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Does Online Information Drive Offline Revenues? Only for Specific Products and Consumer Segments!

Koen Pauwels [a,*], Peter S.H. Leeflang [b], Marije L. Teerling [c,1], K.R. Eelko Huizingh [d]

[a] *Ozyegin University, Kusbakisi Street 2, 34662 Altunizade, Üsküdar, İstanbul, Turkey*
[b] *Marketing Department of University of Groningen, Faculty of Economics and Business, The Netherlands*
[c] *Telematica Instituut, P.O. Box 589, 7500 AN Enschede, The Netherlands*
[d] *Department of Business Development, Faculty of Economics and Business, The Netherlands*

Abstract

While many offline retailers have developed informational websites that offer information on products and prices, the key question for such informational websites is whether they can increase revenues via web-to-store shopping. The current paper draws on the information search literature to specify and test hypotheses regarding the offline revenue impact of adding an informational website. Explicitly considering marketing efforts, a latent class model distinguishes consumer segments with different short-term revenue effects, while a Vector Autoregressive model on these segments reveals different long-term marketing response.

We find that the offline revenue impact of the informational website critically depends on the product category and customer segment. The lower online search costs are especially beneficial for sensory products and for customers distant from the store. Moreover, offline revenues increase most for customers with high web visit frequency. We find that customers in some segments buy more and more expensive products, suggesting that online search and offline purchases are complements. In contrast, customers in a particular segment reduce their shopping trips, suggesting their online activities partially substitute for experiential shopping in the physical store. Hence, offline retailers should use specific online activities to target specific product categories and customer segments.

Keywords: Offline revenue effects of an informational website; Web-to-store shopping; Sensory products; Latent class model; Vector Autoregressive models

Introduction

Since the commercialization of the World Wide Web, most established offline companies have set up websites to increase revenues. Many of these websites do not allow customers to make purchases online (Carroll 2002; Okazaki 2005; Van den Berg 2008)[1]; that is, they are *informational* instead of transactional (Teo and Pian 2004). Retailers may have many reasons to forego a transaction function on their website, including high expected costs and low expected benefits. As to the former, informational websites are easier to implement, because they do not require integration with the follow-up processes demanded by online orders. As to the latter, a majority of consumers still prefer to purchase in physical stores (67 percent according to Accenture, 2007), while using the Internet for information search regarding product features and prices (Mendelsohn, Johnson, and Meyer, 2006). This strategy of researching online and buying offline has been coined 'web-to-store' shopping or 'research' shopping (Verhoef, Neslin, and Vroomen 2007). Interestingly, especially heavy Internet users use the Internet for such pre-purchase information search (Jepsen 2007).

* Corresponding author. Tel.: +90 216 559 2373; fax: +90 216 559 2499.
E-mail addresses: koen.pauwels@ozyegin.edu.tr (K. Pauwels), p.s.h.leeflang@rug.nl (P.S.H. Leeflang), Marije.Teerling@telin.nl (M.L. Teerling), k.r.e.huizingh@rug.nl (K.R.E. Huizingh).

[1] Carroll (2002) and Van den Berg (2008) report that respectively 70 percent and 63 percent of company websites do not allow customers to make purchases online. Okazaki (2005) considers European websites for the US brands in Business Week's 'Top 100 Global Brands'. Even for this select sample, only a minority of websites (49.6 percent, as computed from his table III, line 8) allow for online purchase. Unfortunately we found no references for how many *retailer*'s sites are transactional, a task which is complicated by the current fusion between retailers and manufacturers. Famous examples of 'pure' retailers with an informational website include Ikea, Zara, We and Bailey, Banks and Biddle in the US, and Hema and Kruidvat in the Netherlands.

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Despite the rush of offline retailers to set up informational websites, the revenue implications of such actions are not well understood. Indeed, marketing literature has focused on transactional websites (e.g., Ansari, Mela, and Neslin 2008; Biyalogorsky and Naik 2003; Danaher, Wilson, and Davis 2003; Pentina, Pelton, and Hasty 2009; Zhang and Wedel 2009) and websites supported by third party advertisers (Deleersnyder et al. 2002; Geyskens, Gielens, and Dekimpe 2002; Pauwels and Weiss 2008). As a result, "systematic study of the Internet as an information source has been limited" (Ratchford, Lee, and Talukdar 2003), although informational websites can be an important part of shaping the customer experience (Grewal, Levy, and Kumar 2009).

Studies on the Internet as an *information channel* have concentrated on the benefits to consumers (Ratchford, Lee, and Talukdar 2003), not on the revenue performance implications for the company. The main exception is Lee and Grewal (2004), who investigate the *financial* market valuation impact of adding the Internet as a communication channel. As a result, current marketing literature is still silent on whether and how adding an informational website affects offline customer buying behavior and company revenue performance. The most likely cause is the inability to combine data regarding actual search behavior in one channel with actual buying behavior in another for a specific company (Neslin et al. 2006; Thomas and Sullivan 2005). Indeed, studies relating online browsing with offline buying in general (e.g., Rasch and Lintner 2001; Verhoef, Neslin, and Vroomen 2007) cannot show whether such online search benefits the offline revenues of the company that operates the informational website.

The impact of both the introduction of a website and of its related marketing actions likely depends on product type (Huang, Lurie, and Mitra 2009). As a result, several recent papers (Neslin et al. 2006; Verhoef, Neslin, and Vroomen 2007) call for further research on actual search and purchase behavior from a *single firm* perspective, explicitly distinguishing customer segments and product categories and considering the impact of marketing actions.

This paper aims to answer these calls by studying the revenue performance impact of introducing an informational website for an offline department store with many, and very different product categories. We draw on the information search literature to specify and test hypotheses regarding the offline revenue impact of adding an informational website. We use data from a panel of individual customers that contains offline purchase behavior, customer characteristics, and website use data. We first segment customers based on their short-term response to website introduction and marketing actions using latent-class segmentation (Kamakura and Russell 1989). This analysis reveals three distinctive customer segments. Vector Autoregressive models reveal the differences in short-term and long-term responses of these customer segments to website introduction and online marketing actions (price promotions and non-price communications). Finally, we investigate whether the revenue impact derives mostly from changes in customer numbers, shopping trips per customer, products bought per trip or money spent per product.

To the best of our knowledge, this is the first study to (1) quantify the short-term and long-term effects of introducing an informational website on different offline revenue components, (2) distinguish the performance implications for different types of products and (three) customer segments, and (3) which is based on a methodology that combines latent class analysis and VARX modeling. We find support for our hypotheses that:

1) The revenue impact of web site introduction is positive in the short run, because it draws more customers to the store.
2) The long-run revenue impact of web site introduction depends on the customer segment: while consumers in two out of three segments buy higher margin products, consumers in the remaining segment reduce their shopping trips to the store.
3) The revenue impact of website introduction is higher for sensory products than for non-sensory products.
4) The revenue impact of website introduction is higher for customers living farther away from the store and for customers with high web visit frequency.
5) Online promotions increase revenues in the short run, but non-price online communications do so in the long run.

Conceptual development

By adding an informational website, managers aim to increase offline store revenue components, such as inducing customers to spend more *money* per product, increasing the number of *products* bought per trip, increasing the frequency of store *trips* per week, or increasing the number of weekly *customers* (Lam et al. 2001). All of these intended benefits require (some) customers to adapt their behavior in response to the informational website.

In this study we decompose (weekly) offline buying behavior into managerially relevant elements, as detailed in Eq. (1):

$$\text{Total Offline Revenue}_t = \frac{\tilde{M}_t}{\tilde{P}_t} \times \frac{\tilde{P}_t}{\tilde{T}r_t} \times \frac{\tilde{T}r_t}{C_t} \times C_t \qquad (1)$$

where for week t, $\tilde{M}_t$ is the monetary value spent, $\tilde{P}_t$ is the total number of products purchased, $\tilde{T}r_t$ is the total number of shopping trips and C_t is total number of customers. The first component represents the money spent per product bought (hereafter Money$_t$), that is, the average retail price. The second component represents the number of products bought per shopping trip (hereafter Products$_t$), that is, the size of the basket. The third component represents the frequency of shopping trips among that week's customers (hereafter Trips$_t$). Finally, the fourth component represents all panelists who shopped at least once in week t (hereafter Customers$_t$).

