmed by the results of a model without endogeneity correction, where price effects are negative and significant for three out of four segments. The moderating effect of experience is – contrary to our expectations – positive and significant for the online grocery fan segments 1 and 4 ($\delta_{21,s1} = 1.041$, $p < .01$; $\delta_{21,s4} = 1.050$, $p < .01$) and not significant for the other two segments. So, while the price sensitivity of the online grocery skeptic segment 2 consumers does not change their allocation pattern when they gain additional experience (and online price knowledge), consumers of online grocery fan segments 1 and 4 tend to adjust their spending levels to channel price differences in an upward way (i.e., they increase the online share for categories with larger online price premiums).

Promotions do not lead to higher spending levels in the category except for the new online grocery fan segment 1

($\delta_{30,s1}$ = .737, p < .01), who may pay more attention to online promotional stimuli than online grocery skeptics or experienced online grocery fans. This is also in line with previous observations that – in general – promotions predominantly affect brand choices, and have a much smaller or no effect on category demand and store choices (Bell, Chian, and Padmanabhan 1999). As expected, the effect does not change with higher levels of online buying experience as none of the interactions with experience are significant.

Categories for which *in-store stimuli* are important, are purchased less easily in online stores as indicated by the negative and significant effect on SCS decisions in each of the segments. For the occasional online grocery shopper segment 3, this effect does not change with higher levels of experience (they already adapted their allocation patterns prior to the estimation period) while experience reinforces the negative effect for the online grocery skeptic segment 2 ($\delta_{41,s2}$ = −3.092, p < .01). For online grocery fan segments 1 and 4, the effects are only marginally significant and very small (segment 1: $\delta_{41,s1}$ = −.650, p < .10; segment 4: $\delta_{41,s4}$ = −.367, p < .10). Overall, experience thus appears to have a negligible effect on the sensitivity to in-store stimuli.

In terms of the impact of transaction utility factors, the results provide support for the assumption that consumers will allocate a relatively low share of *sensory* category purchases to the online store: three out of four segments have a significant negative effect for sensory categories ($\delta_{50,s1}$ = −4.527, p < .01; $\delta_{50,s2}$ = −3.379, p < .01; $\delta_{50,s3}$ = −1.695, p < .10), and not for the experienced online grocery fan segment 4. Experience has, as expected, a positive effect on the share of sensory purchases allocated to the online store for online grocery fan segments 1 and 4 ($\delta_{51,s1}$ = 2.054, p < .01; $\delta_{51,s4}$ = .47, p < .05). Experience has no effect on the online share in sensory purchases for the online grocery skeptic segment 2, and a negative reinforcing effect for the occasional online grocery shopper segment 3 ($\delta_{51,s3}$ = −0.519, p < .05), possibly as a result of negative experiences with online sensory purchases.

In line with its shopping convenience benefit, the online store attracts a relatively larger share of *bulky and heavy* category purchases for all segments ($\delta_{60,s1}$ = 2.118, p < .01; $\delta_{60,s2}$ = 5.212, p < .01; $\delta_{60,s3}$ = 4.156, p < .01; $\delta_{60,s4}$ = .681, p < .01). In contrast to our expectations, however, the effect weakens in three out of four segments ($\delta_{61,s1}$ = −.848, p < .01; $\delta_{61,s2}$ = −9.724, p < .01; $\delta_{61,s3}$ = −.762, p < .01) and strengthens in the other segment ($\delta_{61,s4}$ = .552, p < .01). Consumers of the experienced online grocery fan segment 4 that were somewhat more conservative at the start (smaller magnitude of main effect for bulky/heavy) appreciate the shopping convenience benefit more and more over time. Consumers of the other segments that were more convinced about the shopping convenience benefit at the start (larger magnitude of main effect for bulky/heavy) gradually lower the online share of bulky and heavy categories. While the convenience effect of heavy/bulky categories remains positive and significant for all segments, the difference in effect across segments becomes smaller as consumers gain more experience with buying these categories online, but still varies substantially across the four segments.

