Determining the cross-channel effects of informational web sites

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3 The Impact of an Informational Web Site on Offline Customer Buying Behavior[7]

In this chapter, we study the effects of the use of an informational Web site on offline customer buying behavior for a large national retailer. We model the effects of individual online behavior on offline buying behavior at both the overall purchase level and the category level. The results show that informational Web sites may entail more bad than good news, because Web site visitors become more efficient in their offline shopping; that is, they engage in fewer shopping trips and spend less in all categories.

3.1 Introduction

With the commercialization of the World Wide Web, more and more companies offer information via their Web sites. The vast increase of available information has made it much easier for customers to compare offers of competing products and merchants and make well-informed decisions. Academic research regarding the effectiveness of Web sites in terms of customer buying behavior has focused mainly on the impact of transactional Web sites (see e.g., Moe & Fader 2004; Sismeiro & Bucklin 2004). However, Forrester Research also shows that most Internet users conduct research online before buying offline (see e.g., Kelley, Delhagen & Denton 2002; Mendelsohn, Johnson & Meyer 2006). Similarly, the Boston Consultancy Group reports that 88% of Internet users browse online before buying offline (Rasch & Lintner 2001). What these studies do not show is whether online search increases or decreases individual offline buying behavior.

Online information search can lead to various subsequent customer actions. For example, it may be followed by a desire to buy the product via the Web site on which the information was found, though online conversion rates rarely exceed 5% (Moe & Fader 2004). Customers also may decide to leave the site and buy the product at a competitor's Web site. A third option involves online search followed by offline purchase.

[7] This chapter is based on Teerling, M. L., J.E.M. van Nierop, P.S.H. Leeflang and K.R.E. Huizingh (2006), The Impact of an Informational Web Site on Offline Customer Buying Behavior, Working Paper, University of Groningen.

This option is quite likely for products with predominantly search aspects (e.g., Alba & Lynch 1997; Citrin et al. 2003) or in case of customers with technology anxiety or trust issues (see e.g. Hoffman et al. 1999; Meuter et al. 2003; Roy & Ghose 2006).

Various studies investigate the effects of the “new” Internet channel on either aggregate firm performance or individual customer behavior. At the aggregate level, the Internet channel does not appear to cannibalize from the existing channel (see e.g. Deleersnyder, Geyskens et al. 2002; Biyalogorsky & Naik 2003), and the effects of an informational channel may even be positive (Lee & Grewal 2004). At the individual customer level, research thus far has been able to determine only the effects of an online transactional channel, which it posits as both positive and negative effects (Ansari et al. 2006; Kushwaha & Shankar 2005). As Neslin et al. (2006) recommend, more research into the contribution of various channels is needed. In the case of an online informational channel, no empirical results are available at the individual customer level.

The question therefore is what happens at an individual customer level if an organization provides online information to its customers. Do they become more interested in the organization and, as a result shop more often? Alternatively, does the information allow customers to know what the organization and its competitors have to offer, resulting in less frequent shopping trips? From Gensler et al. (2007) and Knox (2005) we know that the effects of an additional transactional channel can vary depending on the product category and that certain product categories are more suitable for online buying than others. So do customers increase or decrease their spending across product categories as a result of an informational Web site? More generally, does the use of an informational Web site alter spending in certain product categories.

This study aims to determine the effects of informational Web sites by investigating how a site influences offline shopping trips (i.e. shopping trips during which customers purchase at least one product) and product category purchases at the individual customer level. We decompose buying behavior in our attempt to answer the following questions:

- Does the use of an informational Web site change the number of offline shopping trips conducted by individual customers?
- Does the use of an informational Web site alter the purchases of individual customers in different product categories?

We link online search behavior with the offline buying behavior of individual customers of a large retailer using customer panel data. From these data, we know to what extent, over time, the customers visit the Web site, what they do online in terms of the frequency and depth of their site visits, and how much and how often they shop at the offline stores. We also can study how the offline buying behavior of customers has changed with the use of the Web site, because purchase data are available for both before and after the implementation of the Web site.

We first review the relevant literature. After discussing the methodology, we describe the data. Then, we present the findings and discuss them in light of previous studies. We end with a summary of the main conclusions.

3.2 LITERATURE REVIEW

Table 3-1 shows an overview of selected multichannel studies that attempt to determine the impact of the addition of an Internet channel on firm performance. We distinguish two possible Internet channel additions: a transactional channel or an informational channel. The impact of either of these additions has been investigated at the aggregate (firm) sales level and at the individual customer level. However, as far as we know, this study is the first to consider the effects from an additional informational channel on the individual customer level.

TABLE 3-1 OVERVIEW SELECTED MULTICHANNEL BEHAVIOR STUDIES

		Level of the Data Analysis	
		Aggregate	*Individual*
Internet Channel Addition	Transactional	Biyalogorsky & Naik 2003 Coelho et al. 2003	Ansari et al. 2006 Danaher et al. 2003 Dholakia et al. 2005 Gensler et al. 2007 Knox 2005 Kushwaha & Shankar 2005
	Informational	Deleersnyder et al. 2002 Geyskens et al. 2002 Lee & Grewal 2004	This study

The impact of an additional online transactional channel on aggregate sales appears in two studies. First, Biyalogorsky and Naik (2003) investigate Tower Records' sales figures during the period 1989-

1999 to determine to what extent the added online transactional channel cannibalizes offline sales. They find a cannibalization rate of 2.8% from online sales, indicating negligible contemporaneous cannibalization (Biyalogorsky & Naik 2003). Second, Coelho, Easingwood and Coelho (2003) show that when a company starts using a new channel, it can expect stronger sales growth from this channel than from its traditional channel. Growth opportunities likely occur because the firm reaches new customer segments, but these authors also indicate that as penetration into these segments increases, growth diminishes and cannibalization might exist between channels (Coelho et al. 2003).

Several other studies investigate the effect of an additional online informational channel at the aggregate sales level. Deleersnyder et al. (2002) find in the newspaper industry hardly any cannibalization between the online and offline channels, possibly because of the different market segments ; depending on the positioning of the channel portfolio, cannibalization or synergy between the channels is possible. Similarly, Geyskens et al. (2002) investigate the effect of an additional online channel on stock market responses in the newspaper industry and show that the online channel addition has a positive effect on stock price. Considering that the newspaper industry can easily take advantage of the special economics of information goods delivered over the Internet, these results may differ for retailers (Bakos & Brynjolfsson 2000). In a retail setting, Lee and Grewal (2004) show that adding the Internet as a transactional channel does not have an effect on the Tobin's Q (a stock market-based measure of firm performance). However, adding the Internet as a communication or informational channel has a positive impact (Lee & Grewal 2004).

Studies investigating the effect of an additional Internet channel on individual customer behavior mostly have focused on transactional channels. This focus probably was probably the only alternative, because individual customer data for online informational and offline transactional channels are rarely available (see e.g., Sullivan & Thomas 2004). However, from these studies, we can infer that (1) marketing efforts can migrate customers to a particular channel (Ansari et al. 2006; Knox 2005), (2) most customers become multichannelers after the addition of an Internet-channel (Dholakia et al. 2005; Gensler et al. 2007), and (3) adding a transactional Internet channel may either decrease (Ansari et al. 2006; Gensler et al. 2007) or increase (Kushwaha & Shankar 2005) customer buying behavior.

