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Going Online for Groceries: Drivers of Category-Level Share of Wallet Expansion

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Abstract

Some grocery product categories may be more successful than others in terms of stimulating consumers to increase their share of wallet (SoW) when they start buying through the online channel of a grocery chain. This study explores the circumstances in which online and multichannel marketing mix instruments determine the extent of category-level SoW expansion. To do so, the authors use U.K. household scanner panel data, covering online and offline purchases by 3,311 households in 59 categories of four multichannel retail chains. The results indicate that the effectiveness of online and multichannel marketing mix instruments for stimulating expansion is moderated by category characteristics, such that a selective approach to making decisions about the online price, online assortment breadth, online/offline assortment integration, and online national brand proliferation, tuned to account for category differences, can increase category-level SoW for the online-visited chain.

JEL classification: M31 Marketing

Keywords: Multichannel retailing; Online grocery shopping; Category expansion; Marketing mix

The online channel offers an increasingly viable option for buying groceries (Planet Retail 2014), a trend that started before but has been intensified by the limited consumer movement required by the global coronavirus pandemic. Most online grocery shoppers visit both online and offline stores (i.e., are multichannel shoppers), to combine online convenience advantages with offline self-service and in-store experience benefits (Alba et al. 1997; Chu et al. 2010; Chu, Chintagunta, and Cebollada 2008; Konuš, Verhoef, and Neslin 2008; Venkatesan, Kumar, and Ravishanker 2007). When consumers start to buy groceries online, they often select an online store that represents the same chain in which they prefer to shop offline (Melis et al. 2015); they also appear to shift their purchases from competing grocery chains to the online-visited chain, implying that online shopping leads to increases in the overall share of wallet (SoW) for the chain they started to visit online (Melis et al. 2016; Pozzi 2013a). The likelihood and magnitude of this expansion has been demonstrated to depend on the chain’s online and multichannel (online/offline) marketing mix strategy, such that better price and assortment integration across the online and offline channel tend to enhance chain-level SoW expansion (across all categories combined; Melis et al. 2016).

In this research, we extend these prior findings by taking a category-specific perspective and investigating the extent to which a consumer’s decision to shop online influences SoW expansion in particular categories. We predict that category-level SoW expansion depends on the online and multichannel (online/offline) marketing mix instruments, category characteristics, but specifically investigate the interaction effects of these drivers. Prior research has established that consumers’ tendency to buy groceries online varies substantially across categories, due to category-level differences in the perceived convenience and risk of buying them online (Chintagunta, Chu, and Cebollada 2012). Such variation could impact consumers’ tendency to shift their purchases from a competitive chain to the online-visited chain and thus the degree of category-level SoW expansion.
To expand on this prior research that investigates the impact of some category characteristics in isolation, we speculate that category-specific marketing mix decisions might reinforce or mitigate differences in category-level SoW expansion. This is because the importance of marketing mix instruments, such as price and assortment, has been demonstrated to vary substantially across categories, allowing retailers to leverage these instruments strategically to enhance the effects on category-level SoW (Briesch, Dillon, and Fox 2013). Optimal marketing mix strategies thus should be devised for specific categories, to stimulate expansion in each particular category. In practice, several chains already provide more similar assortments across channels or charge lower price premiums online for some categories than for others (Campos and Breugelmans 2015), in preliminary support for this view. Our main goal is to study how the effectiveness of online and multichannel marketing mix instruments for stimulating a category’s SoW expansion for a chain that a consumer decides to visit online is moderated by category characteristics.

Our research makes several contributions. First, we address a research gap pertaining to consumer decisions to shop online for groceries, in that prior studies consider purchase shifts at an aggregate, store level (e.g., Melis et al. 2016; Pozzi 2013a). Such a view cannot specify category-level differences or how category-specific marketing mix decisions might enable the retailer to correct for or take advantage of category expansion differences.

Second, with a multichain, multichannel perspective, we also extend research that has included category-level outcomes but that investigates single multichannel chains (e.g., Campo and Breugelmans 2015; Chu et al. 2010; Chu, Chintagunta, and Cebollada 2008; Degeratu, Rangaswamy, and Wu 2000; Milkman, Rogers, and Bazerma 2010; Pozzi 2013b). Such studies lack access to the data needed to investigate the relative impact of online marketing mix instruments across online competitors’ chains. Even when they provide insights into purchase allocation shifts due to channel choice decisions (Campos and Breugelmans 2015; Pozzi 2013a), such insights are restricted by the single-chain focus. With their focus on within-chain measures, these studies cannot address across-chain shifts, which can prompt expansions following consumers’ decisions to start shopping online. Furthermore, the category-level outcomes investigated previously are limited to measures like brand loyalty, size loyalty, and price sensitivity (Chu et al. 2010; Chu, Chintagunta, and Cebollada 2008; Degeratu, Rangaswamy, and Wu 2000). Our dependent variable, category-level SoW change, is a more appropriate and managerially relevant measure for multichannel grocery retail managers, as it captures the net outcome of a consumer’s purchase allocation decisions and thus filters out the competing effects of cannibalization from the own chain and expansion from other competitive chains.

Third, we provide the first investigation of interaction effects between category characteristics and marketing mix instruments, which reveals novel insights into how retailers can use online and multichannel marketing mix instruments to stimulate expansion in specific categories. This contribution in itself is important; specific marketing mix instruments such as price and assortment can be more effective for exploiting category-specific online convenience advantages or compensating for higher perceived online purchase risk. For example, lower online prices or a stronger online presence of national brand (NB) products may reduce the perceived purchase risk for sensory categories that are difficult to evaluate online. Such interaction effects have not been established in prior research, though some studies hint at the importance of category-specific marketing mix effects. Degeratu, Rangaswamy, and Wu (2000) determine that NBs are more important for sensory categories, and Chintagunta, Chu, and Cebollada (2012) identify different promotion effects for heavy/bulky versus perishable categories. Yet, no prior studies have systematically or empirically investigated the interaction effects of marketing mix instruments and category characteristics on SoW expansion.

Fourth, beyond these contributions to retailing research, we provide managers with insights that help them to assess how their marketing mix strategies should vary across different types of categories, to stimulate consumers to buy (more of) some categories when they decide to shop online in their chain. Such insights are highly relevant for multichannel retailers that seek a better trade-off across different marketing mix instruments between and within categories, given their limited budgets. Our findings indicate which online and multichannel marketing mix instruments these managers should use in which categories, to maximize their expansion and minimize the risks of costly, pure cannibalization.

We use a U.K. household scanner panel data set, containing the purchases made by a large panel of households in a broad set of categories with varying characteristics, across online and offline channels of multiple chains (including four multichannel chains) during a two-year period. In these multichain, multichannel data, we find several significant interactions of online and multichannel marketing mix instruments with category characteristics, which reveal that some marketing mix instruments are more important for some categories than for others in stimulating category-level SoW expansion. For example, after they decide to start shopping online through a particular chain, consumers can be stimulated to allocate more of their spending in a sensory category to the online-visited chain, by decreased online prices (relative to online prices of its competitors) and an increased online presence of NBs in these categories. In planned categories in which consumers seek out convenience benefits (e.g., via online shopping lists), SoW expansion increases when the online assortment (relative to that of online competitors) is smaller. This is likely because consumers already have clear

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3 As a notable exception, Dawes and Nenycz-Thiel (2013) adopt a multichain, multichannel perspective to investigate purchase duplication, cross-purchasing among competitors, brand loyalty, and private-label (PL) share. They include 10 categories in their main study only (more to generalize their findings) but do not explore the impact of online or multichannel marketing mix instruments, category characteristics let alone interaction effects. In contrast, we clearly add to this research, by investigating differences in SoW expansion and explicitly accounting for interaction effects between category characteristics and marketing mix instruments for more than 50 categories.
brand preferences in such planned categories and thus do not need a large assortment.

**Conceptual Framework**

**Dependent Variable**

We are interested in the across-category differences in SoW expansion for an online-visited chain. Category-level SoW expansion is the increase in the consumer’s category-level SoW allocated to the chain from which the consumer starts buying online. When starting to shop online, consumers may shift category purchases from competitive chains to the online-visited chain (between-chain shifts) or from the offline to the online channel of the same chain (within-chain shifts). Understanding the net effect of a decision to shop online, which reflects how possible cannibalization gets compensated by expansion coming from switching from other competitive chains, is critical for retail managers seeking optimal performance across channels (Verhoef, Kannan, and Inman 2015) and higher total shares of expenditures per consumer (Keiningham et al. 2011). SoW expansion results from the reallocation of (some) purchases previously made at competitive chains to the online-visited chain.

**Theory of Shopping Utility Maximization**

Previous research on multichannel and multistore shopping indicates that a decision to visit multiple channels or chains and the allocation decisions across them can be explained by shopping utility maximization principles (e.g., Vroegrijk, Gijsbrechts, and Campo 2013). Such principles also apply in our study, where consumers decide to shop via the online channel of a specific chain. This decision may trigger category purchase reallocation decisions that are the main driving force of category-level SoW expansion (cf. Melis et al. 2016, who investigate this effect at the chain rather than category level).