Discussion and Conclusions

The objectives of this research were twofold. First, we wanted to provide a comprehensive analysis of the factors that affect purchase allocation decisions of multichannel grocery shoppers, thereby controlling for potential endogeneity biases in marketing mix effects. Second, we wanted to investigate the effect of online buying experience and test whether and for which factors experience can have an online purchase enhancing or rather reducing effect.

Factors of Multichannel Purchase Allocation Decisions

The results confirm that acquisition and transaction utility based factors can influence the share of category purchases that is allocated to the online store. The large majority of multichannel shoppers (65%) is less inclined to buy categories online for which the online store offers a less attractive (smaller) assortment. Channel differences in price and promotion intensity have respectively a negative and positive effect on a smaller subset of multichannel shoppers (22% price, 29% promotion). All consumers are less sensitive to in-store incentives and buy substantially less impulse categories in the online channel compared to the overall allocation of grocery purchases to the online store. In addition to these traditional allocation factors, we find significant effects of intrinsic category characteristics that affect online transaction utility. As expected, the majority of consumers (65%) is less inclined to buy sensory products online because of the higher perceived online purchase risk and all consumers purchase substantially more heavy/bulky products to take advantage of online convenience benefits.

The Moderating Effect of Category-specific Online Buying Experience

Previous research on general online purchase barriers has stressed the positive impact of online experience in reducing the resistance to buy online caused by factors such as the financial risk of online transactions (Frambach, Roest, and Krishnan 2007; Iyengar, Ansari, and Gupta 2007; Kim, Ferrin, and Raghav Rao 2008). We observe a similar attenuating effect of category-specific online buying experience for risk related category characteristics. The negative effect of a lack of sensory information gradually disappears for about 30% of the multichannel shoppers (‘new online grocery fans’), when they gain more experience with buying sensory categories online and get accustomed to selecting these products without prior physical inspection.

Yet, in contrast to what has been found for online buying experience in general, we show that more experience may also lead to adverse effects for marketing mix based differences in acquisition utility between both channels. Given the customers’ low involvement with grocery purchases and high time pressure during a multi-category shopping task, they are often not prepared to engage in complex evaluations such as detailed comparisons of online–offline assortments. Instead, consumers gain a better insight into actual assortment differences through an experience-based learning process. As a result, more than one third of the respondents ('online grocery skeptics' and 'occasional online grocery shoppers') gradually reduce their online purchases of categories with a smaller online assortment in favor of the offline channel as they become more clearly aware of the restrictions in choice variety. Channel differences in price also have a stronger impact on allocation patterns for some consumers when they gain experience, but in contrast to our expectations, the interaction effect with experience is positive (larger share of category spending for categories with a higher online price) for 'new' and 'experienced online grocery fans'. The results of the endogeneity correction indicate that for segment 4 ('experienced online grocery fans'), management has anticipated channel differences in the online willingness-to-pay correctly (significant price residual coefficient). The results for segment 1 ('new online grocery fans') suggest that these consumers are more quality-oriented (e.g., strong positive main effect of assortment) and not very sensitive to price (no significant main or endogeneity correction effect). This can explain the lack of a negative effect of experience on online purchase shares of categories with a larger price difference.

As expected, we did not find any moderating effect of experience on the reaction to channel differences in promotion intensity which are easy to evaluate from the start and do not require any learning and adjustment process. While we expected a similar (non-significant) effect for impulse purchases triggered by in-store stimuli and online shopping convenience advantages of heavy/bulky categories, experience has a negative effect (marginally significant) for 51% of the consumers on impulse purchases and 65% for heavy/bulky categories. For impulse purchases, this can probably be explained by the fact that consumers unfamiliar with the online grocery shopping environment have to search more to find the needed products which increases their exposure to in-store stimuli. For heavy/bulky categories, experience attenuates the allocation effect for most consumers, but reinforces it for those who initially made less use of the online convenience advantage. As a result, the difference across consumer segments becomes smaller, but the effect remains significant and positive for all consumers.