With this study, we try to fill the gap in the existing literature by determining the impact of an added informational Internet channel on individual customer buying behavior. Firms invest in (informational) Web sites because they expect positive effects on information needs, brand perceptions and buying behavior and negative effects on switching behavior and search time. However, extant research demonstrates that these effects are not always so evident, nor do they always have the expected and intended directions.

Informational Web sites may improve offline buying behavior due to (1) synergy effects between channels, (2) marketing effects, (3) improved brand/product awareness, and (4) increased loyalty. Verhoef et al. (2007) indicate that research shopping, or searching in channel *a* but buying in channel *b*, may create synergy effects, possibly as a result of economic benefits such as better choices informed by improved brand/product awareness or a sense of being a smart shopper.

Neslin et al. (2006) indicate that marketing efforts may provide another explanation for increased buying in the case of multichannel customers. This argument may also hold in the case of an informational Web site, because customers who use both channels are exposed to more marketing efforts than are those who use a single channel. Ansari et al. (2006) and Kumar and Venkatesan (2005) provide empirical support for this effect, and Wallace et al. (2004) show that retailers may receive a loyalty payoff because customers perceive an enhanced portfolio of service outputs provided by the multiple channels.

One of the main reasons informational Web sites may have negative effects on offline buying behavior relates to the decision-making process. Wu and Rangaswamy (2003) demonstrate that Web site features can either decrease or increase the amount of search and thereby influence consumers' consideration sets. Although the Internet is assumed to facilitate better and more efficient decision making (e.g., Alba & Lynch 1997; Mick & Fournier 1998), its availability also can lead to less information search in offline sources. Ratchford et al. (2003) test this claim for the automotive industry and find that consumers gain efficiency, increased information, and bargaining power from an Internet channel.

Shiv and Fedorikhin (1999) indicate that impulse decisions might be reduced through the greater availability of processing resources. An informational Web site that does not offer transaction capabilities, and therefore eliminates impulse buying, stimulates extensive processing of information. Hence, Shiv and Fedorikhin (1999) offer another possible explanation for a negative effect of an informational Web site on offline buying.

In addition to efficiency in decision making and reduced impulse buying, an informational Web site may reduce switching costs. Porter (2001) indicates that on the Internet buyers can easily switch suppliers with just a few mouse clicks. Because informational Web sites do not offer the possibility to transact, customers may switch to competitors' Web sites that provide both information and the ability to make purchases (Neslin et al. 2006).

The benefit of informational Web sites for customers lies in the information provided and their ability to use this information in their decision making. Online information dissemination and communication not only require a different approach than does an offline setting, but the consequences also can differ (e.g., Hoque & Lohse 1999; Stewart & Pavlou 2002). Specifically, customers may make different choices or better informed decisions given the information they find online (Hoque & Lohse 1999). Therefore, it becomes crucial to investigate the effects of an additional online informational channel on offline buying behavior.

3.3 PROPOSED METHODOLOGY

Store choice is frequently modeled with a logit or a probit model determining the utility for the customer of shopping at a particular store (e.g., Rust & Donthu 1995). These types of models explain the preference of a customer for a particular store through variables such as distance and the competitors in the area. In this study, we are interested in determining the effects of the introduction and use of an informational Web site on different elements of store behavior. Hence, a decomposition approach is more suitable.

Van Heerde, Leeflang and Wittink (2004) provide an extensive literature review of decomposition approaches, including the many new insights that stem from decompositions, ranging from front traffic, store entry ratios, closing rations, and average spending (Lam, Vandenbosch, Hulland & Pearce 2001) to purchase incidence, brand choice, and quantity (Gupta 1988; Zhang & Krishnamurthi 2004). In this study, we decompose individual buying behavior for both shopping trips at the overall level and the amount of money spent at the category level.

We focus our analyses at the product category level instead of overall monetary value to determine (1) if an informational Web site has different effects across categories and (2) what the impact of category-specific site pages might be.

3.3.1 Specification

We specify the total purchases, or total money, computed as the product of the number of shopping trips in which a customer purchases at least one product and the total amount of money spent in all categories. More specifically:

$$(1)\quad M_{it} = V_{it} * \sum_{c} \frac{M_{itc}}{V_{it}} \qquad ,i = 1,\ldots,I; c = 1,\ldots,C; t = 1,\ldots,T,$$

where

M_{it} = the total amount of money spent by individual *i* during month *t*,

V_{it} = the total number of shopping trips made by individual *i* during month *t*,

M_{itc} = the total amount of money spent by individual *i* during month *t* in category *c*,

I = the number of individuals,

C = the number of product categories, and

T = number of months.

We assume that the first component of equation (1), V_{it}, follows a Poisson process, so that the distribution of the number of shopping trips in any interval depends only on the length of that interval (e.g., Ehrenberg 1959; Leeflang, Wittink, Wedel & Naert 2000). The probability that υ_{it} shopping trips occur is given by

$$(2)\quad \Pr\left(V_{it} = \upsilon_{it}\right) = \frac{e^{-\lambda_{it}} \lambda_{it}^{\upsilon_{it}}}{\upsilon_{it}!},$$

where λ_{it} reflects the expected number of shopping trips for individual *i* in month *t*. The parameter λ_{it} is explained by regressors as follows:

$$(3)\quad \ln \lambda_{it} = \left(\gamma + \gamma_i\right) X_{it} + \varepsilon_{it}.$$

The vector X_{it} may contain individual-specific sociodemographic covariates, period and individual-specific site-related covariates, promotional activities, period dummies to account for seasonal and trend effects, and lagged dependent variables. The parameter γ describes the average effect, and the parameter γ_i accounts for unobserved household specific heterogeneity.

The second component of equation (1), $\frac{M_{itc}}{V_{it}}$, is modeled with a Type-II Tobit model (Chib 1992; Amemiya 1985, Fox, Montgomery & Lodish 2004; Franses & Paap 2001). We use the Type-II Tobit without correlation between the two stages, also known as a two-part model, to explain whether a customer buys in a particular category (purchase incidence), as well as the actual amount of money spent per category, given that the customer buys. We adopt the multivariate Type-II Tobit approach (Fox et al. 2004) because our application deals with multiple categories that may correlate.