The basic mechanism underlying shopping utility maximization principles is that a single channel (chain) does not always provide the highest overall shopping utility for a category during each shopping trip, and that a trade-off is made between two shopping utility components: **acquisition utility**, which is the net effect of the benefits that consumers receive (e.g., product quality) and the costs (e.g., price) they need to give up to acquire products, versus **transaction utility**, defined as the net (dis)utility derived from the shopping activity, due to both the advantages consumers receive (e.g., convenience) and the disadvantages they must bear (e.g., effort, purchase risks) to transfer products from the store to home. According to utility maximization theory, consumers seek to allocate their purchases to generate the highest overall acquisition and transaction utility (Baltas, Argouslidis, and Skarmeas 2010; Campo and Breugelmans 2015; Chintagunta, Chu, and Cebollada 2012; Gupta and Kim 2010; Vroegrijk, Gijsbrechts, and Campo 2013).

Similarly, we expect both utility components to inform consumers’ allocation of category purchases across channels and chains after they decide to start shopping online from a specific chain. The likelihood and magnitude of the category reallocation decisions likely depend on variables, linked to the online channel of the chain one decides to start using, that can be captured by variables that reflect acquisition utility components (online and multichannel marketing mix instruments), transaction utility components (category characteristics), and their interplay (Fig. 1).

**Acquisition utility.** The advantages of shifting purchases in specific categories to the online-visited chain depend on marketing mix instruments that determine the utility of acquiring the products online. We consider both online (across online chains, relative to online competitors) and multichannel (within-chain overlap, online relative to offline) marketing mix instruments. Following prior research, we use assortment-related aspects as key benefits and price-related aspects as key costs, that determine acquisition utility (Campo and Breugelmans 2015; Vroegrijk, Gijsbrechts, and Campo 2013).

**Assortment attractiveness** is a multidimensional construct (Briesch, Chintagunta, and Fox 2009; Broniarczyk, Hoyer, and McAlister 1998), so we use multiple online category assortment measures: online assortment breadth (number of brands), online assortment depth (variety per brand), and online assortment composition (share of NBs). Prior research also notes the importance of comparing online and offline channels in a multichannel grocery context to address assortment integration (i.e., coordination of assortments between channels; Enrich, Paul, and Rudolph 2015) that reflects consumers’ judgments of the assortment overlap between the online and offline channel of a chain (Melis et al. 2015). With regard to price, we use multiple measures, namely, a relative measure of the chain’s online price level compared with competitors’ online price (Fox, Montgomery, and Lodish 2004) and a price integration variable that compares online and offline prices for that category within the chain (Melis et al. 2016).

Using these measures and in line with prior literature (e.g., Campo and Breugelmans 2015; Vroegrijk, Gijsbrechts, and Campo 2013), we expect that category-level SoW (1) increases with a (a) broader online assortment, (b) deeper online assortment per brand offered, (c) stronger presence of NBs in the online assortment, and (d) better assortment integration between online and offline channels but (2) decreases with a (a) higher online price and (b) lower price integration between online and offline channels.

**Transaction utility.** Transaction utility for online purchases mainly depends on perceived online shopping convenience and purchase risk (Chintagunta, Chu, and Cebollada 2012; Gupta and Kim 2010), which vary across categories (Campo and Breugelmans 2015). Perceived online shopping convenience can be experienced through perceived **ordering** and/or **delivery con-
**convenience.** The former reflects the ease with which consumers can order products online, such as when they can simply click on the desired products, which makes their shopping process more functional and rational (Campo and Breugelmans 2015). Also other features of an online shopping environment, such as personalized shopping lists or the access to previous orders, may ease the ordering process yet also prompt smaller consideration sets and less elaborate or rational decision processes (Chu, Chintagunta, and Cebollada 2008). Perceived delivery convenience instead refers to the ease with which products are picked in the stores and delivered at the doorstep. Shopping online reduces the time spent driving to the store and waiting at the cash register. It also demands less effort, because consumers do not need to physically collect and carry products through the store (Berry, Seiders, and Grewal 2002; Campo and Breugelmans 2015; Chintagunta, Chu, and Cebollada 2012; Gupta and Kim 2010). Shopping online for groceries also may lead to higher perceived online buying risk (Gupta and Kim 2010). This perceived purchase risk is especially high in categories in which consumers prefer to physically inspect (look at, smell, feel) products prior to purchase, due to their intangibility (Campo and Breugelmans 2015; Citrin et al. 2003; Degeratu, Rangaswamy, and Wu 2000). We expect that category-level SoW (1) increases for categories with greater (a) perceived online ordering convenience and (b) perceived online delivery convenience but (2) decreases for categories with greater perceived online purchase risk.

**Interplay of acquisition and transaction utility.** Briesch, Dillon, and Fox (2013) find that the effect of price on category incidence is heterogeneous across categories in a single-channel (offline) context; Broniarczyk, Hoyer, and McAlister (1998) similarly suggest that the optimal (offline) assortment size may vary by category. According to Degeratu, Rangaswamy, and Wu (2000), marketing mix instruments are more important for some categories than for others in an online purchase setting. Therefore, the impact of acquisition utility (with online and multichannel marketing mix instruments as drivers) on the magnitude of category-level SoW expansion may differ depending on transaction utility (which varies across categories). We offer predictions about the interactions of benefits and costs, captured as multidimensional online and multichannel assortment and price measures that determine acquisition utility, with ordering and/or delivery convenience and the perceived risk of buying products online that determine transaction utility.

First, in categories associated with greater online ordering convenience, such as planned categories, two opposing mechanisms may arise. On the one hand, consumers may be more rational and functional in their shopping decisions when buying these categories online (Bell, Corsten, and Knox 2011; Cobb and Hoyer 1986), such that they attend more to the available assortment and prices online. Most consumers have developed reasonable knowledge about the attributes and attribute levels of the available alternatives in these planned categories, through their past purchases, so they might demand wider choice variety, especially in an online context that makes it easy to compare and order products. Price also might exert more influence in planned categories, because price sensitivity tends to be higher in planned categories (Wakefield and Inman 2003), leading to consumers that may not be willing to pay more and actually have the room to more easily scan multiple available alternatives on the price attribute in an online environment. Hence, we might predict that the expected increase (decrease) in category-level SoW due to online and multichannel assortment (price) measures will be more positive (negative) for planned categories that offer greater perceived online ordering convenience.

On the other hand, online environments usually offer consumers online shopping lists, where consumers list items one does not want to forget each shopping occasion, or allow consumers to reuse previous order lists to repurchase regularly bought items with a simple click (Chu, Chintagunta, and Cebollada 2008). Consumers likely rely on such lists for product categories that they plan in advance, to save time. Consumers in turn might be less attentive to marketing mix instruments in planned categories, because they are reluctant to compare various alternatives on each purchase occasion and instead simply reorder a preferred or previously purchased item. Planned prod-
ucts on shopping lists also tend to be bought frequently and are typically necessity products (Chintagunta, Chu, and Cébollada 2012). From this perspective, consumers may have developed clear brand preferences and do not need to make new product comparisons each time. Hence, following the above reasoning, we might also predict that the expected increase (decrease) in category-level SoW due to online and multichannel assortment (price) measures will be less positive (negative) for planned categories that offer greater perceived online ordering convenience.

Second, in categories that benefit more from perceived online delivery convenience, such as heavy or bulky items, consumers may express a higher willingness to pay online, reflecting their perception of fair price differences between online and offline channels (Forman, Ghose, and Goldfarb 2009). In these categories, consumers may be less price sensitive because the price difference is compensated for by delivery convenience. We do not expect perceived delivery convenience to influence online assortment drivers though; online assortment benefits probably do not determine which categories consumers choose in their attempt to gain online delivery convenience. Thus, we predict that the expected decrease in category-level SoW due to online and multichannel price measures will be less negative for heavy/bulky product categories that evoke greater perceived online delivery convenience.

Third, in categories for which the perceived risk of buying online is higher, such as sensory categories, the sensitivity to acquisition costs is expected to be higher. If the online prices for those products are also higher, the risk of buying them online grows, so price would function as an additional barrier. Risk-reducing information cues, such as a more attractive or familiar online assortment, instead may mitigate purchase risk concerns (Degeratu, Rangaswamy, and Wu 2000). Consumers are thus likely to be more careful in making choices in these categories and require more benefits and lower costs to reduce the higher perceived risk of online purchases. We thus predict that the expected increase (decrease) in category-level SoW due to online and multichannel assortment (price) measures will be more positive (negative) for sensory categories with greater perceived online purchase risk.

Data & Methodology

Research Setting & Data

Our research setting is the U.K. online grocery market, which, among all major European markets, is the most developed (Statista 2019a). We use household panel data that are representative for the U.K. population, obtained from Kantar Worldpanel via AiMark. The observation period exceeds two years (September 2006–December 2008), and the data set includes purchases in all major U.K. grocery chains, including the four multichannel chains (Tesco, Asda, Sainsbury’s, and Waitrose) and six single-channel chains. These top 10 U.K. chains cover 80% of total grocery expenditures in the country. The Kantar household panel consists of about 34,000 households, of which 30% have shopped at least once online during our observation period. The online grocery market in the U.K. represented 7.2% of the overall U.K. grocery market in this period and can be considered a first mover, in that the online market share figures of countries such as France and China had only reached around 6% in 2018, and many countries lagged far behind, with 2018 online grocery shares of .5% for Italy, 1.5% for the United States, 1.7% for Germany, and 2.6% for the Netherlands (Statista 2019b).

