Determining the cross-channel effects of informational web sites

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4 Cross-Channel Behavior for an Informational Web Site and an Offline Store[12]

The objective of the study discussed in this chapter is to gain insight into the long-term cross-channel effects given an informational Web site and an offline store. In comparison to Chapter 3, we now consider long-term effects of cross-channel behavior at a more aggregate level. We explicitly consider various marketing efforts, such as the introduction of an informational Web site and online promotions on offline buying. We also consider feedback loops, including the way in which online search might trigger offline buying and vice versa, by estimating a vector autoregressive model. Cross-channel behavior varies with the context characteristics, such as product type and the frequency of site visits. Our findings show that at the aggregate level online and offline behavior do not effect each other strongly. When we split the data based on context characteristics, we find more effects between online and offline behavior. The results for the median splits are unexpectedly compared with findings from previous research. Moreover, online and offline marketing efforts do not necessarily have the same impact on the behavior in the channels.

4.1 INTRODUCTION

The Internet has captured practitioner and research attention during the past decade, leading to an impressive body of marketing literature on the topic. For instance, 6% of all articles in the top five marketing journals in the past seven years (1998-2005) deal with Internet channels. Most of these articles focus on transactional Web sites; only a handful (0.4%) study the effects of informational Web sites on customer behavior.

Most firm Web sites do not allow for transactions and thus may be deemed informational in nature (e.g. 70% in Carroll 2002). Informational Web sites are easier to implement, because they do not require integration with the follow-up processes demanded by online orders. Moreover, consumers predominantly prefer to use the Internet

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for information searches and conduct their subsequent purchases offline. Such 'Web-to-store' shopping, or cross-channel behavior, represents about $1.70 of every dollar spent directly online (CrossMedia Services 2006). In another study, American multichannel retailers indicated that the Web influenced 20% of their in-store sales (Forrester Research 2005).

The inability to combine data regarding actual search behavior in one channel with actual buying behavior in another (Sullivan & Thomas 2004) has prevented insights. This study answers the call for further research (see, e.g. Verhoef et al. 2007) that studies actual channel use regarding search and purchase from a single firm perspective; it also incorporates the sequential process by observing the channel dynamics over time. Unlike Chapter 3 where we focus on immediate effects of online behavior, this study focuses on the long-run effects of cross-channel behavior. These effects might be quite different from the short-term effects in a similar way as has been found in studies measuring the short- and long-term effects of promotions (see e.g., Nijs, Dekimpe, Steenkamp & Hanssens 2001).

Therefore, the objective is to determine the long-term cross-channel effects, i.e., from online search to offline buying and vice versa. Furthermore, this study helps to determine the effects of marketing efforts in channel *a* on buying behavior in channel *b* (i.e., cross-channel effects of marketing efforts), as well as how context characteristics moderate cross-channel behavior and marketing effort effects.

We investigate cross-channel customer behavior in an informational Web site/offline store setting by explicitly considering feedback loops between offline buying and online search behavior. We focus on two channels, a traditional department store (offline channel) and an informational Web site (online channel). We estimate a vector autoregressive (VAR) model that includes four components of offline buying behavior (monetary value per product, products per shopping trip, shopping trips per customer, and number of store customers) and four components of online search behavior (time per page, pages per visit, site visits per visitor, and number of online visitors) for a period of 126 weeks. We also address various marketing efforts (offline promotions, site introduction, online promotions, and online communications) with the VAR model and determine moderating effects of context characteristics through median splits.

Given that we study the long-term impact of cross-channel behavior, we focus on the cumulative impact. The cumulative impact measures the total effect over a period of 26 weeks. For marketing efforts, we determine the immediate impact in the opposite channel, which involves effects in the same week. For this study, we are primarily interested in the immediate cross-channel effect of promotions, although it is known that marketing effects may effect sales in the weeks following the promotion (e.g., Van Heerde, Leeflang & Wittink 2001) We estimate the VAR model at two levels: the aggregate level (over the entire data set), and the median split level. To the best of our knowledge, this chapter describes the first study to

- Analyze sequential cross-channel customer behavior in terms of online search and offline buying for a given firm,
- Determine how context characteristics moderate cross-channel customer behavior, and
- Use a persistence modeling approach to capture dynamic effects and feedback loops between online search and offline buying.