For each individual *i*, we denote the decision to buy in category *c* in month *t* as Z_{itc}. This variable equals 1 if the customer buys and 0 if not. The multivariate Probit model (MVP) that describes this decision is specified as:

$$\begin{array}{lll} (4) & Z_{itc} = 1 & \text{if } Z_{itc}^{*} > 0 \\ & Z_{itc} = 0 & \text{if } Z_{itc}^{*} \leq 0 \end{array}$$

where

$$(5) \quad Z_{itc}^{*} = (\alpha_c + \alpha_{ic})H_{itc} + \varepsilon_{itc}\,.$$

Here Z_{itc}* is the latent utility for individual *i* of buying from category *c* in period *t*. If the utility Z_{itc}* is greater than 0, a purchase is made. The vector H_{itc} contains (mostly) time-varying explanatory variables that may influence the decision to purchase in category *c*. The parameter α_c describes the average effect, and the parameter α_{ic} refers to the household-specific effect. The error terms ε_{itc} follow a multivariate normal distribution, with mean 0 and covariance matrix Σ. For identification purposes, the diagonal elements of Σ are usually set to 1 (Manchanda, Ansari & Gupta 1999).

We denote the amount spent by individual *i* in category *c* in month *t* as Y_{itc}. by

$$(6)\quad Y_{itc} = \begin{cases} Y_{itc}^{*} & \text{if } Z_{itc} = 1 \\ 0 & \text{otherwise} \end{cases},$$

where the natural log of Y_{itc}^{*} is explained by

$$(7)\quad \ln Y_{itc}^{*} = (\beta_c + \beta_{ic})G_{itc} + \eta_{itc}\,.$$

The vector G_{itc} also contains (mostly) time-varying explanatory variables that may influence the amount of money spent in the various categories. The parameter β_c describes the average effects of these explanatory variables, and the parameter β_{ic} accounts for unobserved heterogeneity. The error term η_{itc} follow a multivariate normal distribution with mean 0 and covariance matrix Ω.

The vector G_{itc} contains category-specific variables that describe the individual's online behavior in the month under consideration, and explanatory variables that also occur in the matrix X in equation (3). The vectors H and G can be equal in both stages (decision to buy and the amount of money spent) of the Type-II Tobit or contain different explanatory variables depending on the expectations of each stage. Throughout, we concede that *the effects* of the explanatory variables on the decision to spend and spending levels differ. Therefore, promotional activities may have an insignificant effect on the decision to spend (Z_{itc}*) but significantly influence the amount spent (Y_{itc}*). The unobserved household-specific heterogeneity, modeled by adding α_{ic} and β_{ic} to the intercept parameters in both stages, draws from a multivariate normal distribution with means 0 and variance matrices Σ_α and Σ_β respectively (e.g., Allenby & Rossi 1999).

The multivariate error distributions for ε and η allow for information from one category to influence the conditional predictions of other categories. We expect contemporaneous correlations of the disturbances across categories because excess expenditures in one category may result in less spending in other categories (substitution) or complementary sales.

3.3.2 Estimation

We estimate the Poisson model that describes the number of shopping trips with a log-link function. To incorporate heterogeneity, we estimate a random effects Poisson model, with individual-specific constant and site visits parameter in MLwiN 2.02. The log-likelihood function is (Greene 2003)

$$(8)\quad \ln L = \sum\left[-\lambda_{it} + \upsilon_{it} X_{it}^{'}\left(\gamma + \gamma_i\right) - \ln \upsilon_{it}\,!\right].$$

For discrete response multilevel models, a maximum likelihood estimation is computationally intensive, and therefore MLwiN implements quasi-likelihood methods (Rasbash, Steele, Browne & Prosser 2004). The estimations of the equations are generated through a second-order Penalized Quasi-Likelihood (PQL) procedure, using the first-order Marginal Quasi-Likelihood (MQL) estimates as starting values. Without further instructions, first-order MQL is used to estimate the coefficients, an estimation procedure that may lead to downwardly biased estimates (Rasbash et al. 2004).

The category-specific multivariate Type-II Tobit model for money spent is estimated using Markov chain Monte Carlo (MCMC) methodology in Gauss 5. To obtain posterior results, we use the Gibbs sampling technique of Geman and Geman (1984) with data augmentation (Tanner & Wong 1987). The idea of Gibbs sampling aims to sample iteratively from the full conditional posterior distributions of the model parameters, which creates a Markov chain that converges under mild conditions, such that the draws can be used as draws from the joint distribution (for an introduction, see Casella & George 1992 or Tierney 1994). The posterior means and standard deviations of the parameters of interest thus can be obtained. Appendix III provides the conditional posterior distributions. We use 10,000 draws for the burn-in and store 1 per each 10 of the next 10,000 draws for the inference (see e.g., Fox et al. 2004). We monitor the graphs of the sampled values to ensure convergence of the parameters.

3.4 EMPIRICAL SETTING

To test the model, we collected data among customers of a large, well-known national retailer in the Netherlands, as described in Section 1.6. The organization has 58 outlets in all major urban areas in the country, and each outlet contains a range of different categories, including clothing, cosmetics, toys, books, furniture, and so forth.

3.4.1 Informational Web Site

The informational Web site for this study is a theme-oriented site that supports offline activities to increase the likelihood of purchase in stores. It provides customers with information about lifestyle issues related to the different categories of the store, products offered in the stores, promotions, and the organization itself.

The theme orientation is apparent across various topics, such as fashion, interior design, and sports. For instance, the site contains four fashion pages: a general introduction page, with editorial articles and a summary of what can be found on the remaining pages, and three subject pages related to topics such as style, trends, and cosmetics. These pages also contain editorial articles and pictures of products, such as the latest fashion products.

Table 3-2 shows the various product categories from which customers may purchase offline and the corresponding categories featured on the Web. For each Web category, we provide examples of the site pages to offer a sense how the categories are promoted on the site. In this chapter, we consider six different categories.

TABLE 3-2 MATCHING OFFLINE PRODUCT CATEGORIES AND ONLINE THEMES

	Site Theme	*Site Pages*
Fashion[a]	Fashion	Fashion and beauty related pages[b]
Children's products	Children	Child and family related pages, children's play time
Accessories	Accessories	Accessories, trends and cosmetics
Interior design products	Interior design	Interior design, cooking and dining, bed and bath
Sports	Sports	Feeling in shape, sports and physical activities, care and relaxation

a. Fashion refers to both women's and men's fashion departments.
b. These pages are customized according to the gender of the online visitor. For example, a female visitor to the Web page views women's clothing or beauty products.

3.4.2 Data

We provided a description of the data in Section 1.6.3, in which we noted the data are at the individual customer level. The panel contains 8,615 customers, ranging from those who have never used the Web site to frequent site visitors. Data about the offline buying behavior of these customers are available for 29 months, 14 months before the introduction of the Web site and 15 months after. That is, data on the shopping trips in which customers purchase at least one product is available. Data on the number of browsing trips, i.e. in which a customer does not purchase a product, in the offline stores is not available. We model purchase behavior on a monthly level instead of weekly or biweekly because of the infrequency of department store buying behavior by individual customers. The total number of non-zero buying observations in the data set is 117,537. To keep the estimation of the model manageable, we draw a sample of 209 customers responsible for 3,181 non-zero behavior observations. Only customers who were active for at least 5 of the 29 periods either in the store or on Web site are selected. To validate the results, we also draw four random samples to check for consistency in the findings by comparing the estimates and the fit of the validation samples with the estimation sample.