We use the same data set as adopted by Melis et al. (2015, 2016), but reflecting our focus on category-level SoW expansion, we apply selection criteria to category purchases (rather than chain-level purchases as in Melis et al. 2015, 2016). A category observation of a household is retained when that household (i) started to shop for groceries online during our estimation window (January 2007–September 2008), (ii) purchased in the category both before and after online channel adoption (irrespective of whether the category is purchased online or in the online-visited chain), and (iii) visited more than one chain to purchase that category before or after the household started buying online. We eliminated category observations for which a household did not buy in one of the two periods (or both periods), as this would lead to a null total category expenditure across all chains in that period and prevent an appropriate calculation of SoW (due to a denominator of 0, as we discuss subsequently). We also eliminated single-store shoppers in the category in both periods, because these households would not have a chance to reallocate their purchases from or to competitive chains. Single-store shoppers in the before period only or multiple-store shoppers that become single-store shoppers after the decision to shop online are retained though. With these selection criteria, we filter out null SoW changes from households that do not buy in the category (nonbuyers of the category) or from those that by definition do not have an opportunity to change their category purchase allocation (single-store buyers in the category). Therefore, any null SoW changes truly reflect stable allocation patterns across chains (no shift in category purchases) of households that buy in the category and are multiple-store shoppers.

The four multichannel grocery chains introduced their online grocery services long before the start of our observation period. In line with common practices, they offered a full range of typical grocery products from the start. We investigate the top 59 categories that are available in both online and offline channels; across the four multichannel chains, they account for more than half of all purchases (i.e., 53.36%). These 59 categories are true grocery products; we excluded cigarettes, clothing, and categories without NBs in the assortment (which is the case for many fruit and vegetable categories). Across all households, we selected categories with substantial penetration rate (minimum 25.11% of households buy in the category) and a respectable category-level share of total grocery purchases (minimum of

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5 To rule out left-censoring bias, we obtained data starting in 2004. We only retained households that did not make any online shopping trips prior to the observation period.

6 The numbers of households that stopped buying or started buying the category are small though, resp. 1.15% and 1.29%. When consumers buy the category, they mostly do so both before and after online channel adoption.
.12%). The resulting set includes food (e.g., yogurt, biscuits, soft drinks) and nonfood (e.g., dishwashing products, toilet tissue) categories.

In total, we retain 108,985 category-level SoW observations, involving 3,311 households, across 59 categories and four multichannel chains. On average, a household buys 28 categories (min. = 1, max. = 58). Among multichannel households, 83% shop online at one chain, 15% shop online at two chains, 1.5% shop online at three, and only .15% shop online at all four multichannel chains. Average household penetration per category is approximately 47% (min. = 13.29%, dog food; max. = 85.86%, milk). Average interpurchase days (across all households, chains, and channels) for the 59 categories is approximately 60 days, or about 8.5 weeks (SD = 50.55) (min. = 17.66 days or about 2.5 weeks, SD = 24.55, milk; max. = 97.58 days, or about 14 weeks, SD = 67.68, canned fruit).

**Variable Operationalization & Descriptive Statistics**

In Table 1, we describe how we operationalized the dependent variable and the drivers that capture acquisition utility (online and multichannel assortment, price) and transaction utility (online ordering and delivery convenience, online purchase risk).

**Category expansion.** Our dependent variable category expansion is a household-category-chain measure, operationalized as the difference in category $p$’s SoW in the period after versus before household $h$’s decision to start shopping online at chain $c$ (i.e., $\Delta_{SoW_{h,c}}$). We measure SoW as household $h$’s proportion of (online and offline) category expenditures at the online-visited chain relative to household $h$’s total category expenditures across all (multi and single-channel, in total 10) chains in the period (Leenheer et al. 2007). To filter out price effects, because online prices often are higher than offline ones, we replaced (when possible) the online with the offline price of the same stockkeeping unit (SKU) to calculate SoW changes.7

The before and after periods are household- and chain-specific (depending on when a household decided to go online in that chain). Each period contains 16 consecutive weeks, and the week of the first online visit to the chain is included in the after period. The 16-week span is long enough to capture changes in SoW for less frequently purchased categories but short enough to limit the risk of confounding effects due to other changes during the observation period (see Melis et al. 2016). Each selected category is bought, on average, at least once in the 16-week frame.

Web Appendix A lists the descriptive statistics per category; the summary statistics are in Table 2. Panel A shows that the average relative change in SoW across chains and categories is positive (27.69%); Panel B illustrates in particular that this differs a bit across chains and a lot across categories (min. = 16.07% for one shot drinks; max. = 38.27% for machine wash products). Panel A provides further evidence that consumers shift (part of their) offline purchases to the online channel of the same chain, as indicated by the cannibalization that appears in 40% of the cases, with an average of .402. We also note some evidence of positive spillover effects to the offline channel, in 30% of cases and an average of .362. Still, as we observe on average expansion, it follows that online spending increases compensate for offline spending decreases, and consumers thus shift (part of) their purchases from competitive grocery chains to the online-visited chain. Furthermore, on average, 10.51% of category-level SoW expansion comes from totally new customers who had not visited the chain before shopping online there, and 44.16% comes from new customers who started to buy that category in the online-visited store after their decision to shop online. The multichannel chains thus can grow considerably through both a greater customer base and even more through an increase in the number of categories purchased by customers who have shopped at the chain but had not bought the category in that chain before.

As Web Appendix A reveals, the variation of positive spillover and negative cannibalization across categories is limited, with percentages ranging from 25% to 35% and from 30% to 53%, respectively. More households exhibit a decline in offline SoW for heavy/bulky categories that are planned in advance, like milk (53%) or cat food (52%), though the decline is less steep (.177 and .236, respectively) than the average level (.362) in these categories. These categories can be seen as ‘destination categories’ (as defined by Briesch, Dillon, and Fox 2013) that might be driving households’ decision to shop online (Campro and Breugelmans 2015). These destination categories also reveal the highest correlation between changes in category- and chain-level SoW, such as .61 for milk and .59 for cat food (compared to an average of .49).8 Categories that are less likely to drive (online) traffic include canned food (canned fish, canned fruit, canned pasta), which exhibit declines in offline SoW for fewer households (32–35%) and which have lower correlation with chain-level SoW changes (.42–.48).

**Acquisition utility drivers.** To capture the multidimensional nature of online assortment attractiveness, we use multiple measures (Table 1): relative online assortment breadth (relative number of online brands per category), relative online assortment depth (relative average number of online subbrands per category), online assortment composition (share of NBs offered online per category), and online–offline assortment integration (ratio of online versus offline subbrands available in the category) (Briesch, Chintagunta, and Fox 2009; Broniarczyk, Hoyer, and McAlister 1998; Melis et al. 2015). For price, we use a relative measure that captures the chain’s online price level (Fox, Montgomery, and Lodish 2004) and a price integration variable that compares the category’s online and offline prices within the chain (Melis et al. 2016). Both price variables are derived from

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7 In a few cases when it was not possible (.98%, because online-unique SKUs), the online price was used.

8 We also calculated the correlations between the different category-level SoW changes (not reported in Web Appendix A but available on request). These cross-category correlations are higher for destination categories; for example, milk (cat food) has cross-category correlations $\geq .40$ with 35 (30) of the other categories and an average cross-category correlation of .40 (.39) while this is .30 across all categories.
Table 1
Variable operationalization.

| Variable | Description | Formula |
|----------|-------------|---------|
| **Dependent variable** | | |
| $\Delta \text{SoW}_{hc,p}$ | The difference in category $p$'s SoW between the (16-week) period following household $h$'s decision to start shopping online at chain $c$ ($t_h^c$) and the (16-week) period before household $h$ visited the online channel of chain $c$ ($t_h^c - 1$). SoW is household $h$'s proportion of category $p$ expenditures at a chain $c$ relative to total category $p$ expenditures across all (multi and single-channel, 10 total) chains in that period. Online category expenditures in the after period are rescaled (divided by online/offline price index), to measure the category expenditures in the same unit price and to remove the effect of online/offline price differences. | $\Delta \text{SoW}_{hc,p} = \frac{\sum_{c=1}^{4} \text{Expenditure}_{hc,p,c} - \sum_{c=1}^{4} \text{Expenditure}_{hc,p,c}^{t_h^c - 1}}{\sum_{c=1}^{4} \text{Expenditure}_{hc,p,c}^{t_h^c - 1}}$ |