In terms of differences across consumers, results show that there are clear differences in how segments change allocation patterns when gaining more experience. Segments that are enthusiastic about online shopping and its benefits (new and experienced online grocery fans) are more likely to show attenuating effects that reduce category differences in purchase allocation. Segments that use the online store less frequently (online grocery skeptics and occasional online grocery shoppers) are less likely to adjust allocation over time and can even face reinforcing effects that increase category differences in allocations when their experience level remains low.

Managerial Implications

Grocery retailers increasingly recognize the importance of online stores to retain the existing customer base and nowadays most of the large chains have opened an online store next to their traditional offline supermarkets. By offering an additional distribution channel that complements offline stores and offers unique benefits such as greater accessibility and more convenience and time saving (Chu et al. 2010; Gupta and Kim 2010), they hope to increase their value proposition and gain a competitive advantage over single-channel retailers (Chintagunta, Chu, and Cebollada 2012; Kabadayi, Eyuboglu, and Thomas 2007; Zhang et al. 2010). Yet, to assess and improve the profitability of the multichannel strategy, retailers not only need to understand whether and why customers will adopt the new online channel, but also which share of the shopping baskets the online store can attract to cover its relatively high operational costs. Our findings contribute to a better understanding of the factors underlying category differences in online performance and may in this way help to define appropriate promotional and corrective actions that can be taken to stimulate online purchases of less successful categories.

A first important insight that can be derived from our findings is that different actions may be needed to stimulate online purchases. For marketing mix related factors, retailers should realize that multichannel shoppers may react negatively to excessive online assortment reductions, especially when they gain more online buying experience. Large assortment reductions can then have an important negative effect, implying that online retailers may have to invest in upgrading online assortments to better match the offline product offer. Online shoppers are, on the other hand, more willing to tolerate online price premiums when they gain more online buying experience (and are thus better able to appreciate the online shopping advantages). Nevertheless, for a substantial segment of consumers (about 22%), high online price premiums do significantly reduce the attractiveness of the online offer. While experience does not reinforce this effect as we expected, it does not attenuate it either.

The lower sensitivity to in-store incentives in the online environment calls for promotional tactics that are better tailored to the specific online environment, e.g., personalized promotions, cross-selling opportunities, tailored in-store displays (Bellman et al. 2013; Breugelmans and Campo 2011; Punj 2011) and that may stimulate purchases of impulse categories in the online channel. In addition, marketing communication can play an important role in reducing the perceived risk and uncertainty of online purchases and help customers to adjust decision rules to the new shopping environment (Weathers, Sharma, and Wood 2007). Retailers can, for instance, use customer reviews or other electronic word-of-mouth to highlight the positive experiences of other shoppers with buying sensory categories online (Jiménez and Mendoza 2013; Purnawirawan, De Pelsmacker, and Dens 2012). They can also help consumers by providing substitute information cues (such as expiration dates and quality labels) and by clarifying their usefulness in judging the product quality of sensory categories. Lastly, retailers can stress the online convenience benefits in their marketing communications to further spur the higher tendency of buying heavy/bulky products in the online channel.

A second important finding is that experience can have a positive as well as a negative effect on the tendency to allocate purchases of specific categories to the online channel. Results show, for instance, that an increase in experience can strengthen the negative effect of assortment differences. This points to potential limitations for retailers when using assortment signaling strategies. While less visible assortment reductions (eliminating less popular items) may initially mask the less attractive online offer, increased experience with buying the categories online may improve the customer's assortment knowledge and may result in a stronger negative effect on online category allocations. On the other hand, experience may reduce the perceived risk of buying sensory categories online and thereby enhance online purchases of these categories. Hence, retailers should strive to enhance positive experiences by stimulating trial and repeat purchases for sensory categories as it offers opportunities to reduce online purchase risk.

Lastly, our findings indicate that there are clear differences in how segments adjust their allocation pattern as they gain more online buying experience. For the segment of frequent online buyers, who are also more willing and open to buy several types of categories in the online store, special loyalty programs could be developed to maintain and reinforce their use of the online channel. For the group of customers that spend a smaller share of grocery products in the online channel and who limit their online purchases to a more restrictive, 'safer' set of categories, extension of online purchases could be aimed for, for instance, by stimulating trial purchases of categories with a higher perceived online buying risk (e.g., sensory categories). In this way, these consumers experience (free or with promotion) the positive outcomes of more risky purchases in the online channel, which may help in developing trust in the multichannel retailer's ability to provide a high-quality online service (Urban, Amyx, and Lorenzon 2009).