Previous literature using a decomposition of (sales or revenue) performance has most often analyzed the effects of price promotions (e.g., Gupta 1988; Pauwels, Hanssens, and Siddarth 2002). Price promotions tend to increase products bought in the category over several weeks, but do not affect any component of retailer revenue in the long run (Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002). While we use the price promotion literature for developing hypotheses on the effect of online and offline promotions, the temporary nature of a price promotion clearly differs from the enduring nature of maintaining a website. Moreover, the informational content is typically minimal for price promotions, but key for an informational website. Therefore, literature on the revenue component effects of other informational marketing activities is also relevant to our research purpose. Most importantly, the marketing communications literature has demonstrated that advertising may draw in customers, at least in the short run, and may divert these customers towards more expensive items (Pauwels and Neslin 2008; Tellis 2004). In a retailing context, Van Heerde, Gijsbrechts, and Pauwels (2008) found that communicating a major price decrease boosted customer traffic due to increased search, but only in the short run. Several papers in the marketing communications literature base their conceptual development on information processing and search theory, on which we base ourselves directly to formulate hypotheses on the revenue effects of introducing an informational website.

Information processing/search and its impact on consumer decision-making has been a key focus of marketing and consumer behavior research for several decades (e.g., Bettman 1979; Ratchford, Lee, and Talukdar 2003), but the effects of an information channel on consumer purchase behavior, and hence firm revenues, have yet to be established. In this framework, consumers search for and process information in a goal-oriented fashion. Analysis of the economics of search behavior logically implies a cost-benefit framework: consumers search more if the search costs are low and/or if the benefits of additional search are high. As to the former, the introduction of an informational website offers customers the opportunity to lower search costs (InternetRetailer 2008; Ratchford, Lee, and Talukdar 2003), and should thus increase the likelihood they buy from the company at all in any given week (Pauwels and Neslin 2008), as long as the company's offer is competitive. This boost in customer numbers happens right away. As to the latter, the benefits of this increased information should be especially valuable to reduce the perceived risk consumers feel for higher priced items, thus facilitating purchase of such items (Verhoef, Neslin, and Vroomen 2007). Evidently, this upgrade to more expensive items is unlikely to happen overnight; customers need to obtain a substantial amount of information over time to get more comfortable buying high ticket items. Therefore, we hypothesize that:

H1. The introduction of an informational website (a) increases in the short run the number of Customers that visit the store, and (b) increases in the long run the amount of Money spent per product.

However, increased search efficiency may not always benefit the revenues of the company introducing the informational website. In the automobile market, Klein and Ford (2003) find that online visits substitute for dealer visits and that consumers use "any gains in efficiency to search a broader number of sources and source types". The authors conclude "that, over time, consumers will use the Internet more as both a substitute and a complement to traditional search". Thus, we expect that, over time, some consumers will enjoy the more efficient search, but end up making less shopping trips to the offline retailer providing the website.

Moreover, consumers may not just shop for the utilitarian value of purchasing a product, but also for the hedonic value (Babin, Darden, and Griffin 1994; Bloch and Richins 1983). Such experiential shopping allows consumers to enjoy the benefits of consuming a product without purchasing it (MacInnis and Price 1987).

An informational website allows consumers to (1) entertain themselves with activities unrelated to products (e.g., online games), and (2) visualize/fantasize using the products with product-related activities (e.g., online simulations on how the products fit into the customer's home/lifestyle). These enjoyable activities induce customers to (1) loose themselves in the website and not get into buying action at all, or (2) prefer to continue the positive online experience by purchasing in the online channel, which requires switching to a competitor's transactional website. Thus, the experiential aspects of visiting the informational website partially *substitute* for making trips to the offline store. Again, the switch from offline to online browsing behavior is likely to occur gradually over time.

H2. The introduction of an informational website decreases shopping Trips to the offline store in the long run.

In light of these multiple and often opposing influences, we propose that the revenue effects of an informational website and its related marketing actions depend on the search and experiential shopping characteristics for specific products and specific customers. Hence we expect heterogeneity in the way consumers react to the website's introduction. Given that we do not know a priori which customers react in what way, we apply latent class analysis to define market segments. Fig. 1 visualizes our framework.

Marketing literature implies directional hypotheses for several variables in our framework.

Product type: sensory versus non-sensory products

From the early days of e-commerce, managers and researchers have believed the Internet channel plays a different role for different products depending on whether the medium is able to convey information on the important product attributes (Alba et al. 1997; Peterson, Balasubramanian, and Bronnenberg 1997). The "intangible" nature of e-commerce may increase consumers uncertainty about whether products shown online will fit their needs (Weathers, Sharma, and Wood, 2007). Recently Huang, Lurie, and Mitra (2009) examined online behavior of US consumers gathering information for both search and experience goods. They find that experience goods involve greater depth (time per page) and lower breadth (total number of pages) of search than search goods. Hsieh, Chiu, and Chiang (2005) found that online different bonds (e.g., financial, social, and structural bonds) are important for different kinds of goods. In our study, we distinguish between sensory and non-sensory products. Customers evaluate sensory products using all their

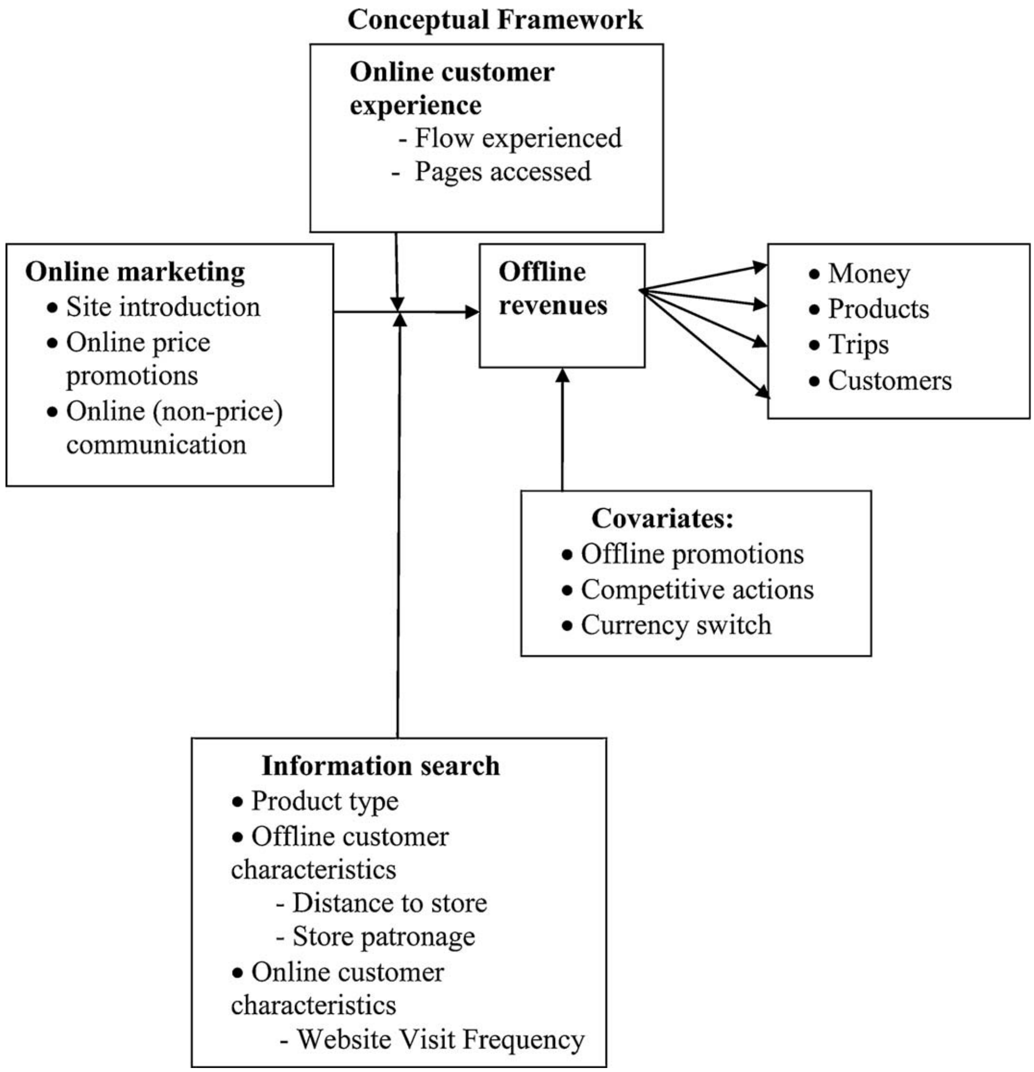

Fig. 1. Conceptual framework.

senses, especially touch and smell, before purchase (Degeratu, Rangaswamy, and Wu 2000). Examples include clothes and cosmetics. In contrast, customers can assess the value of non-sensory products objectively using readily available information conveyed by descriptions (Degeratu, Rangaswamy, and Wu 2000). The classification of sensory and non-sensory products is not identical to the classification of search and experience goods. Crucial in the distinction between sensory and non-sensory is whether the Internet is able to convey all information needed before purchase.