3.4.3 Explanatory Variables

A wide range of variables may influence customers in their purchase decisions, including physical and social surroundings, time, goals and objectives of the task, and antecedent states (e.g., Belk 1975). In considering our data, we include the following explanatory variables:

- Online behavior

For both models, we include the number of site visits by individual *i* in period *t*. For the Tobit-II model, we also include the number of site pages per category. Due to multicollinearity between the total number of site pages and the number of site visits, we eliminate the total number of site pages from the Poisson model.

- Promotional activities by the department store

The organization has three major offline promotional activities during specific periods of the year: the holiday shopping season of November and December; general promotion discounts in all categories in the store; and promotions of fashion categories.

- Individual customer characteristics

Customer characteristics at the zip code level, such as the percentages of loyal households or those in a particular life stage, are gathered from Acxiom[8] In addition, we include the distance the customer has to travel to the nearest outlet of the department store to account for individual effort required to reach the store. Huff (1964) was one of the first to show that store choice depends on the distance between the store and the customer.

- Past behavior

[8] Acxiom is a data management services company that provides customer data and the infrastructure needed to manage and use customer and prospect information and thereby support business decisions and actions.

In both models, we include buying behavior during the previous month, using shopping trips for the Poisson model and average amount spent per category for the Tobit-II model, as well as two-year dummies to capture trends.

3.4.4 Exploratory Insights

Appendix IV shows some descriptive statistics for the most important variables in the data set and the estimation sample. The average number of shopping trips per month drops in the period after site implementation (from 2.6 to 2.1 for the entire data set; from 2.4 to 1.8 for the estimation sample). For most categories, the average amount of money spent also decreases in the period after site implementation for both the overall data set and the estimation sample. The averages of site visits may seem small, but these averages are for all customers, including those who never use the Web site. Appendix IV further shows that buying behavior in the estimation sample is slightly higher than that across the entire data set. Most likely, this finding relates to the selection procedure of the sample, which required customers to be active in at least 5 of the 29 periods.

Table 3-3 compares the months before (e.g., February 2001) and after (e.g., February 2002) the site introduction in terms of both site visitors and non-site visitors.

TABLE 3-3 COMPARISON OF MONTHS BEFORE VERSUS AFTER SITE INTRODUCTION WITHIN GROUPS FOR THE ENTIRE DATA SET

	Non-Site Visitors			*Site Visitors*		
	# of periods lower after SI	*# of periods higher after SI*	*# of periods no change after SI*	*# of periods lower after SI*	*# of periods higher after SI*	*# of periods no change after SI*
# Shopping trips	2	0	10	12	0	0
€ Ladies fashion	0	2	10	5	0	7
€ Men's fashion	1	1	10	6	0	6
€ Children's	0	2	10	7	0	5
€ Accessories	0	1	11	7	0	5
€ Interior design	0	1	11	6	0	6
€ Sports	2	1	9	5	0	7
Total number of periods compared		*12*				

Notes: SI refers to the Web site introduction.

The results show that the non-site visitors display virtually no differences in their offline buying behavior before and after site introduction. Among the site visitors, in at least half the cases, a significant decrease occurs in their offline buying behavior after the introduction (and their use) of the Web site.

With regard to the number of shopping trips, the results for the estimation samples are similar to those for the entire data set. For the other variables, we find more instances of “no change” for the estimation samples than for the entire data set. These results generally indicate that nonvisitors barely changed their behavior over time, whereas the buying behavior of visitors who started using the Web site significantly decreased.

We perform several self-selection analyses to ensure that the visitors to the Web site are not predisposed to be more loyal than nonvisitors. Figure 3-1 shows a comparison over time of both groups, in which the introduction of the Web site is indicated by the line marking period 15 (Appendix V provides the *t*-values of the comparison of both groups in each period).

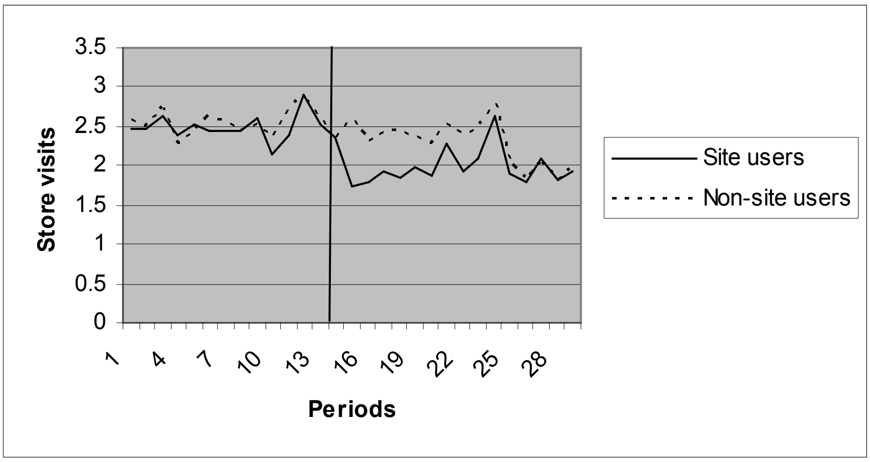

FIGURE 3-1 COMPARISON OF SITE VISITORS AND NON-SITE VISITORS OVER TIME FOR SHOPPING TRIPS

The number of shopping trips per period indicates similar pre-introduction behavior by both groups. After the introduction of the Web site, the site visitors decrease their number of shopping trips per period, as well as the money they spend per category. These results are consistent with the comparisons from Table 3-3. Overall, these analyses provide exploratory insights into the negative effects of site use.

In addition, in Table 3-4, we compare both groups in terms of various sociodemographics. Site visitors are slightly younger and more educated, and more men appear in the site visitors group than in the non-site visitors group. These findings seem to match the general Internet population at the time (2000–2002) of more educated, younger, male customers (e.g., Burke 2002)[9].

Even though Table 3-4 shows differences between the groups, these differences likely are not strong enough to explain the variation over time in the number of shopping trips and money spent per category. Overall, these exploratory analyses show that before the Web site introduction, the buying behavior of both groups was similar. After the introduction, the customers using the Web site change their buying behavior, whereas the non-site visitors do not. Furthermore, a Poisson model of the number of site visits shows that the small differences in sociodemographics between visitors and non-site visitors do not explain online behavior.

TABLE 3-4 COMPARISON OF SOCIODEMOGRAPHICS BETWEEN SITE VISITORS AND NON-SITE VISITORS

	Site Visitors	*Non-Site Visitors*	*Test Value*
Age	39.5	42.7	**3.189**
Number of children	1.2	1.2	0.517
Number of adults	2.2	2.3	0.639
High school education	98.0%	97.5%	0.127
College education	45.7%	29.8%	**12.138**
Distance to closest store	6.5	6.2	-1.587
Gender: male	44.8%	23.1%	**22.655**
Gender: female	55.2%	76.9%	
N	6594.0	951.0	

Notes: Bold test values (*t*-value or χ^2-value) are significant at the 5% level.