**Online and multichannel marketing mix variables**

| **Rel Online Assortment Breadth$_{cp,hc}$** | Relative online assortment breadth in the period following household $h$'s decision to start shopping online at chain $c$ ($t_h^c$), computed as the ratio of the number of online (NB + PL) brands for category $p$ at the online-visited chain $c$, over the average online assortment breadth for the category in the four multichannel chains (Briesch, Chintagunta, and Fox 2009; Fox, Montgomery, and Lodish 2004). | $\text{Online assortment breadth}_{cp,hc} = \frac{\sum_{c=1}^{4} \text{Online assortment breadth}_{cp,hc}}{4}$ |
| **Rel Online Assortment Depth$_{cp,hc}$** | Relative online assortment depth in the period following household $h$'s decision to start shopping online at chain $c$ ($t_h^c$), computed as the ratio of the average number of online (NB + PL) subbrands per brand for category $p$ at the online-visited chain $c$, over the average online assortment depth for the category in the four multichannel chains (Briesch et al. 2009; Fox et al. 2004). | $\text{Online assortment depth}_{cp,hc} = \frac{\sum_{c=1}^{4} \text{Online assortment depth}_{cp,hc}}{4}$ |
| **Online NB proliferation$_{ph,c}$** | Share of NBs in the online assortment of category $p$ at chain $c$, in the period following household $h$'s decision to start shopping online at chain $c$ ($t_h^c$), computed as the ratio of the number of online national subbrands in the category and chain, over the total number of online subbrands in the category and chain. | $\text{Online number of NB subbrands}_{cp,hc} = \frac{\sum_{c=1}^{4} \text{Online subbrands}_{cp,hc}}{4}$ |
| **Online Offline Assortment integration$_{cp,hc}$** | Assortment integration over the online and offline channel of chain $c$ for category $p$, in the period following household $h$'s decision to start shopping online at chain $c$ ($t_h^c$), computed as the ratio of the category's weighted average online unit price over all SKUs (with online SKU market share at the chain as weights) at the online-visited chain $c$, over the category’s weighted average online unit price across all multichannel chains (with online SKU market share across chains as weights) (Fox et al. 2004). | $\text{Online assortment size}_{cp,hc} = \frac{\sum_{c=1}^{4} \text{Online price}_{cp,hc}}{4}$ |
| **Rel Online Price$_{cp,hc}$** | Relative online category price in the period following household $h$'s decision to start shopping online at chain $c$ ($t_h^c$), computed as the ratio of the category’s weighted average online unit price over all SKUs with online SKU market share at the chain as weights) at the online-visited chain $c$, over the category’s weighted average online unit price across all multichannel chains (with online SKU market share across chains as weights) (Sullivan 1998). | $\text{Online price}_{cp,hc} = \frac{\sum_{c=1}^{4} \text{Online price}_{cp,hc}}{4}$ |
| **Online Offline Price integration$_{cp,hc}$** | Price integration over the online and offline channel of chain $c$ for category $p$, in the period following household $h$'s decision to start shopping online at chain $c$ ($t_h^c$), computed as the ratio of category's $p$ online price at chain $c$ (see before) over category $p$'s offline price at chain $c$ (Sullivan 1998). The measure is based on the overlapping assortment across the entire observation period (i.e., all SKUs available in both online and offline channels of chain $c$). | $\text{Online price}_{cp,hc} = \frac{\sum_{c=1}^{4} \text{Online price}_{cp,hc}}{4}$ |

**Category characteristics**

| **Planned$_p$** | The average score of four expert ratings on a 7-point planned purchase Likert scale (1 = not planned to 7 = usually planned). A category is defined as a planned category when purchases are typically planned in advance of the store visit, making a category purchase less prone to in-store stimuli effects (Bell, Corsten, and Knox 2011; Cobb and Hoyer 1986). | |
| **Heavy/Bulky$_p$** | The average score of four expert ratings on a 7-point heavy/bulky Likert scale (1 = not heavy/bulky to 7 = very heavy/bulky). Chintagunta et al. (2012) define heavy/bulky categories as categories that carry items that are heavy or bulky bottled, canned, or bagged. | |
the actual price paid, so they account for discounts. All these variables are derived from the panel data, and are measured using information from the 16-week period following household $h$’s first visit to chain $c$’s online channel (after period). All variables are therefore chain- and household-specific (i.e., depend on the time household $h$ starts shopping online at chain $c$).

**Transaction utility drivers.** The transaction utility drivers (online ordering convenience, online delivery convenience, perceived online risk) are linked to category characteristics (see also Campo and Breugelmans 2015). In line with prior research, acquisition utility components (online and multichannel marketing mix instruments) are time-varying, the transaction utility components are not (Campo and Breugelmans, 2015; Vroegrijk, Gijsbrechts, and Campo 2013).

Categories that tend to be planned in advance (as opposed to impulse categories that are bought in a spur) benefit from the online ordering convenience advantage. Given that grocery planning typically takes place in advance of the store visit (explicitly or as part of routine purchases), purchases in planned categories are less prone to in-store stimuli (Bell, Corsten, and Knox 2011; Cobb and Hoyer 1986). Heavy/bulky categories clearly benefit from online delivery convenience advantages and reflect

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**Table 1 (Continued)**

| Variable | Description | Formula |
|----------|-------------|---------|
| Sensory | The average score of four expert ratings on a 7-point sensory Likert scale (1 = not sensory to 7 = very sensory). A sensory category has attributes that are usually evaluated prior to purchase by using senses such as sight, smell, and touch (Degeratu, Rangaswamy, and Wu 2000). | |
| **Control variables** | | |
| ΔOffline Assortment Breadth$_{hp}$ | Change of the relative offline assortment breadth in the period after and period before household $h$’s decision to start shopping online at chain $c$ ($t_h$). See operationalization relative online assortment breadth. | Rel Offline Assortment Breadth$_{hp, t_h}$ − Rel Offline Assortment Breadth$_{hp, t_h-1}$ |
| ΔOffline Assortment Depth$_{hp}$ | Change of the relative offline assortment depth in the period after and period before household $h$’s decision to start shopping online at chain $c$ ($t_h$). See operationalization relative online assortment depth. | Rel Offline Assortment Depth$_{hp, t_h}$ − Rel Offline Assortment Depth$_{hp, t_h-1}$ |
| ΔOffline NB proliferation$_{hp}$ | Change of the offline NB proliferation in the period after and period before household $h$’s decision to start shopping online at chain $c$ ($t_h$). See operationalization online NB proliferation. | Offline NB proliferation$_{hp, t_h}$ − Offline NB proliferation$_{hp, t_h-1}$ |
| ΔOffline Price$_{hp}$ | Change of the relative offline price in the period after and period before household $h$’s decision to start shopping online at chain $c$ ($t_h$). See operationalization relative online price. | Rel Offline Price$_{hp, t_h}$ − Rel Offline Price$_{hp, t_h-1}$ |
| Cat$_{importance}$ | Share of category $p$ in the household’s overall grocery expenditures, computed over the before period as the ratio of household $h$’s total (offline) expenditures for category $p$ across all single- and multichannel chains over household $h$’s total (offline) expenditures for grocery purchases across all single- and multichannel chains (Campo and Breugelmans 2015). | ∑$_{c=1}^{10}$ Expenditure$_{hp, t_h-1}$ / ∑$_{c=1}^{10}$ Expenditure$_{hp, t_h-1}$ |
| Cat$_{specific}$ | Household loyalty to chain $c$ for category $p$, computed over the before period as the ratio of (offline) expenditures for household $h$ in multichannel chain $c$ and category $p$, over household $h$’s (offline) expenditures in category $p$ across all single and multichannel chains (Leenheer et al. 2007). | ∑$_{c=1}^{10}$ Expenditure$_{hp, t_h-1}$ / ∑$_{c=1}^{10}$ Expenditure$_{hp, t_h-1}$ |
| Category Expertise$_{hp}$ | Expertise of chain $c$ in category $p$ in the period following household $h$’s decision to start shopping online at the chain $c$ ($t_h$), approximated by the chain’s category specific market share relative to the chain’s overall market share during the before online shopping period ($t_h-1$), that is, the ratio of the chain $c$’s share in total offline market sales for category $p$ (across all single and multichannel chains), over total market share of chain $c$ in the offline channel (category development index) (Briesch, Dillon, and Fox 2013; Dhar, Hoch, and Kumar 2001). | (∑$_{c=1}^{10}$ Offline Sales$_{hp, t_h-1}$) / (∑$_{c=1}^{10}$ Offline Sales$_{hp, t_h-1}$) |
| Going online at competitors$_{c}$ | A dummy variable equal to 1 if household $h$ visited the online channel of a competitive chain ($k \neq c$) before period $t_h$. | |
Table 2
Descriptive statistics for relative SoW expansion.

Panel A: Average across chains and categories

| Total number of observations | Relative change in SoW | Observations where offline SoW in the period following household h’s decision to start shopping online | Category-level SoW expansion from new customer in the category for the chain (%) | Category-level SoW expansion from new customer at the chain (%) |
|-----------------------------|------------------------|---------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|---------------------------------------------------------------|
|                             |                        |                                                                                             |                                                                                  |                                                              |
|                             | AverageSD             | Increased # (%) 44.96 4.02 115.97 21.24 59.10 |                                                                                   |                                                              |
|                             |                        | Decreased # (%) 55.73 36.72 113.72 30.42 59.10 |                                                                                   |                                                              |
|                             |                        | Did not change # (%) 31 390 30.44 0 44.16 10.51 |                                                                                   |                                                              |
|                             |                        | Average 33066 44.96 4.02 115.97 21.24 59.10 |                                                                                   |                                                              |

Panel B: Average per chain and per category (summary)

| Total number of observations | Relative change in SoW | Average | SD |
|-----------------------------|------------------------|---------|----|
|                             |                        |         |    |
| Per chain (across categories) |                        |         |    |
| Asda                        | 26 464                | 24.48   | 115.11 |
| Sainsbury’s                 | 16 958                | 21.24   | 113.72 |
| Tesco                       | 55 569                | 30.42   | 115.97 |
| Waitrose                    | 9 961                 | 31.97   | 110.24 |
| Per category (across chains) |                        |         |    |
| Min. (one-shot drinks)      | 1 021                 | 16.07   | 121.54 |
| Max. (machine wash products) | 1 811                 | 38.27   | 118.18 |

*a Category-specific details are in Web Appendix A.

the ease with which products are picked in the store and delivered to the doorstep. Chintagunta, Chu, and Cebollada (2012) define these categories as heavy or bulky bottled, canned, or bagged consumer packaged goods. Finally, for sensory categories, consumers prefer to inspect products physically, which implies higher purchase risk in an intangible, online grocery context (Campo and Breugelmans 2015; Citrin et al. 2003; Degeratu, Rangaswamy, and Wu 2000). Using these definitions (Table 1), four experts scored each of the 59 categories on 7-point Likert scales that measured its planned, heavy/bulky, and sensory characteristics for an average consumer. The intra-class correlation coefficients were .959 for planned, .952 for heavy/bulky, and .974 for sensory categories, indicating excellent inter-rater reliability (McGraw and W on, 1996). Web Appendix A lists the average scores on the three characteristics per category.