A transactional site makes more sense for non-sensory products, as evidenced by the online success of electronics, CDs and books. Online product and price information for such products may yield sufficient information to purchase the product right away. In contrast, research shows that *buying* online is less suitable for products with more sensory attributes. First, customers prefer to buy through channels that accurately portray the characteristics of the product (Burke 2002), which is much tougher online for sensory versus non-sensory products (Degeratu, Rangaswamy, and Wu 2000). Second, consumers typically perceive more risk when buying sensory products and thus need more information in total before purchase (Citrin et al. 2003; Peck and Childers 2003). Therefore, an *informational website* and its online communication may be especially valuable for customers planning to buy a sensory product. Indeed, a recent study found that, as the complexity of the product increases, consumers are more likely to research both online and offline and then complete their purchase at a local store (InternetRetailer 2008). The higher perceived risk and need for information drives customers to search online for product information and prices, and then go to the offline store for touch/smell/sound characteristics and for the ultimate purchase. An informational website is consistent with this consumer search process and should thus increase all four revenue components more for sensory versus non-sensory products.

H3. Compared to non-sensory products, sensory products experience higher short-term and long-term revenue effects from the introduction of an informational website.

Customer offline search cost: distance to the store

In the offline world, customers occur a fixed search cost related to the distance they have to travel to the store (e.g., Fox and Hoch 2005). Customers living in close proximity therefore enjoy high store accessibility and lower search costs. If online browsing (partially) substitutes for offline browsing the introduction of an informational website will even *reduce* trips (Mathwick and Rigdon 2004). The informational website offers customers who live further away a low cost medium to reduce their overall search time (Ratchford, Lee, and Talukdar 2003), and facilitate better and more efficient decision-making (Alba and Lynch 1997; Hoque and Lohse 1999). Such informative and convenient online search experiences increase customer perception that it is beneficial to make the trip to the physical store for purchase. Therefore, the introduction of the informational website could *gradually* increase the number of long-distance customers that make a shopping trip in any given week.

H4. Compared to customers who live close to the offline store, customers who live far from the offline store show higher long-term revenue effects from the introduction of an informational website due to a higher number of Customers in any given week.

Customer online search: website visit frequency

Once the informational website is introduced, managers can observe how often specific customers use the website. Website visit frequency increases the impact of both website introduction and its online communication on the customer's purchases. On the one hand, customers who visit the website more frequently are more likely to be exposed to its (product) information and online communications. On the other hand, as elaborated earlier for Hypothesis 2, some customers with a higher site visit frequency may simply be entertaining themselves, and actually end up visiting the offline store less often. We believe that the positive effects of site visit frequency will overcome this potential negative in the overall revenue impact. For transactional websites, Moe and Fader (2004) find that consumers with a higher visiting frequency also have higher conversion rates online. For informational sites, we propose that higher visits frequency of the particular website indicates search and preference for the products offered by the specific retailer, which should eventually increase revenue.

H5. Compared to customers with low website visit frequency, customers with high website visit frequency show higher long-term revenue effects from the introduction of an informational website.

Other offline and online customer characteristics

Other potentially important customer characteristics include the extent of prior store patronage, website flow experience and the content of the pages accessed. For these variables, marketing literature is unclear as to whether to expect a positive or a negative impact on the revenue effects of introducing an informational website.

First, customers with extensive *store patronage* (prior to website introduction) tend to be familiar with the offline store and the products it offers. In customer search literature, the relationship between knowledge and search is not unequivocal; while some studies found that unfamiliarity increases search (Moore and Lehmann 1980; Reilly and Conover 1983), others found that unfamiliarity may decrease search (Alba and Hutchinson 1987; Johnson and Russo 1984; Punj and Staelin 1983; Urbany, Dickson, and Wilkie 1989).

Second, customer *flow* has been shown to influence cross-channel effects (e.g., Mathwick and Rigdon 2004; Novak, Hoffman, and Yung 2000). Hoffman and Novak (1996) define flow as a state characterized by a seamless, self-reinforcing sequence of responses facilitated by machine interactivity, intrinsically enjoyable, and accompanied by a loss of self-consciousness. Website visitors in flow search deeper (Hoffman and Novak 1996) and have more positive attitudes toward the firm's website (Mathwick and Rigdon 2004). However, shoppers with a high 'flow' experience online may buy less rather than more from the company, even at a transactional website (Moe 2003; Moe and Fader 2004). For an informational website, where customers have to go to the offline store to purchase, the effect of online flow experience on purchases is even more ambiguous.

Finally, the content of the online pages accessed may also be associated with different revenue implications for the company. Because the content of pages is specific to a particular website, we investigate this in an exploratory fashion for the website of our data provider.

Online marketing: price-oriented promotions and non-price oriented communications

The introduction of an informational website enables a company to add channel-specific marketing actions, whose effects may be an important driver of total revenue impact (Neslin et al. 2006; Pauwels and Neslin 2008). We classify online marketing efforts into online price *promotions* and (non-price) online *communications*. Online price promotions *inform* customers about the *price* and availability of a product, whereas non-price online communications inform customers about product *positioning and unique product characteristics*.

We expect that online price promotions have similar effects as offline price promotions do. They increase revenues in the short run, though not necessarily in the long run (Blattberg, Briesch, and Fox 1995; Hanssens 2009; Jedidi, Mela, and Gupta 1999; Pauwels et al. 2002Pauwels, Hanssens, and Siddarth 2002; Pauwels et al. 2004; Srinivasan et al. 2004; Van Heerde, Leeflang, and Wittink 2001, 2004). While they increase the number of customers coming to the store in the week of promotion, many of these customers may be cherry picking cheap products (Fox and Hoch 2005), leading to a lower average revenue per product (Van Heerde, Gijsbrechts, and Pauwels 2008). Hence, we hypothesize:

H6. Online price promotions (a) increase revenue in the short run, through (b) higher number of Customers, while (c) money spent per product decreases.

Table 1
Classification of product type.

Product category	Classification	Studies
Consumer electronics	Nonsensory	Burke (2002), Citrin et al. (2003)
CDs, books, DVDs	Nonsensory	Burke (2002), Citrin et al. (2003)
Computer hard- and software	Nonsensory	Peterson et al. (1997), Van Baal and Dach (2005)
Toys	Nonsensory	Van Baal and Dach (2005)
Clothing	Sensory	Citrin et al. (2003), Van Baal and Dach (2005)
Shoes and accessories	Sensory	Peterson et al. (1997), Citrin et al. (2003)
Cosmetics	Sensory	Van Baal and Dach (2005)
Furniture	Sensory	Van Baal and Dach (2005)

Table 2
Socio-demographics of site visitors versus non-site visitors.[a]

	Site visitors	Non-site visitors	Test value
Age	39.5	42.7	**3.19**
Number of children	1.2	1.2	.52
Number of adults	2.2	2.3	.64
High school education	98.0%	97.5%	.13
College education	45.7%	29.8%	**12.14**
Distance to closest store	6.5	6.2	−1.59
Gender: male	44.8%	23.1%	**22.66**
Gender: female	55.2%	76.9%	
N	6594	951	

[a] Bolded test values are significant at the 5% level.

We expect (non-price) online communications to work in a similar way as non-price oriented advertising. In contrast to price promotions, (non-price) online communications reduce price sensitivity as they are geared toward communicating unique brand or product features (Kaul and Wittink 1995). Therefore, they should lure consumers towards higher-ticket items. Likewise, online communications may entice interest for more products, thus increasing the number of products bought per trip, and for the retailer, increasing the number of trips and the number of weekly customers (Dekimpe and Hanssens 2007; Hanssens 2009; Vakratsas and Ambler 1999). Just like offline (non-price oriented) advertising, these benefits are unlikely to materialize immediately. Instead, they occur several weeks after the marketing action (ibid).

H7. Non-price online communications (a) increase offline revenues in the long run, through (b–e) all four revenue components.

Covariates In our model, we account for the effect of other variables that are likely to influence a retailer's (offline) revenues, namely offline promotions by the retailer, major competitive activity and a switch in the national currency.

Data and variable operationalization

We collect data from customers of a large, well-known national retailer in the Netherlands that offers 58 department stores in major urban areas. A typical outlet carries 13 different departments, such as clothing, interior design, books, and cosmetics (see Table 1). This firm participates in a national joint loyalty program of 21 partner firms in the Netherlands. Customers collect credits by purchasing from these different firms, which range from retail stores to banks to gasoline stations. In turn, they may exchange these credits to receive discounts on products sold by the member firms or theatre or airline tickets. This popular program was established in the early, 1990s, and at the time of the data collection, more than half of all Dutch households were members of this loyalty program.