[9] To determine whether sociodemographics explain online behavior, we ran a Poisson regression of the number of site visits per month. For non-site visitors, the number of site visits is 0. In addition to the sociodemographics from Table 3-4, we include lagged Web visits, year dummies, and promotional activities. The results show that sociodemographics do not explain online behavior.

3.5 FINDINGS

3.5.1 Number of Shopping Trips

We test multiple sets of explanatory variables on the estimation sample and find that most of the individual customer characteristics in Table 3-4, with the exception of distance to the store, do not significantly influence the number of shopping trips. The total amount of time spent on the Web site also does not contribute significantly to the explanatory power of the model.

We obtain the best results from a parsimonious model, the results of which appear in Table 3-5. The first column in the table shows the effects of the explanatory variables on the parameter λ_{it}, and the second column provides the corresponding standard errors. We calculate so-called "partial effects" for each of the k independent variables X_k for 2001 and 2002. Because the expected number of shopping trips per period is given by

$$E(\upsilon_{it} \mid X_{it}) = Var(\upsilon_{it} \mid X_{it}) = \lambda_{it} = e^{\gamma X_{it}} , \tag{9}$$

we can express the partial effect for X_k as:

$$\begin{aligned} \frac{\partial E(\upsilon_{it} \mid X_{it})}{\partial X_k} &= \gamma_k e^{\gamma X_{it}} \\ &= \lambda_{it}\gamma_k \end{aligned} . \tag{10}$$

To capture the individual heterogeneity γ_k is extended with the individual effect

$$\frac{1}{I}\sum_{i=1}^{I}\gamma_{ki} . \tag{11}$$

Because λ_{it} depends on all explanatory variables, this expression reveals that the effect of a particular explanatory variable depends on the value of the other explanatory variables. Except for the year dummies, the explanatory variables are set to their mean value. However, vector X_{it} contains two year dummies. By setting these dummies to 1, independent of each other, we can calculate the partial effects of the explanatory variables for each year; if we set both dummies to 0, we can determine the partial effects for 2000. However, because the Web site was not introduced until March 2001, we do not discuss these effects herein.

TABLE 3-5 PARAMETER ESTIMATES OF THE VARIABLES THAT EXPLAIN THE NUMBER OF SHOPPING TRIPS

	Estimated Parameter	*Std. Error*	*Partial Effects 2001*	*Partial Effects 2002*
Intercept[a]	**0.625**	0.057	--	--
Holiday promotion	**0.192**	0.044	**0.383**	**0.341**
General promotion	**0.133**	0.041	**0.265**	**0.236**
Fashion promotion	0.075	0.043	0.150	0.133
Dummy 2001	**-0.134**	0.035	--	--
Dummy 2002	**-0.250**	0.046	--	--
Site visits[a]	**-0.456**	0.070	**-0.909**	**-0.809**
Distance to closest outlet	**-0.013**	0.005	**-0.026**	**-0.023**
Lagged shopping trips	**0.072**	0.009	**0.144**	**0.128**
Variance intercept	**0.093**	0.015	--	--
Variance site visits	**0.508**	0.074	**0.570**	**0.508**

a. The variable is estimated at the individual level.
Notes: Bold parameter estimates are significant at the 5% level.

From the partial effects in 2001, we determine that the strongest influence on the number of shopping trips in a particular month is the number of site visits. For 2001, with an increase of 1 in the number of site visits, the expected number of monthly shopping trips decreases by .9 trips. The decrease in the number of shopping trips is slightly lower in 2002, with a decrease of .8. Hence, an important part of the decrease in the number of shopping trips over time can be attributed to the introduction and use of the Web site.

Regarding the other partial effects in 2001, the holiday promotion has a partial effect, namely, a .38 increase in the number of shopping trips. The general promotion has a slightly smaller positive influence (.27) than the holiday promotion, whereas the fashion promotion has no significant effect on the number of shopping trips. We find a similar pattern in the promotional activities for the partial effects in 2002.

The negative coefficients for the year dummies illustrate a trend effect that can be explained partly by a decline in the economy. The distance to the closest store has a negative influence on the number of shopping trips, such that the closer customers live to a store, the more often they shop. Finally, we find a positive partial relationship between the number of shopping trips in t and the shopping trips in $t - 1$. We discuss the estimated variance for the site visits parameter in Section 3.5.5.

To determine the predictive power of the model, we calculate a hit rate for the estimation sample and allow for different margins of error. The hit rate describes the percentage of correctly estimated shopping trips per month compared with the actual number of shopping trips per month. The average number of shopping trips per month is 2.05 with a standard deviation of 1.88. When the margin of error is 1 store trip per month, the hit rate is 50.3%, whereas for an error margin of 2 shopping trips per month, the hit rate is 75.9%.

3.5.2 Validation for the Number of Shopping Trips

To determine whether these results are driven by specific features of the estimation sample, we draw four validation samples, estimate the model on each sample, and determine the extent to which the parameters of the validation samples are comparable with the corresponding parameters of the estimation sample. We use three comparisons: (1) the percentage of validation sample parameters that fall within the 95% confidence interval of the estimation sample parameters, (2) the percentage of validation sample parameters that have the same sign as the estimation sample parameters, and (3) the percentage of validation sample parameters that have the same sign and significance as the estimation sample parameters.

Of the validation sample parameters, 75% fall within the confidence interval. Of the 48 parameters, 47 (97.9%) have the same sign as the estimation sample parameter, and 43 (89.6%) have both the same sign and significance level as the estimation sample parameter. We also determine the percentage of customers with a positive coefficient for site visits across all samples; on average, 21% of customers across the five samples experience a positive effect from the Web site on their offline shopping trips. Overall, the results from the validation samples are consistent with the results of the estimation sample.

3.5.3 Amount Spent per Trip per Category

We now consider the estimates for the multivariate Type-II Tobit model, which we estimate for six categories simultaneously.[10] To detect possible cross-category correlation s, we use minimal restrictions on the

[10] We also estimate a Type-I Tobit of the total money spent in month *t* by individual *i*. The parameter coefficients from this model are similar in terms of direction to the parameters presented for the MVP Type-II Tobit.

covariance matrices. The covariance matrices Σ and Ω are set to full, with 1 on the diagonal and full, respectively. The matrix Σ provides information about cross-category effects regarding the decision to buy, such that a high positive correlation indicates that purchases in two categories usually coincide. Matrix Ω indicates the variances and covariances between the error terms of the six categories for the amount spent. The covariance matrices of the unobserved heterogeneity Σ_α and Σ_β are set as the diagonal matrices. Furthermore, Σ_β must be restricted to ones to ensure identification. The covariance matrix of unobserved heterogeneity (Σ_α) provides information about the level of heterogeneity in the sample, for instance minimal variance indicates a low level of heterogeneity. We summarize the settings for the covariance matrices in Table 3-6.

TABLE 3-6 COVARIANCE MATRIX SETTINGS

	Yes/No Decision	*Amount Decision*
Covariance matrix of error term	Σ full with 1 on diagonal	Ω unrestricted
Covariance matrices of unobserved heterogeneity	Σ_α diagonal	Σ_β identity

We test multiple sets of explanatory variables, and just as for the model of shopping trips, we find that most of the customer characteristics do not significantly influence the money spent per category.