Model Specification

To establish the circumstances in which household h’s decision to start buying groceries online from chain c leads to expansion of the chain’s SoW in product category p, we regress household (h)- and chain (c)-specific category (p) expansion against marketing mix instruments, category characteristics, selected interactions (based on theory), and control variables (Xk,hcp) (see Cleeren, van Heerde, and Dekimpe 2013; Van der Maelen, Breugelmans, and Cleeren 2017):9

\[
\Delta SoW^*_{hcp} = \alpha_c + \sum_i \beta_i Marketing_{mixi,hcp} + \sum_j \gamma_j Characteristic_{j,p} + \sum_i \delta_i,j Marketing_{mixi,hcp} + Category_{characteristic_{j,p}} + \sum_k \tau_k \ast X_{k,hcp} + \epsilon_{h,c,p}.
\]

where \( \Delta SoW^*_{hcp} \) is the transformed category-level SoW expansion for household h (h = 1, . . . , 311), for online-visited chain c (c = 1, . . . , 4) in category p (p = 1, . . . , 59). We transform the difference in SoW by making it relative to the average SoW of the before and after period, such that we investigate relative instead of absolute growth; we account for its bounded nature using an approach similar to Cleeren, van Heerde, and Dekimpe’s (2013).10 \( \alpha_c \) captures the average expansion effect for chain c.

9 The period when each household starts to shop online differs. For straightforward notation, we use only the subscript h and c to indicate that household h buys in the online channel of chain c in a 16-week period t that starts in the week when its first online visit to the chain occurred.

10 \( \Delta SoW^*_{hcp} = \ln \left( \frac{\Delta SoW_{hcp}^* + 2.01}{\Delta SoW_{hcp}^* - 0.01} \right) \) where

\( \Delta SoW^*_{hcp} = \left( \frac{\Delta SoW_{hcp}^*}{\Delta SoW_{hcp}^* + \Delta SoW_{hcp}^* - 1/2} \right) \).
These category-independent, time-invariant intercepts capture characteristics that mainly differ across chains, not over time or across categories (e.g., service levels, positioning, or delivery fees charged by the chain). Marketing mix instruments and category characteristics are operationalized as follows:

\[ \sum_i \beta_i \text{Marketing}_{mix_{i,h,c,p}} = \beta_1 \ast \text{RelOnlineAssortmentBreadth}_{h,c,p} + \beta_2 \ast \text{RelOnlineAssortmentDepth}_{h,c,p} + \beta_3 \ast \text{OnlineNBProliferation}_{h,c,p} + \beta_4 \ast \text{OnlineOfflineAssortmentIntegration}_{h,c,p} + \beta_5 \ast \text{RelOnlinePrice}_{h,c,p} + \beta_6 \ast \text{OnlineOfflinePriceIntegration}_{h,c,p}, \]  

(2a)

and

\[ \sum_j \gamma_j \text{Category.characteristics}_{j,p} = \gamma_1 \ast \text{Planned}_{p} + \gamma_2 \ast \text{Heavy/Bulky}_{p} + \gamma_3 \ast \text{Sensory}_{p}. \]  

(2b)

Several control variables (\(X_{k,h,c,p}\)) might influence SoW expansion. We first include control variables measured at the offline level. Specifically, we consider differences in four offline marketing mix instruments, measured after versus before going online: offline price, offline assortment breadth, offline assortment depth, and offline NB proliferation. We add changes in these offline marketing mix variables and not the after-period effects because our dependent variable is the change in SoW and consumers have already bought offline. As the online and multichannel marketing mix variables were not part of the cost–benefit trade-off in the before period, they are included for the after period only. Next, to correct for magnitude effects, we include the category–specific chain loyalty of the household (Cleeren, van Heerde, and Dekimpe 2013; Van der Maelen, Breugelmans, and Cleeren 2017) and the importance of the category for the household’s overall shopping. On top, the chain’s (offline) expertise in the focal category, reflected by its strength in that category, might reduce the perceived risk of purchasing products online in that category from the chain, so we include it as well. Loyalty is a household–category–chain–specific measure; importance is a household–category–specific measure; and category expertise is a category–chain–specific measure. Thus, we add three different aspects that are important to control for. Finally, most online consumers only visit one chain’s online channel, but a few explore multiple online stores after they gain some initial expertise with online grocery shopping (Melis et al. 2015; see also reported % in our data section before). In these cases, the consumer visits the online channels of both the focal chain and competitive chains. We include a dummy variable to capture whether a household shopped online at another chain prior to shopping online at the focal chain, to control for any effect of such visits to online competitors.

Estimation Procedure

We account for several issues before estimating the model in Eq. (1).

Selection bias. If households that shop online at a particular chain differ in important, unobserved characteristics from those that do not, sample selection bias might arise. We control for this with a two-stage estimation, where we model category-level SoW expansion at a chain for a specific household (Eq. (1)), conditional on the household’s decision to shop online with that chain during our observation period (first-stage selection equation). The first-stage selection equation is estimated with a probit model where we model a household’s online choice for each of the four multichannel chains. The dependent variable, online chain choice, is a function of chain-fixed effects and a set of household-specific variables that may explain the decision to shop online at a particular chain, including the household’s SoW for each multichannel chain; the shares of heavy/bulky, planned, and sensory categories in its total spending; its total spending; and social class and number of household members (Degeratu, Rangaswamy, and Wu 2000; Melis et al. 2016; Morganosky and Cude 2000; see Web Appendix B). The inverse Mills ratio (IMR) derived from the first-stage online chain choice probit model then enters the second-stage SoW expansion regression model.

Household heterogeneity in chain-specific intercepts. To accommodate unobserved consumer heterogeneity, we model the four parameters of the average (category–independent) chain constants (\(\alpha_i\)) as normally distributed random coefficients.

Endogeneity. Retailers likely adjust their online and multichannel marketing mix instruments to boost sales in a category, which would influence category-specific SoW changes across consumers. This is a type of temporal correlation of the marketing mix variables with the error term in Eq. (1). We correct for this type of endogeneity with Gaussian copulas (Burmester et al. 2015; Datta, Foubert, and van Heerde 2015; Park and Gupta 2012). The six copulas, linked to each online and multichannel marketing mix variable in Eq. (1), are operationalized as \(COPULAS_i = \phi^{-1}(H(\text{OnlineMarketingMix}_i)), \) where \(\phi^{-1}\) is the inverse of the cumulative normal distribution function, and \(H(.)\) the empirical distribution of the respective marketing mix variable. We comply to the assumption that the endogenous variables should be non-normally distributed (based on a Kolmogorov–Smirnov test, all p’s <.01), in order to be able to partial out the exogenous variation (Park and Gupta 2012). In line with Mathys, Burmester, and Clement (2016), we only retain the copula terms that are found to be endogenous (p <.10) in a model in which we do not yet include the interaction terms and with error clustering at the household level instead of random coefficients (to keep the model parsimonious). In our case, the copula for the relative online price is found to be significant.

Results

Selection Equation: Online Chain Choice

The maximum variance inflation factor (VIF) for the selection equation is 2.40, so multicollinearity does not appear to be a major issue. We obtain a hit rate of 94.85%, which is significantly better than chance (90.24% = \(\alpha^2 + (1-\alpha)^2\), with \(\alpha = 5.14\%\)). The parameter estimates can be found in Web Appendix B. Throughout the entire discussion, we use 10% as a significance threshold and two-sided tests. The results indicate that a household is more
likely to shop online at a chain when its SoW with the chain is higher (Melis et al. 2015 similarly find that consumers tend to shop online at the store they prefer most offline), its share of sensory products in its total spending is lower (which is a barrier to online shopping; Campo and Breugelmans 2015), its total spending is higher, and it represents a higher social class (Melis et al. 2016) and includes more members (Raijás and Tuunainen 2011). The model fit and face validity of the parameter estimates provide support for the validity of this selection equation.

**Outcome Equation: Category-Level SoW Expansion**

The maximum VIF is 2.60, and the maximum correlation is -.57 (sensory and online NB proliferation) (Table 3), so multicollinearity is not a major concern. Table 4 contains the estimation results when we include the IMR from the online chain choice selection equation. For ease of interpretation and to reflect our focus on within-chain, across-category differences, we mean-center all the chain-specific explanatory variables in our SoW expansion equation per chain; the three category characteristics are grand mean-centered. All effects thus reflect the results when all other variables are at their (within-chain) mean level. The model fits the data well (average log-likelihood = −254,969.23, pseudo $R^2 = 9.47\%$).