The remainder of this chapter is organized as follows: We describe the relevant literature, then present several hypotheses related to marketing efforts and context characteristics that may influence multichannel behavior in this particular setting. In our methodology section, we focus on the persistence modeling approach for estimating long-term and feedback effects and show that this method can be used to determine effects for different moderators. After describing our data set, we present and discuss our findings and conclude with some avenues for further research.

4.2 LITERATURE REVIEW

We first discuss previous research in multichannel behavior and then detail relevant studies in online consumer information search. Given our research theme of cross-channel effects, we also discuss the decomposition of customer behavior.

4.2.1 Multichannel Behavior

The general assumption is that multichannel customers are better customers for a firm, because they generate more revenue and purchase more items. This is confirmed in a number of studies (see e.g., Thomas & Sullivan 2005). However, Sullivan and Thomas (2004) indicate that introducing the Internet as a transactional channel does not necessarily increase the customer's spending amount. Ansari et al. (2006) and Gensler et al. (2007) both show that customers who increasingly use the Internet have lower behavioral loyalty, manifested as lower purchase quantities. Ansari et al. (2006) speculate that this effect results from the lower switching costs, easy comparison across firms, and less personal contact involved with the Internet, all of which loosen the psychological bonds between the customer and the firm. Another explanation of these results suggests that customers may free ride. This means that customers use online information in their decision-making process but purchase elsewhere (Van Baal & Dach 2005). These consumers are also called "research shoppers" (Verhoef et al. 2007).

The key question for these studies is how search behavior in one channel influences buying behavior in another. Both studies collect cross-sectional survey data, but Verhoef et al. (2007) do not focus on a particular firm, whereas Van Baal and Dach (2005) do. This difference probably explains why Verhoef et al. (2007) find that for 73% of consumers, Internet search leads to offline store purchases, whereas Van Baal and Dach (2005) find a similar relationship for only 10% of consumers. Furthermore, they indicate that multichannel companies lose more customers across channels than they retain (Van Baal & Dach 2005).

The choice of a particular channel depends on context characteristics, such as product attributes, consumer and situational characteristics (e.g., Neslin et al. 2006). These characteristics likely also influence cross-channel behavior. Verhoef et al. (2007) note that customers evaluate channels for the different stages in their decision-making processes, on the basis of channel attributes, such as search convenience and risk. We expect multichannel behavior to differ depending on the following characteristics: (1) product type, (2) level of flow experienced, and (3) frequency of site visits as we discuss in more detail below.

Product type. Empirical research demonstrates that product type can explain some variation in channel choice. Consumers evaluate sensory products using all their senses, especially touch, smell, and sound, before purchase (Degeratu, Rangaswamy, & Wu 2000). In contrast, they usually can assess the value of nonsensory products objectively using readily available information conveyed by descriptions (Peterson et al. 1997; Degeratu et al. 2000).

Research shows that buying via the Internet is less suitable for products with more sensory attributes, such as clothing, for several reasons. First, the offline environment offers more total information about sensory products (Degeratu et al. 2000). Second, consumers prefer channels that accurately portray the characteristics of the product (Burke 2002). Third, consumers need more tactile information (Peck & Childers 2003; Citrin et al. 2003). That is, Peck & Childers (2003) indicate converting consumers with a high need for touch to non-touch media, such as the internet, will be difficult. For these customers, an integrated click and brick strategy is necessary (Peck & Childers 2003). Because nonsensory products are more suitable for online shopping, a consumer probably will not need an offline channel to select them, unlike sensory products.

Level of flow experienced. The extent to which a customer experiences flow while visiting a web site influences cross-channel effects (e.g., Novak, Hoffman, & Yung 2000; Mathwick & Rigdon 2004). Hoffman and Novak (1996) define flow as a state that is characterized by a seamless sequence of responses facilitated by machine interactivity, intrinsically enjoyable, accompanied by a loss of self-consciousness, and self-reinforcing. This state enhances attitudes toward a firm's Web site (Mathwick & Rigdon 2004), as well as behaviors such as depth of search and repeat visits (Hoffman & Novak 1996; Novak et al. 2000). Customers who experience higher levels of flow engage in more online activity and find the online channel more enjoyable, which suggests a high state of flow mainly drives same-channel effects.