The focal firm, which previously focused solely on its offline stores, introduced an informational website in March 2001. In 2001, the majority of Dutch consumers already had Internet access on the home PC (CBS 2002). This site was designed to support the firm's offline promotions, to improve store image, and to increase the likelihood of buying in the stores. The site introduction was announced through mass media and mailings. To get access to the site, customers had to register during their first website visit using their loyalty card number. Contentwise, the site includes category-specific pages such as fashion and home, but also general pages such as lifestyle issues, tips on gift giving, and 'especially for you' recommendations. Products shown on the website pages include both nonsensory products (46 percent) and sensory products (54 percent). Moreover, entertainment pages unrelated to company products include games, sports and Ecards. In sum, the informational website is not simply an electronic brochure; it allows customers to search for specific information, to explore themes and to have fun.

In addition to the permanent themes, the site uses temporary pages to alert customers to price promotions, such as the annual Christmas promotions and other major promotions in the department store. These online price promotions are coded as dummies in our dataset.

The company regularly changed the (non-price) communication on the informational website; represented as (non-price) 'online communication' dummies in our data. Customers were notified of both online promotions and online communications via e-mail.

The data used in our model estimation pertain to the behavior of 6594 customers, all of them have visited the website at least once. How typical is this group for the full retailer's clientele? We also have data on 967 customers that did not sign up for, and thus never visited the website. Table 2 compares these two groups in terms of shopping and demographic variables. Consistent with the general characteristics of Internet users versus nonusers (e.g., Ratchford, Lee, and Talukdar 2003), company website users are younger, more likely to be male and to have a college education. In other aspects, customers using the website are similar to other customers. In any case, they are numerous and they are the ones whose purchase behavior may be affected. Our analysis therefore focuses on the customers that have visited the website at least once.

The data include these customers' offline buying behavior for 127 weeks: 60 weeks before the introduction of the website, and 67 weeks after the introduction of the website; for which we also have data on online search behavior. Fig. 2 shows the timeline and the data periods used in our analysis.

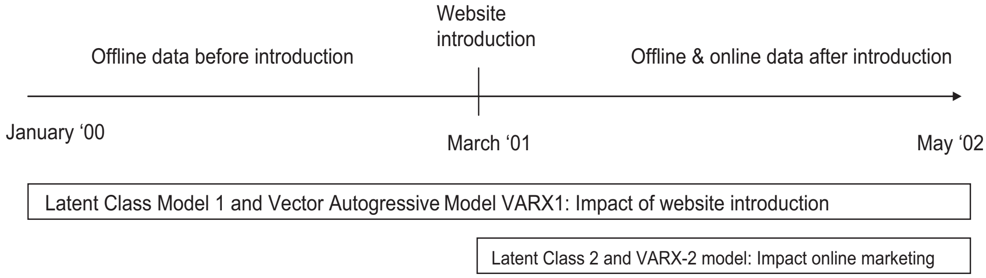

Fig. 2. Timeline of data and model estimation periods.

The time span of the panel is 2.5 years, so we were concerned with the potential of panel attrition limiting the generalizability of our results. However, a very high percentage (92 percent) of the store's customers stays in the panel for the full period. The low attrition of this panel is intuitive because of the type of store (department store with a large assortment), few competitors (department stores) and the popularity of the joint loyalty program of 21 partner firms, which is not dependent on any one retailer.

For each variable used in our analysis,[2] Table 3 details the operationalization. The marketing actions are captured by a pulse dummy during the week they were executed. As for competition, we include a pulse dummy indicating publicly announced competitive actions. Six such actions occurred in our data period, including a web store opening in 2000, a loyalty program introduction and (national TV-) advertisements with extensive promotions in 2001 and a new magazine distribution in 2002. As a final control variable, the national switch from the Dutch guilder to the Euro currency is included as a step dummy (0 before, 1 after Euro introduction). This currency switch may be important because of popular opinion that retailers used the Euro introduction to raise prices "under the radar", which could have boosted company revenue (El Sehity, Hoelzl, and Kirchler 2005). On the other hand, it is well documented that Dutch consumers became reluctant in their spending because of this suspicion (Folkertsma, van Renselaar, and Stokman 2002), and thus may have reduced their spending at the retailer. The introduction of the Euro occurred 45 weeks after the site introduction[3].

Two variables in Table 3 deserve further explanation. First, the impact of website introduction is captured both with a step dummy ('siteintrostep') and with a pulse dummy ('siteintro') variable. The step variable equals 0 before website introduction, and 1 afterwards. Thus, its coefficient reflects an intercept shift in the relevant dependent variable (total offline revenue and each of its components). In contrast, the pulse dummy variable only equals 1 in the week of website introduction. Thus, its coefficient reflects the short-run (immediate) effect of website introduction on the relevant dependent variable. Second, the information on the online flow experience (and on demographics and web use variables) is obtained through two online questionnaires, conducted three months after the introduction of the website in May 2001 and one year later in May 2002. The response rate to this online questionnaire was 39 percent in 2001 and 61 percent in 2002. Flow is a multi-item construct represented by the mean of responses to questions in both questionnaires, shown in Appendix A. All questions use a five-point scale. As a reliability measure, the Cronbach alpha of the flow construct is .93 for 2001 and .94 for 2002.[4]

Methodology

We model the short-term and the long-term effects of website introduction and marketing actions by means of both (1) a customer-level latent class analysis and (2) an aggregate Vector Autoregressive (VARX) model. The former model allows us to examine different customer response to web site introduction and to group customers based on their response. The logic behind latent class segmentation is that we empirically capture response heterogeneity without having to formulate a priori hypotheses, which would not be possible due to the dearth of previous literature. The mixture modeling technique that we apply un-mixes the sample into (latent) classes as we do not know a priori the number of these classes, their identification and their behavior.

The VARX model offers a flexible way of relating revenue components and marketing actions over time. We also divide the data set into 2 periods: the full dataset and the period after web site introduction (see Fig. 2). The full dataset allows us to analyze how company performance changed with the introduction of the website, while the latter dataset allows us to study the specific effects of online marketing actions. Combining methodology with data period yields four model specifications, as detailed below.

[2] The highest correlation coefficient amongst the models' variables is 0.43; between online and online promotions. We re-estimated all models using a different operationalization (no promotion, online promotion only, offline promotion only and online + offline promotion), and found results consistent with the reported model findings. Moreover, we note that the Vector Autoregressive model is especially suited to deal with correlated variables, as each variable is explained by all the other endogenous variables. For instance, if more customer visits implies a lower number of products bought per visits, this effect is captured through the residual covariance matrix and visualized in the generalized impulse response function (Dekimpe and Hanssens 1999; Pesaran and Shin 1998).

[3] Given the long period between website introduction and Euro introduction, we also estimated our models on the data before Euro introduction. All of our substantial results hold up in this shorter time period. We thank an anonymous reviewer for this suggestion.

[4] We also repeated our analysis without the flow construct, including all the customers that failed to fill out the flow questionnaire. Our substantive results did not change.

Table 3
Variable operationalization.

Construct	Abbreviation	Operationalization
Before versus after site introduction	SiteIntroStep	Step dummy variable with value 0 before site introduction and 1 after site introduction
Week of site introduction	SiteIntro	Pulse dummy variable with value 1 in the week of website introduction, 0 otherwise
Online communication	OnComm	Dummy variable indicating presence of non-price oriented online communication that week
Online price promotion	OnProm	Dummy variable indicating presence of online price promotion that week
Offline promotions	OffProm	Dummy variable indicating presence of online price promotion that week
Competitive action	Comp	Dummy variable indicating prominent actions by a competing retailer that week
Switch to Euro currency	Euro	Step dummy variable with value 0 before the switch to Euro currency and 1 afterwards
Sensory product	Sens	Dummy variable indicating if the product bought by customer i in week t is a sensory product
Distance to the store	Dist	Distance in km of the customer residence to the nearest store of the company
Store patronage	Patron	Customer total revenue spent at the store before the introduction of the website
Frequency of site visits	Freq	Average weekly frequency of website visits by the customer
Flow experienced in web site visits	Flow	Self-reported flow experienced by customer *i* while visiting website
Customer revenue	Revenue	Total revenue for the company from customer *i* in week *t*
Revenue per product	Money	Average retailer revenue per product sold to customer *i* in week *t*
Products per trip	Product	Average number of products sold per shopping trip of customer *i* in week *t*
Trips per customer	Trips	Average shopping trips by customer *i* in week *t*, provided at least one trip
Number of customers	Customers	Number of customers that bought at least once in week *t*

Model 1: individual level latent class analysis (LCA1) – full data set

Recognizing the importance of customer heterogeneity for customer management (Ansari, Mela, and Neslin 2008), we estimate an individual level data model that groups customers according to their short-term response using latent class analysis (Kamakura and Russell 1989). As the model was designed for a single performance variable (instead of all four revenue components), we explain the logarithm of the *total offline revenues* (adding .000001 to account for 0 revenues) of each individual consumer *i* in period *t* with the variables in Fig. 1. Eq. (2) displays the model specification:

From Eq. (2), note that we do not include a main effect of web site visit frequency and flow because they do not exist before site introduction. Prior patronage (operationalized as customer revenue before website introduction) is not included as a main effect because it is by definition related to customer revenue.