The chain-specific intercepts indicate that, on average, all multichannel chains achieve category expansion, led by Tesco, closely followed by Waitrose ($\alpha_{ASDA} = .79$, $p < .01$; $\alpha_{SAINS} = .71$, $p < .01$; $\alpha_{TESCO} = 1.00$, $p < .01$; $\alpha_{WAIT} = 1.00$, $p < .01$). The estimated standard deviations for the four chain-specific intercepts (“St. Dev.” in Table 4) reveal substantial heterogeneity across households. We find weak evidence that positive changes in the offline marketing mix, related to offline assortment breadth ($\tau_1 = .10$, $p < .10$) and offline NB proliferation ($\tau_3 = .34$, $p < .10$), stimulate category SoW expansion, whereas changes in offline assortment depth ($\tau_2 = -.06$, $p > .10$) and offline prices ($\tau_4 = .06$, $p > .10$) do not influence category expansion. The category-specific retailer loyalty control variable exerts a significant, negative effect on category expansion ($\tau_5 = -5.56$, $p < .01$), indicating a smaller category expansion for categories for which the already high SoW in the online-visited chain restricts further expansion (ceiling effect). In contrast, SoW expansion is more likely in categories that are important to a household, likely because it weights these categories more heavily and pays more attention to reallocation decisions when shopping online ($\tau_6 = 1.66$, $p < .01$). More expansion also occurs in categories in which the chain has more expertise ($\tau_7 = .61$, $p < .01$), so a chain’s category-specific expertise may be a risk-reducing cue for buying online. Category expansion for a chain is higher if a household has visited a competing online chain in the past ($\tau_8 = .13$, $p < .05$). Perhaps such households already have some online grocery buying experience, which attenuates their perceived online buying risks and enables them to obtain online channel advantages more readily (Campo and Breugelmans 2015). Therefore, these consumers likely shift a greater share to (other) online-visited chains. Finally, the negative and significant IMR ($\tau_9 = -2.13$, $p < .01$) underscores the importance of using a selection model.11

**Online and multichannel marketing mix instruments.** We obtain mixed findings for the online and multichannel marketing mix variables. There are no significant effects for relative online assortment depth ($\beta_1 = .0003$, online NB proliferation ($\beta_3 = -.05$), or online/offline price integration ($\beta_6 = .15$) (all $p > .10$). The chain-specific intercepts, indicating an overall expansion effect, might capture the effects related to the general chain positioning in terms of online assortment and price, and category-specific online marketing mix effects vary across categories, as shown by the interaction effects that we discuss subsequently. We find a weakly significant negative effect of online assortment breadth ($\beta_1 = -.10$, $p < .10$). A broader online assortment thus leads to a smaller category expansion. Although somewhat counterintuitive, this result aligns with prior findings that too much choice may “kill” a choice (Boatwright and Nunes 2001; Iyengar and Lepper 2000; Mathmann et al. 2017), which may be especially relevant in an online grocery environment where shopping ease and convenience are crucial (Morganosky and Cude 2000). Assortment integration has the expected positive influence on category expansion ($\beta_3 = .24$, $p < .01$), suggesting more SoW expansion for categories with a stronger overlap between online and offline channels. So, while online grocery shoppers do not necessarily prefer large assortments, they seem to prefer more familiar ones, which corroborates with the ease and convenience strived for in online grocery shopping. Finally, a chain’s relative online price in the category has the expected negative, albeit somewhat weak, effect on category expansion ($\beta_5 = -.48$, $p < .10$).

**Category characteristics.** For planned categories with higher ordering convenience advantages, category expansion effects are larger ($\gamma_1 = .02$, $p < .01$). The heavy/bulky categories with higher delivery convenience also indicate higher category expansion ($\gamma_2 = .01$, $p < .05$). We find no significant direct effect of sensory categories on category expansion ($\gamma_3 = -.004$, $p > .10$), but as we discuss in the next section, the sensory level of a category strongly influences category-level SoW expansion by moderating the online and multichannel marketing mix instruments.

**Interaction of online and multichannel marketing mix instruments and category characteristics.** The significant interactions in Table 4 indicate that the effectiveness of the online and multichannel marketing mix instruments depends on category characteristics. We graph these significant interactions in Fig. 2 to display the impact of a gradual increase in the different marketing mix variables across the full range observed in our data.

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11 The significant IMR reveals the need to control for selection bias. The model fit significantly improves when we include the IMR (likelihood ratio test: $\chi^2(1) = 770.39$, $p < .01$). We also tested if our findings are robust across another specification of the selection equation, in which we use, rather than chain-specific dummies in selection Eq. B.1, household-weighted marketing mix chain instruments (relative online assortment breadth and depth, online national proliferation, and relative online price). We then included the resulting IMR in the outcome equation. (Due to serious multicollinearity issues, we excluded assortment integration and price integration from the selection equation for this robustness check.) We obtained substantively the same findings.
Table 3
Descriptive statistics and correlations for explanatory variables.

|                                | Mean  | S.D.  | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9     | 10    | 11    | 12    | 13    | 14    | 15    | 16    | 17    | 18    | 19    |
|--------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1 Relative change in SoW       | 0.28  | 1.15  | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| 2 Relative online assortment breadth | 1.11  | 0.24  | 0.01  | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| 3 Relative online assortment dept | 1.02  | 0.12  | 0.01  | −0.16 | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| 4 Online NB proliferation      | 0.61  | 0.20  | 0.01  | −0.06 | −0.03 | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| 5 Online/offline assortment integration | 0.64  | 0.11  | 0.02  | 0.29  | 0.17  | 0.12  | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| 6 Relative online price        | 0.93  | 0.15  | 0.01  | −0.26 | −0.22 | 0.18  | 0.11  | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| 7 Online/offline price integration | 0.99  | 0.08  | 0.01  | 0.09  | −0.06 | −0.04 | 0.03  | 0.18  | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| 8 Planned                      | 4.85  | 1.81  | 0.02  | −0.03 | 0.00  | −0.15 | 0.08  | 0.11  | −0.03 | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |
| 9 Heavy/Bulky                  | 2.51  | 1.50  | 0.01  | −0.05 | 0.01  | 0.18  | −0.02 | −0.01 | −0.21 | 0.15  | 1.00  |       |       |       |       |       |       |       |       |       |       |       |       |
| 10 Sensory                     | 3.04  | 2.08  | 0.02  | 0.08  | −0.13 | −0.57 | −0.12 | −0.06 | 0.17  | −0.07 | −0.34 | 1.00  |       |       |       |       |       |       |       |       |       |       |       |
| 11 Δ Offline assortment breadth | 0.03  | 0.18  | 0.01  | 0.10  | −0.04 | −0.12 | −0.19 | −0.09 | −0.02 | 0.12  | −0.02 | 0.08  | 1.00  |       |       |       |       |       |       |       |       |       |       |
| 12 Δ Offline assortment depth  | 0.00  | 0.08  | 0.00  | −0.02 | 0.06  | 0.04  | 0.02  | −0.01 | 0.00  | −0.02 | 0.05  | −0.06 | −0.51 | 1.00  |       |       |       |       |       |       |       |       |       |       |
| 13 Δ Offline NB proliferation  | −0.01 | 0.05  | 0.02  | −0.07 | 0.05  | 0.13  | 0.03  | 0.07  | −0.03 | −0.02 | 0.03  | −0.03 | −0.02 | −0.01 | 1.00  |       |       |       |       |       |       |       |       |       |
| 14 Δ Offline price             | 0.00  | 0.08  | 0.00  | −0.02 | −0.01 | 0.00  | −0.03 | 0.09  | −0.12 | 0.00  | 0.01  | 0.00  | −0.01 | 0.03  | 0.00  | 1.00  |       |       |       |       |       |       |       |
| 15 Δ Category-specific retailer loyalty | 0.36  | 0.38  | 0.52  | 0.10  | 0.04  | −0.03 | −0.01 | −0.14 | 0.00  | −0.02 | 0.00  | 0.04  | 0.01  | 0.00  | −0.02 | −0.01 | 1.00  |       |       |       |       |       |
| 16 Δ Category importance       | 0.03  | 0.03  | 0.00  | 0.02  | −0.03 | −0.04 | −0.04 | 0.04  | −0.02 | 0.01  | 0.12  | 0.12  | 0.00  | −0.01 | 0.03  | 0.01  | 0.08  | 1.00  |       |       |       |       |
| 17 Δ Category expertise        | 0.99  | 0.14  | 0.00  | 0.05  | 0.16  | −0.07 | −0.02 | −0.16 | −0.05 | 0.06  | 0.00  | 0.06  | 0.08  | 0.03  | 0.00  | −0.05 | 0.07  | 0.05  | 1.00  |       |       |       |
| 18 Δ Going online at competitors | 0.19  | 0.39  | 0.09  | −0.15 | −0.05 | 0.02  | −0.04 | 0.07  | −0.02 | 0.01  | 0.00  | −0.01 | 0.00  | −0.01 | 0.08  | 0.01  | −0.20 | −0.20 | −0.20 | 1.00  |       |       |

a Before ln-transformation and mean-centering.
Table 4
Results of category expansion model.