Directions for Further Research

Although our study provides interesting new insights into the effect of multichannel category allocation factors and the moderating effect of category-specific online buying experience, it also has important limitations and points to several interesting areas for additional research. For one, more refined definitions of the category allocation factors could help to obtain a better insight into their effect on online buying behavior. For instance, a focus on assortment composition in addition to size may lead to additional and more refined insights. Likewise, using a household-specific rating of impulsiveness (rather than assuming it is a characteristic that is constant across consumers) or allowing price and assortment to vary over time are important refinements that are worthwhile to investigate in more depth. Second, it would be valuable to obtain an in-depth insight into experience effects and how they work, exploring their impact on mediating variables such as learning processes and online retailer trust. Third, an interesting extension of our study would be to explore cross-category effects, such as the potential weakening effect of buying one sensory category as experience reduction for another sensory category, or the accumulated negative effect of encountering a large number of categories with price and assortment disadvantages. Fourth, because of data availability, the focus of this paper is on consumers' shopping behavior in a single chain multichannel grocery context. While this approach has the advantage of eliminating confounding effects of differences in assortment composition and retail strategy across different grocery chains, for instance and although previous research has demonstrated that the large majority of multichannel shoppers visit the same chain in the online and offline channel (Melis et al. 2013), a more detailed and complete analysis could be carried out if data of competitive chains would also be available. This would allow for a simultaneous analysis of category allocation decisions over different channels and chains providing a more complete picture of the complex competitive relationships in a multichain multichannel retail context. Finally, examining the impact of category allocation decisions in a non-grocery shopping context (where characteristics like perishability overlap less with sensory characteristics) could offer a useful and interesting extension.

Acknowledgments

The authors thank the online grocery retailer who provided the data used in this study, and Huiying He and Kim Goeleven for their help. They further thank Koert van Ittersum, Siegfried Dewitte, Vera Blazevic and Lien Lamey for their helpful suggestions on previous versions of this article.

Appendix A. Supplementary Data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.intmar.2015.04.001.

References

Alba, Joseph and J. Wesley Hutchinson (1987), "Dimensions of Consumer Expertise," *Journal of Consumer Research*, 13, 4, 411–54.

———, John Lynch, Barton Weitz, Chris Janiszewski, Richard Lutz, Alan Sawyer, and Stacy Wood (1997), "Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces," *Journal of Marketing*, 61, 3, 38–53.

Andrews, Rick L., Andrew Ainslie, and Imran S. Currim (2002), "An Empirical Comparison of Logit Choice Models With Discrete Versus Continuous Representations of Heterogeneity," *Journal of Marketing Research*, 39, 4, 479–87.

Ansari, Asim, Carl F. Mela, and Scott A. Neslin (2008), "Customer Channel Migration," *Journal of Marketing Research*, 45, 1, 60–76.

Avery, Jill, Thomas J. Steenburgh, John Deighton, and Mary Caravella (2012), "Adding Bricks to Clicks: Predicting the Patterns of Cross-channel Elasticities Over Time," *Journal of Marketing*, 76, 3, 96–111.

Babin, Barry J. and William R. Darden (1995), "Consumer Self-regulation in a Retail Environment," *Journal of Retailing*, 71, 1, 47–70.

Baltas, George, Paraskevas C. Argouslidis, and Dionysis Skarmeas (2010), "The Role of Customer Factors in Multiple Store Patronage: A Cost–Benefit Approach," *Journal of Retailing*, 86, 1, 37–50.

Bass, Frank M., Norris Bruce, Sumit Majumdar, and B.P.S. Murthi (2009), "Wearout Effects of Different Advertising Themes: A Dynamic Bayesian Model of the Advertising-sales Relationship," *Marketing Science*, 26, 2, 179–95.