We allow the latent class model to segment customers based on all their individual response coefficients in Eq. (2). The *best fitting model* reveals three latent classes, which are further discussed in “Empirical results” section.

Model 2: VARX1 model – full data set

To determine the *long-term effects* of website introduction on the company’s aggregate performance, we estimate a flexible aggregate level model relating the four revenue components to the variables of interest. Because we have little a priori knowledge about the dynamics of those effects, we employ the persistence-modeling framework (Dekimpe and Hanssens 1999) and specify Vector Autogressive (VARX) models to uncover interactions among key variables instead of determining them a priori.

$$\begin{aligned}\mathrm{Ln(Revenue)}_{i,t} = {} & A_i + \beta_1\,\mathrm{SiteIntroStep}_t + \beta_2\,\mathrm{SiteIntro}_t + \beta_3\,\mathrm{SiteIntro}_{t-1} + \beta_4\,\mathrm{SiteIntro}_{t-2} + \\ & \beta_5\,\mathrm{Sens}_{i,t} + \beta_6\,\mathrm{Dist}_i + \beta_7\,\mathrm{SiteIntroStep}_t \times \mathrm{Sens}_i + \beta_8\,\mathrm{SiteIntroStep}_t \times \\ & \mathrm{Dist}_i + \beta_9\,\mathrm{SiteIntroStep}_t \times \mathrm{Patron}_i + \beta_{10}\,\mathrm{SiteIntroStep}_t \times \mathrm{Freq}_i + \beta_{11} \\ & \mathrm{SiteIntroStep}_t \times \mathrm{Flow}_i + \beta_{12}\,\mathrm{OffProm}_t + \beta_{13}\,\mathrm{OffProm}_{t-1} + \beta_{14} \\ & \mathrm{OffProm}_{t-2} + \beta_{15}\,\mathrm{Comp}_t + \beta_{16}\,\mathrm{Euro}_t + \varepsilon_{it}\end{aligned} \qquad (2)$$

where A stands for the deterministic components (constant, trend and seasonal dummies estimated as random effects), coefficients $\beta_{1\text{–}4}$ represent the customer revenue impact of the website introduction, while coefficients $\beta_{5\text{–}6}$ control for the customer preference for sensory products and the distance to the store before website introduction. Next, we interact the web site introduction step dummy with the variables of interest $\beta_{7\text{–}11}$. Finally, the effect of control variables is captured with coefficients $\beta_{12\text{–}16}$ (specification tests suggest that 2 lags suffice to capture dynamic effects of offline promotions, while competitive effects show no significant carry-over). Our original model specification included quadratic effects of the independent variables (to capture possible diminishing returns), but all failed to reach significance in this and following models. In the interest of parsimony, we deleted the quadratic terms from the final model specifications.

Based on unit root and structural break test results (see Appendix B), we specify the VARX1 model in Eq. (3). We include the four offline revenue components as endogenous variables, while controlling for trend, seasonality, offline promotions, competitive actions and the switch to the Euro currency (i.e., all the non-customer specific variables in Eq. (2)) The impact of the website introduction is modeled based on the outcome of unit root and structural break tests. Similar to the introduction of new media channels in the Netherlands (Kornelis, Dekimpe, and Leeflang 2008), the likely scenario is that all series are stationary in the periods before and after the site introduction, with a structural break at the time of introduction. Adding pulse dummies (SiteIntro = SiteIntroPulse) in the week of and the weeks following the introduction (with lag number L determined by specification tests) allows for temporary effects around the web site introduction:

$$\begin{bmatrix} \text{Money}_t \\ \text{Products}_t \\ \text{Trips}_t \\ \text{Customers}_t \end{bmatrix} = C + \sum_{k=1}^{K} B_k \begin{bmatrix} \text{Money}_{t-k} \\ \text{Products}_{t-k} \\ \text{Trips}_{t-k} \\ \text{Customers}_{t-k} \end{bmatrix} + \Gamma \begin{bmatrix} \text{SiteIntroStep}_t + \sum_{j=0}^{L} \text{SiteIntro}_{t-j} \\ \text{SiteIntroStep}_t + \sum_{j=0}^{L} \text{SiteIntro}_{t-j} \\ \text{SiteIntroStep}_t + \sum_{j=0}^{L} \text{SiteIntro}_{t-j} \\ \text{SiteIntroStep}_t + \sum_{j=0}^{L} \text{SiteIntro}_{t-j} \end{bmatrix} + \begin{bmatrix} u_{\text{money},t} \\ u_{\text{products},t} \\ u_{\text{trips},t} \\ u_{\text{cust},t} \end{bmatrix} \quad (3)$$

with C the matrix of control variables, K the order of the model, as suggested by the Bayesian Information Criterion, B_k the (4×4) vector of dynamic coefficients relating the revenue components to each other, Γ the (4×4) vector of coefficients relating the site introduction variables to each revenue component and the disturbance terms $[u_{money,t}, \ldots, u_{cust,t}] \sim N(0, \Sigma_u)$. After applying the VARX1 model to all customers, Eq. (3) is also estimated for each of the three segments identified by the latent class analysis.

Model 3: Individual level model (LCA2) – data period after website introduction

In this model we keep the same three segments as those identified earlier and now examine the effects of online price promotions and online non-price communications. We also account for possible interactions among marketing actions, and between sensory product type and each marketing action (as suggested by our conceptual development, online communication should be especially valuable for sensory products):

$$\begin{aligned} \text{Ln(Revenue)}_{i,t} = \; & A_i + \lambda_1 \text{Sens}_{i,t} + \lambda_2 \text{Dist}_i + \lambda_3 \text{Freq}_i + \lambda_4 \text{Flow}_i + \lambda_5 \text{OnComm}_t + \lambda_6 \\ & \text{OnComm}_{t-1} + \lambda_7 \text{OnComm}_{t-2} + \lambda_8 \text{OnProm}_t + \lambda_9 \text{OnProm}_{t-1} + \lambda_{10} \\ & \text{OnProm}_{t-2} + \lambda_{11} \text{OffProm}_t + \lambda_{12} \text{OffProm}_{t-1} + \lambda_{13} \text{OffProm}_{t-2} + \lambda_{14} \\ & \text{OnComm}_t \times \text{OnProm}_t + \lambda_{15} \text{OnComm}_t \times \text{OffProm}_t + \lambda_{16} \text{OnProm}_t \\ & \times \text{OffProm}_t + \lambda_{17} \text{Sens}_{i,t} \times \text{OnComm}_t + \lambda_{18} \text{Sens}_{i,t} \times \text{OnProm}_t + \\ & \lambda_{19} \text{Sens}_{i,t} \times \text{OffProm}_t + \beta_{18} \text{Comp}_t + \beta_{19} \text{Euro}_t + \varepsilon_{it} \end{aligned} \quad (4)$$

Model 4: VARX2 model – period after website introduction

The VARX2 model is specified as in Eq. (3), replacing the site introduction variables with the marketing variables from Eq. (4).

The VARX2 model estimates the baseline of each endogenous variable and forecasts its future values based on the dynamic interactions of all jointly endogenous variables. Based on the VARX2 coefficients, impulse-response functions track the over-time *response* of a performance variable (in our case, the revenue components) to a change (*impulse*) in the marketing variable. We use the generalized, simultaneous-shocking approach (Pesaran and Shin 1998), which uses information in the residual variance-covariance matrix of the VARX2 model instead of requiring the researcher to impose a causal ordering among the endogenous variables (Dekimpe and Hanssens, 1999). We follow established practice in assessing the statistical significance of each impulse-response value by applying a one-standard error band (Pesaran, Pierse, and Lee 1993). In the absence of permanent effects, we obtain the long-term effect of the marketing action by adding all significant impulse response coefficients (Pauwels, Hanssens, and Siddarth 2002). Thus, we operationalize '*short-term'* as the effect in the *week of the marketing action*, while '*long-term'* adds the effects of all following weeks in which the impact is significant.