| Variable                  | Main effects | Interaction effects |
|---------------------------|--------------|---------------------|
|                           | Mean (Std. Dev) | Std. Error | Mean | Std. Error |
| **Intercepts**            |              |          |      |              |
| Asda (αAsda)              | .786*** (.1259*** | .048 (.034) | -067* (.035) |
| Sainsbury’s (αSAINS)      | .714*** (.1258*** | .057 (.041) | .030 .028 |
| Tesco (αTESCO)            | .999*** (.1282*** | .032 (.023) | .102** .046 |
| Waitrose (αWAIT)          | 1.000*** (.1442*** | .088 (.064) | .155*** .023 |
| **Online and Multichannel Marketing Mix** |          |          |      |              |
| Relative online assortment breadth (β1) | -104* .060 |   |   |   |
| Relative online assortment depth (β2) | .0003 .083 |   |   |   |
| Online NB proliferation (β3) | -045 .061 |   |   |   |
| Online/offline assortment integration (β4) | .237*** .080 |   |   |   |
| Relative online price (β5) | -482* .256 |   |   |   |
| Online/offline price integration (β6) | .148 .114 |   |   |   |
| **Category Characteristics** |          |          |      |              |
| Planned (γ1)              | .018*** .005 |   |   |   |
| Heavy/Bulky (γ2)          | .013** .006 |   |   |   |
| Sensory (γ3)              | .004 .005 |   |   |   |
| **Control Variables**     |          |          |      |              |
| Δ Offline assortment breadth (τ1) | .999* .054 |   |   |   |
| Δ Offline assortment depth (τ2) | 0.059 .106 |   |   |   |
| Δ Offline NB proliferation (τ3) | .343* .185 |   |   |   |
| Δ Offline price (τ4)       | .061 .098 |   |   |   |
| Category-specific retailer loyalty (τ5) | 5.555*** .030 |   |   |   |
| Category importance (τ6)   | 1.655*** .258 |   |   |   |
| Category expertise (τ7)    | .607*** .057 |   |   |   |
| Going online at competitors (τ8) | .129* .063 |   |   |   |
| Inverted Mills Ratio (τ9)  | -2.128*** .074 |   |   |   |
| Copulas Correction Rel online price (τ10) | .058* .034 |   |   |   |

*p < .10, **p < .05, ***p < .01 (two-tailed).

Random coefficients (St. Dev.) are only estimated for the chain-specific constants.

at low (i.e., 1 SD below mean) and high (i.e., 1 SD above mean) values of the category characteristics. To obtain insights into the importance of each interaction, we calculate, for each significant interaction, how much category-level SoW would change relatively if the marketing mix variable were to increase from 1 SD below its mean to 1 SD above it, at low (i.e., 1 SD below mean) and high (i.e., 1 SD above mean) values of the focal category characteristic, keeping all other variables fixed at their mean value (Dhar and Stephen 1997; Lamey et al. 2018). These

12 For relative online assortment breadth, we derive the relative change in category-level SoW expansion for low planned categories (−1SD = −1.806) and high planned categories (+1SD = 1.806). For example, for low planned categories, the transformed category-level SoW expansion for assortment breadth (SD = .165) at 1SD below 0 (given mean-centering) for Asda is .786 + −.104 × (−.165) + .018 × (−1.806) + −.067 × (−.165) × (−1.806) = .742, where .786 is the chain-fixed effect, −.104 is the parameter estimate for online assortment breadth, −.067 is planned, and −.067 is their interaction in Table 4. The resulting relative change in category-level SoW expansion (i.e., ΔSoWcntr = ΔSoWcntr,thc + ΔSoWcntr,thc −1.177), after reconversion, is 2.46%. We estimate similar measures for each multichannel chain and compute a weighted average across the four chains (with market shares as weights). Next, we repeat these calculations at 1 SD above the mean for assortment breadth. The difference (in relative growth) for a variation of 1 SD on both sides of the marketing mix variable’s
findings appear at the bottom of the graphs in Fig. 2. For ease of interpretation, we classify the magnitude of each effect as large (>25%), medium (10–25%), or small (<10%) (Cohen 1988). The average relative SoW effect is 27.69% (Table 2), so a relative SoW effect of one SD around the mean of at least 25% should be considered strong (change in relative SoW of at least 6.92% = .25 × 27.69%), one of at least 10% might be a medium effect (change in relative SoW of at least 2.77%), and lower changes indicate small effects.

The estimation results suggest that for planned categories, online assortment benefits are less important; the interactions of the category characteristic planned with two online assortment-related marketing mix instruments, online assortment breadth (δ_{11} = −.07, p < .10) and online/offline assortment integration (δ_{41} = −.10, p < .05), are significant (weakly for the former) and negative. The positive impact of the online assortment on category-level SoW expansion thus appears attenuated for categories associated with perceived online ordering convenience. These findings confirm that the online assortment is less important in planned categories, in which consumers tend to use predefined shopping lists where the preferred item (that they regularly and out of routine buy) is registered.

Panel A in Fig. 2 reveals that online assortment breadth has a strong negative effect on SoW expansion in high planned categories (strong decreasing slope from small to large assortment breadth) but hardly any effect in low planned categories (no change in slope). The effect sizes are respectively −3.96% (medium) and .59% (small). The negative main effects for online assortment breadth again support the notion that providing too much choice in an online grocery context where assessment orientation tends to be low, can overload consumers, especially in relation to high planned categories. Panel B in Fig. 2 indicates that the interaction between planned and online/offline assortment integration exerts an effect in low planned categories, for which we find a strong positive effect of assortment integration (i.e., .62%, medium effect), but it has almost no influence on category-level SoW expansion in high planned categories (.25%, small effect). Thus, in low planned categories, retail chains should strive for a strong fit between their online and offline assortments, but in high planned categories, they should try to limit their online assortment breadth. Consumers thus do not need a huge set of brands in planned categories, because they use shopping lists to register their preferred brand while for categories that are bought in a spur, they prefer an online assortment that looks like the offline one, perhaps because familiarity helps them find the (low planned) item quickly.

For price, we find a significant negative interaction between planned and online/offline price integration (δ_{61} = −.12, p < .05). In an online environment, price comparisons are easier, so the price attribute becomes more important for planned categories in which consumers already are aware of the price level. In Panel C in Fig. 2, regarding high planned categories, a lower price integration between a chain’s online and offline channel ameliorates SoW expansion (2.99%, medium effect), but in low planned categories, we find the opposite (albeit weaker) result (−.73%, small effect).

We expected that in categories that would benefit from online delivery convenience, consumers should be willing to pay a price premium in the online channel, to compensate for the delivery advantages, but we find no evidence in support of this expectation (δ_{52} = −.01, p < .01 and δ_{62} = −.03, p < .01). Consumers may believe they already pay for these services in the delivery fee (which differs across chains but is likely constant over time and categories, so it gets captured in the chain-specific intercepts).

Finally, the risk of buying sensory categories online makes consumers more sensitive to the costs of shopping (online price), resulting in lower category expansion (δ_{33} = −.16, p < .01), and more reliant on risk-reducing factors such as online NB prolifer-
ation, leading to higher category expansion ($\delta_{33} = .14, p < .01$). Panel D in Fig. 2 shows that a chain’s online price, relative to its online competitors’ prices, strongly drives SoW expansion in sensory categories (-7.16%, large effect), whereas a high relative online price has hardly any effect in nonsensory categories (1.22%, small effect). Thus, large online prices prevent SoW expansion, especially for high sensory categories, or the other way around, expansion in high sensory categories can be stimulated by a lower online price. As Panel E in Fig. 2 shows, for high sensory categories, online NB proliferation positively influences SoW expansion (4.61%, medium effect), whereas it negatively influences expansion in low sensory categories (−6.39%, medium effect). As expected, NBs offer an important risk-reducing information cue for high sensory categories, but, in contrast to expectations, a large share of them actually has a negative effect on SoW expansion in categories that score low on sensory attributes. We speculate that consumers’ PL proneness might already be higher in categories with lower functional risk (e.g., low sensory categories) (Erdem, Zhao, and Valenzuela 2004; Steenkamp and Geyskens 2014), so they actually prefer an assortment with a smaller NB presence.

Robustness Checks

The results of a series of robustness tests to check the stability of our results are in Table 5.

Household-level heterogeneity in marketing mix effectiveness. Households might differ in their sensitivity to marketing mix instruments, so we reestimated our model, allowing for a random effect specification for each online and multichannel marketing mix driver. The estimated standard deviations indicate substantial heterogeneity across households for all marketing mix instruments ($p < .10$), except online assortment depth. Yet adding household heterogeneity to the slopes of the online and multichannel marketing mix variables does not change the other substantive findings. We retain our focal model because it had a better fit according to the Bayesian information criteria ($\text{BIC}_{\text{focal model}} = 510,425.6, \text{BIC}_{\text{random slopes}} = 510,474.0$).

Time-varying effects. We added trend variables (general and chain-specific) but then dropped them because they do not contribute to the model ($\text{BIC}_{\text{focal model}} = 510,425.6, \text{BIC}_{\text{general trend}} = 510,431.9, \text{BIC}_{\text{chain trend}} = 510,464.9$). The general trend variable turned out to be significant and positive and in the chain-specific trend model, only the trend variable for Sainsbury’s was positive and significant. In neither case did the addition of the variables affect the substantive findings. Finally, we divided our observation window into quarters and included quarter-chain dummies. This model also achieved worse fit ($\text{BIC}_{\text{focal model}} = 510,425.6, \text{BIC}_{\text{chain quarter}} = 510,654.3$), and the substantive findings did not change.

Discussion

With the rapid increase of multichannel grocery retailing, research in related topics has also surged, and existing studies show that multichannel buying behavior can vary across categories (Campo and Breugelmans 2015; Chintagunta, Chu, and Cebollada 2012) and thus that marketing mix decisions may have to be adapted accordingly (Briesch, Dillon, and Fox 2013; Broniarczyk, Hoyer, and McAlister 1998; Degeratu, Rangaswamy, and Wu 2000). Yet clear insights into the differential effects of online and multichannel marketing mix instruments on category performance are still lacking, despite their relevance for developing marketing mix strategies that can stimulate SoW expansion at the category level. While the past has concentrated on expansion effects at the aggregate chain level, covering all grocery purchases (Melis et al. 2016; Pozzi 2013a), it is of equal interest to focus on the category level.