Bell, David R., Jeongwen Chian, and V. Padmanabhan (1999), "The Decomposition of Promotional Response: An Empirical Generalization," *Marketing Science*, 18, 4, 504–26.

Bellman, Steven, Jamie Murphy, Shiree Treleaven-Hassard, James O'Farrell, Lili Qiu, and Duane Varan (2013), "Using Internet Behavior to Deliver Relevant Television Commercials," *Journal of Interactive Marketing*, 27, 2, 130–40.

Borle, Sharad, Peter Boatwright, Joseph B. Kadane, Joseph C. Nunes, and Galit Shmueli (2005), "The Effect of Product Assortment Changes on Customer Retention," *Marketing Science*, 24, 4, 616–22.

Breugelmans, Els and Katia Campo (2011), "Effectiveness of In-store Displays in a Virtual Store Environment," *Journal of Retailing*, 87, 1, 75–89.

Cheng, Jacqui (2010), "The New Age of Online Grocery Shopping," [Available at http://arstechnica.com/web/news/2010/03/the-new-age-of-online-grocery-shopping.ars].

Chintagunta, Pradeep K., Junhong Chu, and Javier Cebollada (2012), "Quantifying Transaction Costs in Online/Offline Grocery Channel Choice," *Marketing Science*, 31, 1, 96–114.

Chu, Junhong, Pradeep Chintagunta, and Javier Cebollada (2008), "A Comparison of Within-household Price Sensitivity Across Online and Offline Channels," *Marketing Science*, 27, 2, 283–99.

———, Marta Arce-Urriza, José-Javier Cebollada-Calvo, and Pradeep K. Chintagunta (2010), "An Empirical Analysis of Shopping Behavior Across Online and Offline Channels for Grocery Products: The Moderating Effects of Household and Product Characteristics," *Journal of Interactive Marketing*, 24, 4, 251–68.

Cleeren, Kathleen, Harald van Heerde, and Marnik Dekimpe (2013), "Rising From the Ashes: How Brand and Categories Can Overcome Product-harm Crises," *Journal of Marketing*, 77, 2, 58–77.

Cooper, Lee and Masao Nakanishi (1996), *Market Share Analysis, International Series in Quantitative Marketing*. Kluwer Academic Publishers.

Degeratu, Alexandru M., Arvind Rangaswamy, and Jianan Wu (2000), "Consumer Choice Behavior in Online and Traditional Supermarkets: The Effects of Brand Name, Price, and Other Search Attributes," *International Journal of Research in Marketing*, 17, 1, 55–78.

Dhar, Ravi (1997), "Consumer Preference for a No-choice Option," *Journal of Consumer Research*, 24, 2, 215–31.

Dholakia, Utpal M., Barbara E. Kahn, Randy Reeves, Aric Rindfleisch, David Stewart, and Earl Taylor (2010), "Consumer Behavior in a Multichannel, Multimedia Retailing Environment," *Journal of Interactive Marketing*, 24, 2, 86–95.

Foekens, Eijte W., Peter S.H. Leeflang, and Dick R. Wittink (1999), "Varying Parameter Models to Accommodate Dynamic Promotion Effects," *Journal of Econometrics*, 89, 1/2, 249–68.

Fox, Edward J. and Stephen Hoch (2005), "Cherry Picking," *Journal of Marketing*, 69, 1, 46–62.

Frambach, Ruud T., Henk C.A. Roest, and Trichy V. Krishnan (2007), "The Impact of Consumer Internet Experience on Channel Preference and Usage Intentions across the Different Stages of the Buying Process," *Journal of Interactive Marketing*, 21, 2, 26–41.

Gijsbrechts, Els, Katia Campo, and Patricia Nisol (2008), "Beyond Promotion-based Store Switching: Antecedents and Patterns of Systematic Multiple-store Shopping," *International Journal of Research in Marketing*, 25, 1, 5–21.

Gupta, Sumeet and Hee-Woong Kim (2010), "Value-driven Internet Shopping: The Mental Accounting Theory Perspective," *Psychology & Marketing*, 27, 1, 13–35.