Empirical results

Effect of website introduction

Tables 4 and 5 display the results for effects of web site introduction, from estimation of the latent class analysis (LCA1) and VARX1 model over the full data period. The best fitting latent class model (based on the AIC criterion) identifies 3 segments.

The first key observation from both models is that *website introduction did not significantly change overall offline revenue in the long run*. Indeed, the coefficient for SiteIntroStep which indicates a permanent shift in revenues is insignificant for 'all customers' in the latent class model and for each revenue component in the VARX1 model. We obtain this null result despite initial customer enthusiasm for the site, showing up in both models as significantly positive coefficients for the SiteIntro(Pulse)$_t$ variables. In support of hypothesis H1a, web-

Table 4
Latent class analysis (LCA1) results: impact of web site introduction variables on revenues (*t*-statistics between brackets).

	All customers	Segment 1	Segment 2	Segment 3
SiteIntroStep	.0139 (.47)	.0761 (2.47)	−.0677 (−2.00)	.0038 (.11)
$SiteIntro_t$	.3626 (14.14)	.5724 (10.00)	.2635 (4.74)	.2407 (4.76)
$SiteIntro_{t-1}$	.1000 (3.52)	.2223 (3.86)	.0072 (.11)	.0746 (1.33)
$SiteIntro_{t-2}$	−.4662 (−11.25)	−.6135 (−6.21)	−.4630 (−3.67)	−.3861 (−3.91)
Sensory Product (Sens)	.3306 (33.77)	.3767 (16.97)	.3548 (17.55)	.2443 (12.15)
Distance to store (Dist)	−.0021 (−1.99)	−.0011 (−.83)	−.0005 (−.24)	−.0032 (−2.98)
SiteIntroStep × Sens	.0525 (1.98)	.0642 (2.05)	.1962 (7.10)	.0514 (1.85)
SiteIntroStep × Dist	.0163 (2.02)	.0272 (2.22)	.0101 (1.43)	.0123 (1.87)
SiteIntroStep × Patron	−.0006 (−.88)	−.0005 (−.65)	−.0003 (−.43)	−.0009 (−.99)
SiteIntroStep × Freq	.0007 (1.81)	.0009 (1.75)	−.0001 (−.39)	.0012 (2.24)
SiteIntroStep × Flow	−.0069 (−1.01)	−.0094 (−1.28)	−.0017 (−1.56)	.0024 (.31)
$OffProm_t$	.0695 (5.58)	.1278 (6.60)	.0461 (2.27)	.0545 (2.67)
$OffProm_{t-1}$	−.0365 (−3.81)	−.0364 (−1.75)	−.0521 (−2.61)	−.0137 (−.68)
$OffProm_{t-2}$	−.0438 (−4.00)	−.0914 (4.36)	.0178 (.85)	−.0502 (−2.51)
Competitive action (Comp)	−.0611 (−3.23)	−.8965 (−2.94)	−.0492 (−1.55)	−.0801 (−3.26)
Euro	−.084 (−5.46)	−.1225 (−6.83)	−.6391 (−36.44)	−.0635 (−3.46)
Segment size		29.4%	34.3%	36.3%

site introduction *attracts more Customers in the short run* for all segments (Table 5). Unfortunately for the company, these effects do not last.

In view of this overall result, our segment-specific findings reveal substantial differences in the revenue impact of website introduction. Table 4 shows that, after website introduction, revenue increased in segment 1 (29.4 percent of customers), decreased in segment 2 (34.3 percent of customers), and did not significantly change in segment 3 (36.3 percent of customers). Likewise, the site intro dummy and its lags indicate that revenue increased for all segments in the week of website introduction, but that, within two weeks, this gain shrinks substantially for segment 1, turns negative for segment 2 and is negated for segment 3. Thus, these 3 segments critically differ in their reaction to the introduction of the informational website.

Table 5
Latent class VARX1 models: the impact of web site introduction on 4 revenue components[a] (*t*-statistics between brackets).

All Customers	Money (€)	Products	Trips	Customers
SiteIntroStep	3.07	−.18	−.05	−60.29
	(1.14)	(−.73)	(−1.58)	(−.92)
$SiteIntro_t$	1.87	.10	.71	**993.02**
	(1.78)	(.20)	(1.51)	(2.78)
$SiteIntro_{t-1}$	1.69	−.05	.10	477.18
	(1.52)	(−.09)	(1.40)	(1.27)
$SiteIntro_{t-2}$	−1.89	−.08	.01	−225.07
	(−1.78)	(−.16)	(.21)	(−.63)
Segment 1	**Money (€)**	**Products**	**Trips**	**Customers**
SiteIntroStep	**2.35**	**2.05**	.07	−17.19
	(2.11)	(2.12)	(1.10)	(−.84)
$SiteIntro_t$	−1.38	.02	.35	**223.66**
	(−.25)	(.22)	(1.16)	(2.28)
Segment 2	**Money (€)**	**Products**	**Trips**	**Customers**
SiteIntroStep	2.33	−.53	**−.28**	−16.94
	(1.02)	(.74)	(−1.96)	(−.79)
$SiteIntro_t$	1.43	.11	**1.44**	**251.03**
	(.13)	(.11)	(2.15)	(2.50)
Segment 3	**Money (€)**	**Products**	**Trips**	**Customers**
SiteIntroStep	**5.23**	−.38	.08	−28.91
	(2.78)	(.47)	(1.03)	(−1.69)
$SiteIntro_t$	.20	.02	.36	**211.88**
	(.02)	(.13)	(.90)	(2.46)

[a] Bold parameter estimates are significantly different from zero at the 95% level.

Table 6
Latent class model LCA2 results: marketing effects after site introduction on revenues (*t*-statistics between brackets).

	All customers	Segment1	Segment 2	Segment 3
Sensory product	.4521 (46.38)	.4218 (22.81)	.5790 (35.02)	.2749 (21.21)
Distance to store	−.0025 (−2.61)	−.0009 (−.62)	−.0007 (−.56)	−.0048 (−4.69)
OnProm	.0470 (3.86)	.0585 (2.65)	.0445 (2.11)	.0248 (1.50)
OnProm_{t-1}	−.0664 (−4.74)	−.1279 (−5.15)	−.0448 (−1.85)	−.0642 (−3.38)
OnProm_{t-2}	−.0314 (−2.46)	−.0167 (−1.06)	.0184 (.84)	−.0490 (−2.83)
OnComm	.0016 (.08)	.0541 (2.46)	.0864 (2.42)	−.0613 (−2.93)
OnComm_{t-1}	.1715 (9.98)	.1525 (4.61)	.1254 (4.19)	.1206 (5.12)
OnComm_{t-2}	.0386 (2.32)	.0881 (2.54)	.0314 (1.07)	.1145 (5.21)
OnComm × OnProm	.0013 (.06)	.0242 (1.43)	.0189 (1.12)	−.002 (− .13)
OnComm × Sens	.1984 (5.66)	.2673 (4.25)	.0934 (1.50)	.2219 (4.74)
OnProm	.0470 (3.86)	.0585 (2.65)	.0445 (2.11)	.0248 (1.50)
OnProm_{t-1}	−.0664 (−4.74)	−.1279 (−5.15)	−.0448 (−1.85)	−.0642 (−3.38)
OnProm_{t-2}	−.0314 (−2.46)	−.0167 (−1.06)	.0184 (.84)	−.0490 (−2.83)
OffProm	.0893 (6.21)	.1388 (5.49)	.0431 (1.99)	.0386 (1.96)
OffProm_{t-1}	−.0957 (−5.09)	−.0364 (−1.75)	−.1578 (−5.61)	−.0663 (−3.19)
OffProm_{t-2}	−.0471 (−3.20)	.0914 (4.36)	−.0675 (−2.65)	−.0217 (−1.08)
Competitive action	−.0697 (−3.97)	−.1025 (−3.28)	−.0450 (−1.47)	−.0786 (−3.26)
Euro	−.081 (−5.47)	−.1218 (−7.28)	−.6342 (−38.32)	−.0617 (−3.31)

We now consider the outcomes of the hypotheses testing:

- In partial support of Hypothesis H1b, *Money per product increases* for segments 1 and 3, but not for segment 2.
- In partial support of H2, *shopping Trips decrease* after website introduction in segment 2 (Table 5) – the key explanation for the reduction in overall revenue from this segment (Table 4).
- In support of H3, each segment shows a higher revenue impact for sensory products versus nonsensory products.
- Consistent with H4, revenues increase more from *distant Customers*, particularly in segment 3. Hence, the introduction of the website indeed increases the number of Customers who live farther away from the store.
- Customers with higher *web visit frequency* significantly increase revenues with the company for segment 3, in partial support of H5.