To determine the final model, we first estimate six different models[11] with the specific elements pooled or unpooled across the six product categories. Appendix VI shows the fit criteria for the models and the results of the Chow test to determine which variables can be pooled. The fit criteria show that the models have a comparable fit, but the Chow test comparing model 1 with model 2 shows that pooling is not justified. However, comparing model 1 with models 3–6 indicates that pooling in these cases is justified. Comparing model 3 (only constant unpooled) with model 4 (constant and site visits unpooled)

[11] Model 1 has all variables unpooled across the categories. In model 2, all variables are pooled. In model 3, only the constant is unpooled. In model 4, both the constant and the number of Web site visits are unpooled. In model 5, the constant and the number of Web site pages per category are unpooled. In model 6, the constant, Web site visits, and number of Web site pages per category are unpooled.

shows that choosing not to pool site visits significantly improves the model, whereas models 5 and 6 (site pages unpooled) show no significant improvement. Therefore, we use model 4 with the constant and site visits unpooled.

We provide the estimation results of model 4 in Tables 3-7 and 3-8. The intercept and site visits are category specific; the “Yes/No” columns indicate the effect of each variable on whether someone purchases in a particular category. The “Amount” columns indicate the effect of each variable on the amount of money spent per shopping trip in a specific category, given that an individual buys from the category.

We used Morrison’s Proportional Chance Criterion (Morrison 1969) to determine whether the first stage of the model, i.e. the classification of the decision to buy, outperforms chance. For each of the categories the chance proportion is calculated (i.e. ladies’ fashion = .59; men’s fashion = .84; children = .68; accessories = .56; living = .78; sports = .87) with which the hit rate is compared. For the categories ladies, children and accessories the model did significantly better than expected by the chance proportion. For the categories men, living and sport the model did not do significantly better than the chance proportion. Most likely the low number of purchases in these categories causes this result.

The number of site visits significantly decreases purchase incidence (yes/no) and the amount spent for almost all categories, though the negative effect for decision to buy in the men’s fashion category is insignificant. These negative effects are consistent with those we found pertaining to site visits on offline shopping trips. The effect of the number of site pages viewed per category is insignificant.

The general promotion has a positive effect on the decision to buy and, given this decision, the amount of money spent, but the fashion promotion has a significant effect only on the amount of money spent. A similar effect occurs for the holiday promotion. Therefore, even though these promotional activities do not significantly increase the probability of deciding to buy, they increase the amount of money spent.

From the estimation results, we deduce that there is virtually no (economic) trend effect on the probability of buying and amount of money spent. The distance to the closest store has a negative effect on both stages, but it is only significant for the decision to buy. In other words, if the customer lives farther away, he or she is less likely to decide to buy in the department store. Finally, the effect of the last purchase occasion is insignificant.

The variance of unobserved heterogeneity in the number of site visits indicates small individual differences in the effect of Web site visits. For the constant, the variances are slightly higher, which suggests that missing variables could reduce the differences between individuals. The largest unobserved heterogeneity occurs in the Children's category.

TABLE 3-7 PARAMETER ESTIMATES OF VARIABLES THAT EXPLAIN THE BUYING DECISION AND AMOUNT SPENT FOR LADIES' FASHION, MEN'S FASHION, AND CHILDREN'S PRODUCTS

	Ladies Fashion		*Men's Fashion*		*Children*	
	Yes/No	*Amount*	*Yes/No*	*Amount*	*Yes/No*	*Amount*
	Category-specific effects					
Intercept	**-0.379**	**0.469**	**-1.087**	**-0.612**	**-0.840**	**-0.178**
Site visits	**-0.311**	**-0.901**	-0.076	**-0.449**	**-0.256**	**-0.816**
	Pooled effects[a]					
Promotions:						
• Holiday			0.059	**0.165**		
• General			**0.215**	**0.517**		
• Fashion			0.039	**0.144**		
Year dummies:						
• 2001			-0.008	0.040		
• 2002			**-0.075**	-0.016		
Distance			**-0.007**	-0.014		
Lagged spending			0.001	-0.004		
Site pages			-0.004	-0.017		
	Variance of unobserved heterogeneity $(\Sigma_\alpha, \Sigma_\beta)$[b]					
Intercept	**0.142**	1	**0.216**	1	**0.572**	1
Site visits	**0.051**	1	**0.056**	1	**0.054**	1
Yes/No hit rate	0.71		0.85		0.82	

Notes: The intercept and the site visits are category specific. Bold parameter estimates are significant at the 5% level (95% HPD region).

a. Pooled effects indicate coefficients that are pooled across the (six) categories.
b. For Σ_α the estimated diagonal elements are shown. For Σ_β (an identity matrix) the ones are shown.
c. The multivariate Probit Yes/No hit rates show in what percentage of occasions the model correctly predicts that an individual will buy for each category.

TABLE 3-8 PARAMETER ESTIMATES OF VARIABLES THAT EXPLAIN THE BUYING DECISION AND AMOUNT SPENT FOR ACCESSORIES, LIVING, AND SPORT

	Accessories		*Living*		*Sport*	
	Yes/No	*Amount*	*Yes/No*	*Amount*	*Yes/No*	*Amount*
			Category-specific effects			
Intercept	**-0.355**	**0.205**	**-0.809**	**-0.285**	**-1.142**	**-1.098**
Site visits	**-0.349**	**-0.867**	**-0.348**	**-0.980**	**-0.190**	**-0.717**
			Pooled effects[a]			
Promotions:						
• Holiday			0.059	**0.165**		
• General			**0.215**	**0.517**		
• Fashion			0.039	**0.144**		
Year dummies:						
• 2001			-0.008	0.040		
• 2002			**-0.075**	-0.016		
Distance			**-0.007**	-0.014		
Lagged spending			0.001	-0.004		
Site pages			-0.004	-0.017		
			Variance of unobserved heterogeneity ($\Sigma_\alpha,\Sigma_\beta$)[b]			
Intercept	**0.205**	1	**0.100**	1	**0.115**	1
Site visits	**0.054**	1	**0.061**	1	**0.055**	1
Yes/No hit rate[c]	0.71		0.78		0.87	

Notes: The intercept and the site visits are category specific. Bold parameter estimates are significant at the 5% level (95% HPD region).

a. Pooled effects indicate coefficients that are pooled across the (six) categories.
b. For Σ_α the estimated diagonal elements are shown. For Σ_β (an identity matrix) the ones are shown.
c. The multivariate Probit Yes/No hit rates show in what percentage of occasions the model correctly predicts that an individual will buy for each category.