Hamilton, Rebecca W. and Debora Viana Thompson (2007), "Is There a Substitute for Direct Experience? Comparing Consumers' Preferences After Direct and Indirect Product Experiences," *Journal of Consumer Research*, 34, 4, 546–55.

Hoch, Stephen J. (2002), "Product Experience Is Seductive," *Journal of Consumer Research*, 29, 3, 448–54.

Hoyer, Wayne D. and Deborah J. MacInnis (2010), *Consumer Behavior*. Mason: South-Western Cengage Learning.

Huffman, Cynthia and Barbara E. Kahn (1998), "Variety for Sale: Mass Customization or Mass Confusion?" *Journal of Retailing*, 74, 4, 491–513.

Iyengar, Raghuram, Asim Ansari, and Sunil Gupta (2007), "A Model of Consumer Learning for Service Quality and Usage," *Journal of Marketing Research*, 44, 4, 529–44.

Jiménez, Fernando and Norma A. Mendoza (2013), "Too Popular to Ignore: The Influence of Online Reviews on Purchase Intentions of Search and Experience Products," *Journal of Interactive Marketing*, 27, 3, 226–35.

Kabadayi, Sertan, Nermin Eyuboglu, and Gloria P. Thomas (2007), "The Performance Implications of Designing Multiple Channels to Fit with Strategy and Environment," *Journal of Marketing*, 71, 4, 195–211.

Kamakura, Wagner A. and Gary J. Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research*, 26, 4, 379–90.

Kim, Dan J., Donald L. Ferrin, and H. Raghav Rao (2008), "A Trust-based Consumer Decision-making Model in Electronic Commerce: The Role of Trust, Perceived Risk, and their Antecedents," *Decision Support Systems*, 44, 2, 544–64.

Konuş, Umut, Peter C. Verhoef, and Scott A. Neslin (2008), "Multichannel Shopper Segments and their Covariates," *Journal of Retailing*, 84, 4, 398–413.

Kopalle, Praveen K., Carl F. Mela, and Lawrence Marsh (1999), "The Dynamic Effect of Discounting on Sales: Empirical Analysis and Normative Pricing Implications," *Marketing Science*, 18, 3, 317–32.

Laroche, Michel, Zhiyong Yang, Gordon H.G. McDougall, and Jasmin Bergeron (2005), "Internet versus Bricks-and-Mortar Retailers: An Investigation into Intangibility and Its Consequences," *Journal of Retailing*, 81, 4, 251–67.

Leenheer, Jorna, Harald van Heerde, Tammo Bijmolt, and Ale Smidts (2007), "Do Loyalty Programs Really Enhance Behavioral Loyalty? An Empirical Analysis Accounting for Self-selecting Members," *International Journal of Research in Marketing*, 24, 1, 31–47.

Lesaffre, Emmanuel, Dimitris Rizopulos, and Roula Tsonaka (2007), "The Logistic Transform for Bounded Outcome Scores," *Biostatistics*, 8, 1, 72–85.

Luan, Jackie and K. Sudhir (2010), "Forecasting Marketing Mix Responsiveness for New Products," *Journal of Marketing Research*, 47, 3, 444–57.

McPartlin, Sue and Lisa Dugal (2012), "Understanding How US Online Shoppers Are Reshaping the Retail Experience," [Available at http://www.pwc.com/en_us/us/retail-consumer/publications/assets/pwc-us-multichannel-shopping-survey.pdf].

Melis, Kristina, Katia Campo, Els Breugelmans, and Lien Lamey (2013), "Buying Groceries Online: Which Factors Drive Online Store Choice?" .

Neslin, Scott A., Dhruv Grewal, Robert Leghorn, Venkatesh Shankar, Marije L. Teerling, Jacquelyn S. Thomas, and Peter C. Verhoef (2006), "Challenges and Opportunities in Multichannel Customer Management," *Journal of Service Research*, 9, 2, 95–112.

——— and Venkatesh Shankar (2009), "Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions," *Journal of Interactive Marketing*, 23, 1, 70–81.