In contrast, neither prior store patronage nor reported flow with the website experience has a significant impact on customer revenues.

As for the control variables, offline promotions significantly boost revenues immediately, but decrease it over the following weeks. For segments 1 and 3, this negative adjustment effect is even larger than the immediate positive effect. As expected, competitive actions decrease company revenues. Most seasonal and trend effects are insignificant, but revenues are significantly higher in March, October and December. Finally, the switch to the Euro currency decreased customer-level revenues in all segments. Thus, the analyzed retailer suffers from the general negative reaction of consumers to the Euro currency introduction (Folkertsma, van Renselaar, and Stokman 2002).

In sum, results from two very different models offer support for our hypotheses that website introduction temporarily increases the number of customers shopping at the store and that its long-term revenue impact is higher for sensory products than for non-sensory products. The remaining effects differ per segment: customers in segment 1 buy more expensive products and products per trip; customers in segment 2 ultimately make less trips to the store and customers in segment 3 buy more expensive products, but show no significant increase in overall revenues spent at the store.

Effects of online marketing actions

Based on the estimation of models LCA2 and VARX2 on the data after website introduction, Tables 6 and 7 display our results on online marketing effectiveness. For ease of readability, we do not display interaction effects that failed to reach significance.

First, *online price promotions* (OnProm) increase revenue in the short run by *drawing customers into the store*, in support of H6. However, they do not increase revenue in the long run (Table 7). Instead, their long-run revenue effect is negative, mostly because customers reduce Money per product and Products bought per trip (segments 1 and 2) and because they fail to return in the weeks following the promotion (negative impact on Customers in all segments). Thus, online price-oriented promotions are not a revenue-generating activity, unless they are combined with information on product characteristics, as shown in the positive interaction between online promotion and online communication for segments 1 and 2 (Table 7). Our findings for online promotions are consistent with empirical generalizations on price promotions for fast moving consumer goods: after a positive short-run effect (Blattberg, Briesch, and Fox 1995), they typically fail to increase retailer revenue in the long run (Srinivasan et al. 2004).

Second, *online non-price communications* fail to generate revenue in the short term, but do so *in the long run by raising each revenue component*, in support of H7. This increase shows up in all segment-revenue component combinations, but fails to reach significance for segment 2's Money and Products. Moreover, online non-price communications are especially effective for sensory products (Table 6).

Table 7
Latent class VARX2 models: marketing effects on 4 revenue components from impulse response functions.[a]

Segment 1: Smart fans	Term	Money	Products	Trips	Customers
Online price promotions	Short-term	−.078	.071	.016	88.98
	Long-term	−.252	−.064	.007	−19.17
OnComm × OnProm	Short-term	.089	.000	.027	.00
	Long-term	.089	.000	.014	6.30
Online non-price communications	Short-term	.169	.148	.004	49.65
	Long-term	.169	.142	.002	49.65
Offline price promotions	Short-term	−.549	−.137	.000	39.71
Segment 2: Fun loving locals	**Term**	**Money**	**Products**	**Trips**	**Customers**
Online price promotions	Short-term	.098	.096	.000	62.92
	Long-term	−.425	−.054	−.007	−14.97
OnComm × OnProm	Short-term	.083	.000	.007	1.82
	Long-term	.083	.000	.007	4.66
Online non-price communications	Short-term	.000	.014	97.36	
	Long-term	.000	.005	97.36	
Offline price promotions	Short-term	−.460	.000	.000	24.96
	Long-term	−.460	.067	.000	−6.59
Segment 3: Fashionables	**Term**	**Money**	**Products**	**Trips**	**Customers**
Online price promotions	Short-term	.000	.000	.012	81.62
	Long-term	.000	.000	.002	−19.40
OnComm × OnProm	Short-term	.000	.000	.000	.00
	Long-term	.000	.000	.000	.00
Online non-price communications	Short-term	.282	.045	−.001	51.02
	Long-term	.282	.035	.008	51.02
Offline price promotions	Short-term	.000	.000	.039	41.11
	Long-term	.000	.000	.033	−35.24

[a] Only significant impulse response coefficients are included in these numbers.

As a comparison benchmark, observe that offline promotions have a similar effect pattern as their online counterparts: a short-run revenue boost followed by a post-promotion dip. Both the short-run revenue boost and the long-run negative impact are larger for offline versus online promotions in segments 1 and 2. Again, the short-run revenue boost followed by a post-promotion dip is consistent with effect patterns observed in previous literature (e.g., Blattberg, Briesch, and Fox 1995).

Characteristics of the latent class segments: an exploratory analysis

First, Tables 4–7 indicate that the 3 segments differ in their response to marketing actions. Segment 1 shows the highest response to web site introduction, online and offline price promotions and competitive actions. Segment 2 reduces revenues after website introduction and after the currency switch to the Euro. Segment 3 spends more Money per product after website introduction and is least affected by the switch to the Euro.

Second, analysis of the demographic differences between the segments reveals that customers in the segment in which revenue significantly increased with web site introduction (segment 1) received more higher education, have more kids and are more likely to be male. In contrast, customers in the segment in which customer revenue declined with web site introduction (segment 2) live closer to a company store, received less higher education and have less kids than customers in the other segments. The demographic variables for segment 3 did not significantly differ from those for the full dataset.

Third, we analyzed 45 web usage variables (available upon request) that detail the content of the Website pages accessed. To guard against falsely rejected hypotheses in these multiple comparisons (if one uses the single test $\alpha = .05$ for each comparison), we control for the false discovery rate using the procedure in Benjamini and Hochberg (1995), which has uniformally higher power than alternatives, including the Bonferroni method. Seven null hypotheses were significantly rejected in this procedure. Customers in segment 1 have the highest number of topics of interest and consult more online pages on price-oriented ‘special actions’ than customers in the other segments. In contrast, customers in segment 2 consult more online pages on games and sending ecards than other customers do. Finally, customers in segment 3 consult more fashion, gift giving and ‘especially for you’ online pages than customers in any other segment.

Together, these exploratory findings yield the following profiles of each segment. Customers in segment 1 (which we label 'smart fans') appear to have a stronger need for the products offered by the company and/or its competitors: they have larger families and indicate an interest in more product categories. At the same time, they are also more responsive to price promotions, consult more price oriented special actions and react more to competitor actions. This suggests it is important for these customers to make the 'right' purchase, and is consistent with our finding that gaining additional information through the website helps them to buy more products and upgrade to more expensive items.

In contrast, customers in segment 2 (which we label 'fun loving locals') do not demonstrate a strong need for the products: they have a smaller family size and neither company promotions nor competitor actions have much power to change their buying behavior. While they live closer to the offline store, they mostly access website pages on games and e-cards; all unrelated to the company's products. This suggests that customers in this segment are interested in entertainment, which they can now (partially) obtain from the online site instead of taking trips to the store.

Finally, customers in segment 3 (which we label 'fashionables') are not very price sensitive and focus on accessing pages on broader themes such as fashion, gift giving and 'especially for you'. This information apparently allows customers in this segment to upgrade to more expensive products (see Table 5).

Conclusions

In this study, we investigate the short-term and the long-term effects of the introduction of an informational website. Based on information search theory, we formulate hypotheses on how this impact changes with product type, and with online and offline customer characteristics. We use latent class analysis to define different segments and specify VARX models that capture the relationships among offline revenue components and the long-term revenue implications of the introduction of an informational website and its related marketing actions. Table 8 summarizes our findings and the empirical support for most of our hypotheses.

Consistent with our conceptual development, we find that the long-run revenue impact of the introduction and marketing efforts of an informational website critically depends on the product type and the customer segment. First, our study shows that the website introduction and its (non-price) online communications improve the offline revenue performance components more for sensory than for non-sensory products. Thus, in contrast to the original online focus on non-sensory products (Degeratu, Rangaswamy, and Wu 2000; Peterson, Balasubramanian, and Bronnenberg 1997), our results imply that the online channel may yield even higher performance benefits for sensory products. A likely explanation is that observing these products in theme-oriented contexts allows customers to explore how these products fit into their consumption behavior.