Therefore, our primary research objective was to provide a structural analysis of category differences in expansion opportunities to establish how a differentiated online and multichannel marketing mix strategy might capitalize on the expansion advantages provided by some categories, while also reducing barriers to expansion for others. With an extensive, U.K. panel data set, covering all purchases in the online and offline channels of all major (single- and multichannel) supermarket chains over a varied and large set of categories during a more than two-year period, we estimate a two-stage model of differences in SoW expansion across categories, due to category characteristics, online and multichannel marketing mix instruments, and their interaction, conditional on a household’s decision to shop online at that chain. The findings reveal:

1. Some categories benefit more from online shopping convenience advantages than others. Planned and heavy/bulky categories benefit from the online channel’s ordering and delivery convenience, respectively, and also experience a greater SoW expansion.
2. We do not find a diminished online buying tendency for sensory categories with high perceived online purchase risk, but several interaction effects arise, as we discuss subsequently.
3. A higher online price and a broader online assortment, relative to online competitors, minimizes the SoW expansion; a better integration between the online and offline assortments strengthens it.
4. Several interactions between marketing mix instruments and category characteristics exhibit medium/large effect sizes (Fig. 2). A selective approach to online prices, online/offline price integration, online assortment breadth, online/offline assortment integration, and online NB proliferation that accounts for category differences in online-driven expansion can enhance a multichannel chain’s overall results. We discuss the specifics in the next section.

Managerial Implications

Our insights are especially relevant for multichannel retailers that need to develop an online and multichannel marketing mix strategy to stimulate category-level SoW expansion among consumers that have decided to start shopping online in the chain. In addition to multichannel retailers, our findings may be of use for nongrocery retailers like Amazon that are experimenting with which grocery categories to offer first or for manufacturers
that want to bypass retailers and offer their products directly to end-consumers on online platforms.

First, multichannel retailers should leverage online shopping advantages to exploit the results in categories that benefit most. For example, they should explicitly emphasize the benefits of online shopping, such as its ordering and delivery convenience. Such efforts might prompt consumers to try the online store and increase category purchases allocated to the chain.

Second, the significant main effects of relative online price, relative online assortment breadth, and online/offline assortment integration suggest that online grocery shoppers tend to make price comparisons across chains, because competitors’ online stores are just one click away, but they prefer small, familiar category assortments that allow them to make quick and convenient purchase decisions (see Melis et al. 2016 for similar findings at a chain SoW expansion level).

Third, we offer multichannel grocery retailers a roadmap for designing optimal marketing mix strategies for categories that score high or low on planned and sensory attributes (see Fig. 3). To enhance positive SoW expansion in planned categories, multichannel retailers should choose to offer a smaller assortment and highlight unique benefits, such as personalized online shopping lists, to nurture the habitual purchase behaviors that tend to arise in these planned categories. The suggestion to avoid large assortments, which evoke negative effects, is in accordance with studies that illustrate information overload influences (Iyengar and Lepper 2000). Such influences are likely to be stronger in an online shopping environment, which tends to evoke low assess-

| Table 5 | Robustness checks\(^a\) | Focal model | Random slopes marketing mix | Trend | Chain-specific trends | Chain-specific quarter quarter dummies |
|---------|--------------------------|-------------|----------------------------|-------|-----------------------|----------------------------------------|
| **Online and multichannel marketing mix** | | | | | | | |
| Relative online assortment breadth | – | ✓ | ✓ | ✓ | ✓ | ✓ |
| Relative online assortment depth | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online NB proliferation | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online/offline assortment integration | + | ✓ | ✓ | ✓ | ✓ | ✓ |
| Relative online price | – | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online/offline price integration | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Category characteristics** | | | | | | | |
| Planned | + | ✓ | ✓ | ✓ | ✓ | ✓ |
| Heavy/Bulky | + | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sensory | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Interactions** | | | | | | | |
| Relative online assortment breadth*Planned | – | ✓ | ✓ | ✓ | ✓ | ✓ |
| Relative online assortment breadth*Sensory | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Relative online assortment depth*Planned | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Relative online assortment depth*Sensory | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online NB proliferation*Planned | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online NB proliferation*Sensory | + | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online/offline assortment integration*Planned | – | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online/offline assortment integration*Sensory | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Relative online price*Heavy/Bulky | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Relative online price*Planned | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Relative online price*Sensory | – | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online/offline price integration*Heavy/Bulky | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online/offline price integration*Planned | – | ✓ | ✓ | ✓ | ✓ | ✓ |
| Online/offline price integration*Sensory | 0 | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Extra variables** | | | | | | | |
| SD Relative online assortment breadth | sig. | | | | | |
| SD Relative online assortment depth | 0 | | | | | |
| SD Online NB proliferation | sig. | | | | | |
| SD Online/Offline assortment integration | sig. | | | | | |
| SD Relative online price | sig. | | | | | |
| SD Online/Offline price integration | sig. | | | | | |
| Trend dummy | + | | | | | |
| Trend Asda | 0 | | | | | |
| Trend Sainsbury's | + | | | | | |
| Trend Tesco | 0 | | | | | |
| Trend Waitrose | 0 | | | | | |
| Chain-specific quarter dummies | +*\(^b\) | | | | | |

\(^a\) Control variables are omitted due to space constraints.

\(^b\) All chain-specific quarter dummies are positive and significant except for one that is positive and significant at \(p = .139\).

\(\sqrt{\text{indicates the parameter is similar in significance and, if significant (}p < .10\text{), in direction to the focal model results; 0 is not significant (}p > .10\text{), sig. is significant (}p < .10\text{), and - is negative significant (}p < .10\text{).}}\)
ment orientation and that does not lend itself easily to a quick and complete assortment overview (e.g., multiple screens are needed to see the whole assortment). Especially for planned categories where consumers prefer the use of a shopping list, consumers may consider the task to make a decision via the category selection in the webshop as an additional barrier when they face at that moment a large assortment, where they need to scroll down multiple screens. SoW expansion for categories that are bought in a spur can be reinforced by better integration between the online and offline channel, in terms of both price and assortment. In their relatively impulsive purchase decisions, consumers seem to appreciate simple decision cues in an environment, as can be evoked by familiarity due to similarity across channels.

Furthermore, in high sensory categories that induce high online purchase risk, multichannel retailers should reduce purchase barriers by charging lower online prices or including a large share of NBs. In low sensory categories though, retailers can opt to highlight their PL assortment, as results suggest that a large share of NBs in such categories hinders SoW expansion.

In these categories where there is low need for touch and feel, consumers clearly prefer PLs above NB offerings (Steenkamp and Geyskens 2014).

**Limitations**

Some limitations of this study point to several interesting areas for additional research. First, we investigate category expansion effects following consumers’ decision to shop online in the short run. Some research in the consumer durables sector indicates that multichannel consumers’ spending behavior converges with that of single-channel consumers in the long run (Bilgic et al. 2015). Yet other studies of the online grocery sector reveal a medium to long-lasting increase in SoW due to shopping online (Melis et al. 2016). It would be interesting to investigate whether category expansion effects persist and to check explicitly whether category purchase allocation processes are dynamic.

Second, shopping basket compositions and cross-category relationships (for complementarity or substitutive categories)
might change when consumers go online. Also, the question which competitive chains are most hurt by a consumer’s reallocation of his/her category spending needs further attention. Continued research might develop a model that accounts for interdependencies among categories and among chains within a household. Another direction for research might explore the gross and net profit implications of a consumer’s reallocation of category spending across chains. Such insights can help retailers target the “right” customer in the “right” category to maximize short- and long-run profits.

Third, our model includes the actual price paid, capturing both regular prices and discounts (Gicheva, Hastings, and Villas-Boas 2010; Hökelekli, Lamey, and Verboven 2017). Overall and category-specific promotional activities like price discounts, displays, features, and advertising, both online and offline, likely exert influences though. On the basis of our conceptual framework, we expect that cost-related factors like online price discounts and promotion integration between channels may be more influential in categories that evoke more perceived risk but less influential in those that offer high convenience benefits. Further research might extend our model with promotion-oriented variables to test these predictions. Also alternative assortment measures, reflecting specific product features (e.g., size, flavor), might prove insightful.

Fourth, we lack information about other, external, time-varying events (dissatisfaction due to a service failure, revised website design, change to the service delivery policy, advertising) that may influence online chain choice and category spending allocations across chains. Additional research should control for these elements.

Fifth, our descriptive statistics indicate a spillover to offline outcome measures, but more detailed analyses would be worthwhile. Future research could develop a model that allows one to disentangle the sources of overall SoW expansion (i.e., online, offline, or both) and the impact of the marketing mix on each component. In addition to formally exploring whether SoW expansion also results from greater offline expenditures, it may be pertinent to identify different sources of category-level SoW expansion (increased category purchase incidence, volume, more expensive brands).

Sixth, we include some household-specific control variables and allow the chain-specific intercepts to vary across households (random effects), but continued research could examine customer heterogeneity in more detail, such as by accounting for consumer-level differences in assortment or price sensitivity or measuring the category characteristics (planned, heavy/bulky and sensory) at the household level.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at https://doi.org/10.1016/j.jretai.2020.05.003.

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