Nielsen (2014), "Convenience, Continuous Innovation Key to Retail Success," [Available at http://www.progressivegrocer.com/nielsen-convenience-continuous-innovation-key-retail-success#sthash.huriH3eL.dpuf].

Oppewal, Harmen and Kitty Koelemeijer (2005), "More Choice Is Better: Effects of Assortment Size and Composition on Assortment Evaluation," *International Journal of Research in Marketing*, 22, 1, 45–60.

Pauwels, Koen, Peter S.H. Leeflang, Marije L. Teerling, and K.R. Eelko Huizingh (2011), "Does Online Information Drive Offline Revenues? Only for Specific Products and Consumer Segments!," *Journal of Retailing*, 87, 1, 1–17.

Peck, Joann and Terry L. Childers (2003), "To Have and to Hold: The Influence of Haptic Information on Product Judgments," *Journal of Marketing*, 67, 2, 35–48.

Petrin, Amil and Kenneth Train (2010), "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research*, 47, 1, 3–13.

Pozzi, Andrea (2012), "Shopping Cost and Brand Exploration in Online Grocery," *American Economic Journal: Microeconomics*, 43, 3, 96–120.

Punj, Girish (2011), "Effect of Consumer Beliefs on Online Purchase Behavior: The Influence of Demographic Characteristics and Consumption Values," *Journal of Interactive Marketing*, 25, 3, 134–44.

Purnawirawan, Nathalia, Patrick De Pelsmacker, and Nathalie Dens (2012), "Balance and Sequence in Online Reviews: How Perceived Usefulness Affects Attitudes and Intentions," *Journal of Interactive Marketing*, 26, 4, 244–55.

Shankar, Venkatesh and Manjit S. Yadav (2010), "Emerging Perspectives on Marketing in a Multichannel and Multimedia Retailing Environment," *Journal of Interactive Marketing*, 24, 2, 55–7.

Sloot, Laurens M., Dennis Fok, and Peter C. Verhoef (2006), "The Short- and Long-term Impact of an Assortment Reduction on Category Sales," *Journal of Marketing Research*, 43, 4, 536–48.

Urban, Glen L., Cinda Amyx, and Antonio Lorenzon (2009), "Online Trust: State of the Art, New Frontiers, and Research Potential," *Journal of Interactive Marketing*, 23, 2, 179–90.

Venkatesan, Rajkumar, V. Kumar, and Nalini Ravishanker (2007), "Multichannel Shopping: Causes and Consequences," *Journal of Marketing*, 71, 2, 114–32.

Vermunt, Jeroen K. and Jay Magidson (2013), *Technical Guide for Latent GOLD 5.0: Basic, Advanced and Syntax*. Belmont Massachusetts: Statistical Innovations Inc.

Vroegrijk, Mark, Els Gijsbrechts, and Katia Campo (2013), "Close Encounter With the Hard Discounter: A Multiple-store Shopping Perspective on the Impact of Local Hard-discounter Entry," *Journal of Marketing Research*, 50, 5, 606–26.

Warschun, Mirko (2012), "A Fresh Look at Online Grocery," [Available at http://www.atkearney.com/paper/-/asset_publisher/dVxv4Hz2h8bS/content/a-fresh-look-at-online-grocery/10192].

Weathers, Danny, Subhash Sharma, and Stacy L. Wood (2007), "Effects of Online Communication Practices on Consumer Perceptions of Performance Uncertainty for Search and Experience Goods," *Journal of Retailing*, 83, 4, 393–401.

Wolk, Agnieszka and Christine Ebling (2010), "Multi-channel Price Differentiation: An Empirical Investigation of Existence and Causes," *International Journal of Research in Marketing*, 27, 2, 142–50.

Wooldridge, Jeffrey M. (2013), *Econometric Analysis of Cross Section and Panel Data*. second edition. Cambridge, MA: MIT Press.

Zhang, Jie, Paul W. Farris, John W. Irvin, Tarun Kushwaha, and Thomas J. Steenburgh (2010), "Crafting Integrated Multichannel Retailing Strategies," *Journal of Interactive Marketing*, 24, 2, 168–80.