Table 3-9 offers the correlations among the different categories estimated through the Type-II Tobit model; these correlations are not very strong. The ladies' fashion, men's fashion, accessories, and sports categories indicate significant correlations that suggest cross-category or co-occurrence effects (Manchanda et al. 1999). Categories can be considered complementary when promotional activities in category x lead to additional buying in category y (for instance, coffee and creamer), but they are substitutes if a significant negative relation characterizes the sales of x and y. Manchanda et al. (1999) also describe co-occurrence, which takes place if categories co-occur in the same basket because they have similar purchase cycles, such that sales levels of category *x* influence the sales levels of category *y*. The strongest correlation appears for [Men's Fashion, Sports] and [Ladies Fashion, Accessories]. Intuitively, the latter pair could be a matter of co-occurrence, but it also may be that when ladies' fashion items are discounted, women are more inclined to buy accessories to match their new clothes, which implies cross-category effects. The expenditures for living do not correlate with expenditures in any other category.

TABLE 3-9 CORRELATION MATRIX FOR THE DECISION TO BUY PER CATEGORY

	Ladies	*Men's*	*Children*	*Access*	*Living*	*Sports*
Ladies	**1**	**0.125**	**0.100**	**0.182**	0.017	**0.158**
Men's	**0.125**	**1**	0.031	**0.145**	0.035	**0.202**
Children	**0.100**	0.031	**1**	**0.130**	0.014	0.061
Accessories	**0.182**	**0.145**	**0.130**	**1**	0.068	**0.090**
Living	0.017	0.035	0.014	0.068	**1**	0.066
Sports	**0.158**	**0.202**	0.061	**0.090**	0.066	**1**

Notes: Bold parameter estimates are significant at the 5% level.

Table 3-10 shows the variance–covariance matrix Ω for the second stage of the Tobit model, spending. The highest variance occurs in the unexplained part of the ladies' fashion category; in other words, behavior in this category is the hardest to explain with our set of explanatory variables. The largest covariances again occur for the pairs [men's fashion, sports] and [ladies' fashion, accessories], but we also find another relatively high covariance for [men's fashion, accessories].

TABLE 3-10 VARIANCE–COVARIANCE MATRIX FOR THE AMOUNT OF MONEY SPENT

	Ladies	*Men's*	*Children*	*Access*	*Living*	*Sports*
Ladies	**1.214**	**0.100**	**0.093**	**0.163**	-0.006	**0.095**
Men's	**0.100**	**0.883**	0.027	**0.125**	0.005	**0.121**
Children	**0.093**	0.027	**0.828**	**0.092**	0.009	0.028
Accessories	**0.163**	**0.125**	**0.092**	**0.929**	**0.064**	**0.047**
Living	-0.006	0.005	0.009	**0.064**	**0.954**	**0.033**
Sports	**0.095**	**0.121**	0.028	**0.047**	**0.033**	**0.765**

Notes: Bold parameter estimates are significant at the 5% level.

3.5.4 Validation for Amount Spent per Trip

To determine whether the results are driven by the composition of the estimation sample, we estimate the multivariate Type-II Tobit model on four random validation samples. We use the same three comparisons as those we performed for Poisson model, namely (1) the percentage of validation sample parameters that fall within the 95% confidence interval, (2) the percentage of validation sample parameters that have the same sign, and (3) the percentage of validation sample parameters that have the same sign and significance.

With regard to the confidence interval, across both stages, 60.6% (65% for stage one, 56.3% for stage two) of the validation sample parameters fall within the confidence interval. Of the 160 total parameters, 153 (95.6%; 100% for stage one and 91.25% for stage two) have the same sign as the estimation sample parameter, and 119 parameters, or 74.38% (75% for stage one and 73.75% for stage two), have both the same sign and significance level as the estimation sample parameters. An inspection of the hit rate and the mean average percentage error (MAPE) also shows a comparable fit across samples. Overall, the results from the validation samples again are consistent with the estimation sample.

3.5.5 Further Investigation of the Individual Site Parameters

Although the effect of the number of site visits on shopping trips is negative, the Web site may have positive effects for at least some customers. The unobserved heterogeneity parameters for both the Poisson model and the MVP Type-II Tobit model enable a deeper investigation. In the Poisson model, it appears that approximately 20% of the customers in the estimation sample experience a positive effect of the Web site on the number of shopping trips. For other customers, the expression $(\gamma + \gamma_i)$ from equation (3) regarding the effects of site visits is negative.

The unobserved heterogeneity parameters for the Type-II Tobit model suggest an investigation of the positive effects of the site visits on some customers' decision to buy and the amount spent. With respect to the decision to buy (first stage of the Tobit-II model), in the estimation sample, 0–9% of the customers experience a positive effect from using the Web site. With regard to money spent, it ranges from 9% to 16%. We display the percentages for the estimation sample and the average percentages across all five samples in Table 3-11.

TABLE 3-11 PERCENTAGE OF CUSTOMERS WITH POSITIVE EFFECTS (POSITIVE COEFFICIENTS IN THE MVP) FOR THE NUMBER OF SITE VISITS

	Estimation Sample		*Average: 5 Samples*	
	Yes/No (%)(α_{ic})	*Spending (%)(β_{ic})*	*Yes/No (%)(α_{ic})*	*Spending (%)(β_{ic})*
Ladies	0	14	0	12
Men's	9	16	2	8
Children	1	11	0	10
Accessories	0	10	0	10
Living	0	9	1	11
Sports	1	11	0	7
Average	2	12	0	10

Note that for the men's category, a substantial number of customers in the estimation sample suggest that site use has a positive effect on their decision to buy and the amount of money they spend. In the other four samples, we find similar patterns, through not similarly high percentages.

We perform various post hoc analyses for the Type-II Tobit parameters (see Appendix VII for the results). Across the 5 samples, 341 of the 1,286 customers display positive site use coefficients. With this approach, a customer may have 12 positive coefficients (i.e., 2 stages, 6 categories per stage), and among the group of customers with positive coefficients, 92.4% reveal 3 positive coefficients at most.

Customers with at least one positive coefficient live closer to the store. At the *zip code level*, the group with at least one positive coefficient contains more single households, which buy significantly less from catalogs. None of the *individual* sociodemographics is significant except for distance. Therefore, these results indicate that sociodemographics do not convincingly contribute to explaining the different effects of the Web site.

Customers with at least one positive coefficient buy significantly more items, spend more money, and visit the store more often. At the category level, we find similar effects for all categories except for the living and sports categories. Customers with positive coefficients also have viewed significantly more Web pages.

Finally, we performed an overall calculation to determine how much more the customers with a positive effect from the Web site (i.e. approximately 20% of the sample for the Poisson model) had to visit the

Web site to make up for decrease in behavior by the customer with a negative effect from the Web site. The analysis shows that if both groups of customers (i.e. customers with a positive coefficient and customers with a negative coefficient) have an equal number of Web site visits, the total effect on offline buying behavior is negative. If the customers with a negative effect of the Web site only visit the Web site once, the total effect is positive. If these customers visit the Web site twice, the customers with a positive effect from the Web site have to visit the Web site at least seven times to counteract the negative effect. Hence, it seems that given the low percentage of customers with a positive effect from the Web site a total positive effect on offline buying behavior is unlikely.