As we expected from information search theory, the revenue impact of an informational website is larger when the benefits of search are higher (for sensory versus non-sensory products) and when the prior search costs are higher (for customers living farther away from the physical store). Moreover, customers who search more online (higher online visit frequency) spend more at the offline store for segment 3 (i.e., the fashionables). Smart fans (segment 1), that is, customers with a high product need but also high price sensitivity, start buying more products and slightly more expensive items. Fashionables (segment 3) upgrade to more expensive products. These findings are consistent with the web usage behavior of these segments: smart fans focus on specific product- and price-related pages, while fashionables focus on theme-related pages.

In contrast, fun loving locals (segment 2) increase their store visit frequency in the week of website introduction, but then reduce it in the long run. They appear to start using the informational website as an alternative to browsing in the store and thus to a store visit. This 'experiential substitution' effect is consistent both with experiential shopping theory as with a redirection of search activity to where search is least expensive.

How can the company identify and act on this 'dark side' of the informational website? Negative offline revenue effects are more likely for customers living closer to the physical store and who use the website mostly for entertainment. This suggests the informational website substitutes for the entertainment they used to enjoy when browsing in the physical store. Product-related online communication appears the primary weapon in

Table 8
Summary of hypotheses and their empirical support.

Hypotheses		Support?
H1a:	Website introduction increases Customers in the short run	Yes
H1b:	Website introduction increases Money per product in the long run	Partial (2 segments)
H2:	Website introduction decreases shopping Trips in the long run	Partial (1 segment)
H3:	Sensory Products obtain a higher revenue impact from site introduction	Yes
H4:	Customers living far away from the store obtain a higher revenue impact from site introduction, due to higher number of Customers each week	Yes
H5:	Customers with higher web visit frequency obtain a higher revenue impact from site introduction, due to higher number of Customers each week	Partial (1 segment)
H6:	Online price promotions (a) increase revenue immediately (short-run) through (b) higher number of Customers, while (c) Money spent per product decreases	Yes
H7:	Non-price online communications (a) increase offline revenues in the long run, through (b–e) all four revenue components.	Yes

the company's arsenal to increase offline revenues, for all segments. In contrast, price-related promotions, whether online or offline, are not effective in increasing revenues in the long run. Both findings are consistent with previous literature on product-versus price related marketing actions (e.g., Pauwels et al. 2004), but had yet to be demonstrated for informational websites.

Within the specific product types and customer groups, different offline components are affected by the informational website and the online marketing actions. These multifaceted findings suggest that retailers should be very clear about which performance components they aim to improve, and which products and customer segments they want to target with the informational site and its marketing actions. Because informational websites are a communication medium, our results may apply to other such media that inform consumers but do not allow them to buy. Therefore, it would be hazardous for retailers to assume that more information necessarily translates into higher revenues.

Although our research provides several new insights, as is any research, it is limited to the variables to which we have access. Most importantly, we only had the opportunity to analyze data for one (large) retailer and its customers that were part of a national loyalty program. Therefore, future research should extend the analysis to other customers and other retailers in other countries and time periods. The marketing communications literature provides a rich framework to embed this research, and can be further enhanced by it. Together with further theory development, empirical studies can generate empirical generalizations and scientific understanding in the ET research tradition (Ehrenberg 1994). For one, the comparison of different studies may identify informational websites that did yield a long-term increase in offline revenue and study the influencing factors of this revenue impact. Additional research may also improve our insights by determining how cross-channel behavior varies, given that consumers use multiple providers to search for and purchase particular products. However, obtaining actual individual consumer search and buying behavior in multiple channels for multiple organizations represents a great challenge. A third promising area is an analysis of the functions in informational websites that stimulate offline purchases in more direct ways. One option is a click and reserve system, where customers reserve products online while making the actual purchase decision in the shop, upon inspection of the product. Such systems increase customer service, while offering valuable pre-purchase information for the retailer. A fourth area for future research is to extend beyond our analysis of the revenue consequences of an informational website (once the decision has been made to have one). How is this choice itself made, in the context of alternatives such as a full-fledged transactional website (having no website at all is likely not viable in today's market)? Future research may also address causality questions, such as whether higher store involvement or high general Internet visit frequency drives higher website visit frequency. Next, shopping styles and motivations may influence the revenue impact of retailer sites, as recent research indicates that compulsive buyers tend to prefer online shopping (Kukar-Kinney, Ridgway and Monroe 2009). Finally, our data were collected in 2001–2002. In that period, the majority of consumers in the Netherlands already had home internet access (CBS 2002), while broadband access was quickly getting more popular, almost a third of the Dutch households had broadband access by the end of 2002 (TNS NIPO2003). A more current study would probably find more store customers comfortable browsing the site, which could also offer a higher quality experience due do advances in technology and web design, making it even easier to substitute offline store visits by online search and browsing. Neither of these changes is likely to qualitatively alter the finding that the informational website increases offline store revenues for some, but not for other consumers. Also, the increased availability and use of price comparison sites, and the increased consumer expectations with regard to online experiences, may even further stimulate channel substitution.

In conclusion, our study provides new insights into consumer purchase behavior for online search and offline buying. Given that the offline performance effects of an information website substantially depend on the product type and customer segment, managers should consider customized promotions and/or customized loyalty systems (Zhang and Wedel 2009). Thus, we recommend offline retailers to target specific products and customer segments, instead of operating a one-size-fits-all informational website.

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Appendix A. Measurement of the flow construct

Appendix Table A1 below lists the 4 items (measured on a five-point scale) of the flow construct, their factor loadings and the reliability (Cronbach's alpha) in 2001 and 2002. Table A2 provides the correlation matrix for respectively 2001 and 2002.

Table A1
Items, factor loading and reliability for the flow construct.

Flow: Items During my visit;	Reliability	Factor loadings2001	Factor loadings2002	Means2001	Means2002
I often forget my immediate surroundings.	.93 in 2001	.89	.91	2.56	2.52
I often do not realize the duration of my Web visit.	.94 in 2002	.92	.92	2.65	2.66
I lose self-consciousness.		.93	.92	2.28	2.43
Time seems to fly by.		.91	.92	2.46	2.62

Table A2
Correlation matrix for the items in the flow construct.

Inter-item correlation matrix	2001				2002				Total
	A_1	B_1	C_1	D_1	A_2	B_2	C_2	D_2	
I often forget my immediate surroundings (A_1)	1	.79	.77	.72	.47	.44	.48	.48	.81
I often do not realize the duration of my Web visit (B_1)	.79	1	.78	.81	.43	.45	.044	.48	.86
I lose self-consciousness (C_1)	.77	.78	1	.86	.47	.44	.49	.48	.86
Time seems to fly by (D_1)	.72	.81	.86	1	.45	.47	.56	.48	.84
I often forget my immediate surroundings (A_2)	.47	.43	.47	.45	1	.78	.79	.75	.84
I often do not realize the duration of my Web visit (B_2)	.44	.45	.44	.47	.78	1	.78	.81	.85
I lose self-consciousness (C_2)	.48	.44	.49	.46	.79	.78	1	.80	.86
Time seems to fly by (D_2)	.48	.48	.48	.48	.75	.81	.80	1	.86

Appendix B. Test for unit roots and structural breaks around website introduction

We assess the temporal behavior (evolution/stationarity) of the revenue components series by means of unit root tests (Dekimpe and Hanssens 1999). To obtain convergent validity (Maddala and Kim 1996), we perform two tests: the Augmented Dicky Fuller (ADF) method and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test, which maintain respectively evolution and stationarity as the null hypothesis. Next, we test the revenue components for a structural change with a known breakpoint, Namely, the first week after the introduction of the website (Maddala and Kim 1996). Specifically, the Chow breakpoint test reveals significant differences in the estimated equations before and after the site introduction. Finally, the Zivot and Andrews (1992) test uncovers potential structural breaks at unknown points, which may be due to leads and lags in the impact of site introduction (customer anticipation and gradual change in behavior) and/or due to events unrelated to the site, such as the introduction of the Euro currency.

The results of the pre-model tests confirm the model specification choice presented in Eq. (3). First, both unit root tests find convergent evidence that all series are trend stationary when allowing for a structural break at the site introduction. This result increases our confidence in the classification of marketing series, in contrast to macroeconomic series, for which Maddala and Kim (1996, p. 128) report little test convergence. The structural break Chow test indicates a significant structural break at site introduction (week 61) in the number of trips ($F = 6.32$, Prob. = .00; Chi-squared log likelihood ratio = 24.45, Prob. = .00). In addition, the Zivot–Andrews test indicates that "Products" and "Trips" experienced a structural break at the introduction of the Euro. Unit root tests for each of the periods separated by a structural break reveal stationarity for all series. Therefore, it is appropriate to estimate the model with all variables in levels (Kornelis 2002, p. 49), accounting for structural breaks by step dummies for introduction of the site and the Euro.

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