3.6 DISCUSSION

For most customers, the effects of visiting the Web site on shopping trips, the decision to buy in a particular category, and the amount of money spent in that category are negative. Ansari et al. (2006) and Gensler et al. (2007) reveal similar negative effects on individual customer behavior in the case of an added transactional Web site. We extend their work by demonstrating that an added informational Web site causes the same negative effects on individual customer behavior. Our results also fall in line with those of Van Baal and Dach (2005), who find customer retention levels within the same organization of 10% across the online and offline channels.

Ansari et al. (2006) focus on transactional channels, Van Baal and Dach (2005) base their results on a survey, and our study is based on actual behavior given an informational channel. The differences among these studies clearly show that on the firm-specific level, multiple channels provide customers, but not necessarily firms, with benefits.

The negative effects for firms, and the positive effects for customers, may result from (1) better and more efficient customer decision-making processes, (2) reduced impulse buying, and/or (3) reduced switching costs. We review our findings in light of these three possible explanations.

Efficient decision-making processes. Customers pursuing economic goals are likely to use online channels to form their consideration sets, because it is easier to compare products in this medium, unless the hedonic dimension is important for the particular product category (Balasubramanian et al. 2005). Mathwick and Rigdon

(2004) indicate that attitudes toward a firm's Web site and its brands and/or products may be enhanced when customers participate in an engaging, enjoyable online experience. Combining this finding with the distinction made by Hoffman and Novak (1996) between experiential and goal-directed Internet users; we posit that most customers in our panel use the site in a goal-directed manner. Therefore, on the one hand our respondents may become more efficient in their decision-making process. On the other hand, for experiential visitors, the Web site may not offer sufficiently compelling experience to enhance their attitudes and behavior toward the firm.

Reduced impulse buying. Shiv and Fedorikhin (1999) indicate that in situations in which processing resources are scarce, customers with higher impulsivity choose products on the basis of spontaneous evoked affect rather than cognitions. Providing highly impulsive customers with a medium like the informational Web site with which they can interact but not transact, makes their processing resources highly available. After gathering information online, they must consciously decide to go to the store, which minimizes the chances that they will engage in impulse buying. In other words, highly impulsive customers who have easy access to sufficient processing recourses will choose on the basis of cognitions rather than impulses. Our findings indicate that customers who use the Web site make fewer shopping trips, which means they have fewer opportunities to choose products on the basis of evoked affect as they walk through the store. Therefore, site visits may reduce impulse buying behavior.

Reduced switching costs. The last explanation relies on reduced switching costs, which might occur because competitors are just a click away (Porter 2001) or because the online context loosens psychological bonds (e.g., Neslin et al. 2006). An informational Web site always has a disadvantage, compared with competitors who offer transactional Web sites, because it cannot offer the customer a possibility to buy the product immediately. Informational Web sites therefore force the customer to visit the offline store if they wish to purchase a particular product. In this situation, a customer might just as easily click to a transactional Web site, especially for generic or nonsensory products such as books or compact discs.

3.7 CONCLUSIONS

In this chapter, we study the effects of informational Web sites on individual offline buying behavior. With our decomposition, we model two components to determine whether the use of the informational Web site changes the frequency of offline shopping trips or the average amount of money spent per shopping trip in six different categories. We also determine whether category-specific site pages affect the amount of money spent per category.

For most customers, use of the informational Web site (i.e., site visits) has a negative influence on offline shopping behavior, in terms of the number of shopping (offline) trips, the likelihood of buying, and the amount of money spent in a particular product category. Previous studies (e.g., Moe & Fader 2004) indicate that in a pure online setting, more online visits increase the propensity to buy online, but according to our results, this relationship does not hold in an online/offline setting; rather, more online visits decrease people's propensity to shop and buy offline. However, we argue that this result is not driven by a negative perception of the Web site; the May 2002 survey reveals average satisfaction with the Web site of 3.43 and average satisfaction with the store of 3.78 on 5-point scales—quite satisfactory. Furthermore, as we discussed in Chapter 2, customers with positive site attitudes actually spend less money. The results also show that category-specific site pages do not significantly affect the money spent in a particular category.

For only a small percentage of customers, visiting the Web site has a positive impact on offline behavior. Specifically, 20% of customers visit the offline store more often and about 10% buy more products. Our post-hoc comparison shows that customers who experience a positive effect from using the Web site on average spend more at the department store. Therefore, an informational Web site can be beneficial among a small percentage of the company's customers. If these customers spend more, an exclusive Web site makes sense. The overall calculation confirms that a Web site should be exclusive, as the small percentage of customer with a positive impact on their offline behavior cannot make up for the customers with a negative impact on offline behavior. Introducing an informational Web site to the majority of customers makes them more efficient and conscious of their decisions.

The results from studies focusing on a more general (non-firm specific) level indicate that consumers benefit from using multiple channels (see e.g., Nicholson et al. 2002; Burke 2002). However, these studies seem to indicate that firms' offline channels can also benefit from this behavior. The findings from our study and Gensler et al. 2007, Ansari et al. 2006 and Van Baal and Dach 2005 indicate that this might not be the case. Further research is needed to determine under which circumstances and/or conditions both firms and customers benefit from the multichannel environment.

Many variables may affect cross-channel behavior, but we restrict our consideration to those to which we had access. Most of these variables pertain to individual behavior either offline or online, whereas virtually no data are available for marketing instruments other than the Web site, such as pricing, features, displays, or competitors' marketing efforts. Because we deal with many product categories sold in the department store, the potential competitors are also many. Furthermore, the competitive profiles of the 58 outlets of the department store differ, which makes it impossible to collect data about all potential competitors. The negative effects from visiting the Web site and its pages might be more logical in a competitive setting. Customers with a higher degree of technology readiness (e.g., Parasuraman 2000) might also visit competitors' Web sites more frequently. If these competitors offer the possibility to buy online, then a negative effect between Web visits or page views and offline store patronage might be expected. An interesting avenue for future research would be not only to include competitive effects but also variables such as "share of Web visits or page views".

Because of the few time-varying variables included in this study, our results are less suitable for forecasting purposes. Rather, they are intended primarily to provide deeper insights into how the use of an informational Web site may influence buying behavior in the offline store. We acknowledge that the fit of the model likely would increase with more time-varying variables.

Furthermore, our study is limited to one Web site for one organization, which makes it hard to indicate the extent to which these results are generalizable to other organizations or Web sites. With our customer panel, we also cannot determine if the Web site provided the organization with new customers but instead are limited to investigating its effect on existing customers. The likelihood that the Web site attracted new customers is small given that the Web site is only promoted through the offline stores. Our study does provide a preliminary clarification of the impact an informational Web site can have on offline buying behavior, and the models we have developed easily can be applied to other situations in which both online and offline information about individual customers is available.

Consequently, we offer evidence that the use of an informational Web site influences customers' buying behavior, especially when the site itself does not provide customers with the opportunity to buy online. Our research also demonstrates that implementing an informational Web site should be considered with great care, because the majority of customers will likely become more efficient as they gather the readily available online information.