Frequency of site visits. Consumers with a higher visiting frequency also have higher conversion rates online (e.g., Moe & Fader 2004) and tend to have greater loyalty toward or preference for a particular channel (e.g., Shankar et al. 2003). In the setting of an informational Web site, a conversion must take place offline, and from the firm perspective, more frequent Web visits should lead to increased offline behavior. However, as previous research indicates, it is more likely that a high frequency of Web visits signals preference for the online channel.

4.2.2 Online Information

The vast amount of easily accessible information on the Internet and the relative newness of the medium prompt questions about the type of information that can add value for the customer, how online experiences might influence the effects of that information, and whether crucial differences exist between online information and classical advertising.

We assume that the elements that determine advertising effectiveness also determine site effectiveness, on the basis of empirical outcomes from various studies. For example, Chen and Wells (1999) demonstrate that consumers evaluating Web sites consider entertainment and informativeness important just as they do when they evaluate traditional media. Similarly, Alpar, Porembski and Pickerodt (2001) show that Web sites with special-interest content tend to be more effective than those with general interest content. Gallagher, Parsons and Foster (2001) and Gallagher, Foster and Parsons (2001) show that given an equal opportunity for exposure, a print advertisement transferred to the Web is as effective as it has been in print, even when it does not take full advantage of the Internet's capabilities.

However, we must note a crucial difference between the effects of online and traditional media. Traditional media are limited by consumers' tendency to avoid advertising, the potentially limited relevance of messages at the time of exposure, and the nature of the advertising, which may not be worth the consumer's attention (e.g., Ducoffe 1996). In contrast, online consumers have control over what they view and for how long, which implies they engage in much more active dealing with the available information. On the Web, consumers actively search for specific information about, for instance, the latest promotions, which implies a greater level of consumer involvement. Thus, differences in the effectiveness of each type of information are likely.

Regarding active search, Ratchford et al. (2003) demonstrate that the Internet reduces search for an item on average and that the presence of information on the Web leads to a substantial reduction in the search time devoted to offline sources, such as visiting a dealer. The value of the information depends on what the consumer is trying to accomplish, as well as the fit between the consumer's shopping goals and the properties of the retail environment (Mathwick, Malhotra &

Rigdon 2002). However, given the relative ease of searching on the Internet, it seems surprising that current search levels remain low and that consumers tend to be loyal to just one site (Johnson, Moe, Fader, Bellman & Lohse 2004).

4.2.3 Decomposing Offline Buying and Online Search Behavior

To capture cross-channel behavior, we turn to previous studies on decomposing customer behavior into various components. Decomposition customer behavior can provide additional insights in a variety of research settings, including promotional effectiveness in both the short (e.g. Gupta 1988; Bell, Chiang & Padmanabhan 1999) and the long (e.g. Pauwels, Hanssens & Siddarth 2002; Van Heerde et al. 2004; Van Heerde & Bijmolt 2005) run. In a store context (see e.g., Lam et al. 2001), managers often have a keen interest in improving specific performance components, such as switching customer purchases to higher-revenue products, increasing the number of products bought per visit, increasing store trips by existing customers, or increasing the customer base overall. Ideally, site content and promotions can induce customers to cherry-pick and buy only cheap brands (Fox & Hoch 2005), or upgrade to higher-margin brands (Chandon, Wansink & Laurent 2000). We focus on two decompositions, namely offline buying behavior and online search. With regard to offline buying behavior, we focus on the money spent per product, products bought per shopping trip, shopping trips per customer, and the number of unique customers in the store per period. In the online search arena, we consider the time spent per page, pages seen per online visit, online visits per visitor, and number of unique visitors online per period.

4.3 HYPOTHESES

Our hypotheses involve the marketing efforts that influence offline buying and online search behavior. The marketing efforts differ according to the channel (offline versus online) and focus (price versus nonprice). We focus on the immediate impacts of marketing efforts, because previous research shows that promotions usually do not change sales structurally over time (e.g., Nijs, Dekimpe, Steenkamp & Hanssens 2001; Pauwels et al. 2002).

4.3.1 Hypotheses: Marketing Efforts

Following Kaul and Wittink (1995), we classify marketing efforts into price promotions (promotions) and nonprice promotions (communications). Promotions inform customers about the price and availability of a product, whereas communications inform the customer about product positioning and unique product characteristics. We consider the introduction of the web site as a communication decision.

Research on promotions demonstrates that temporal price discounts supported by featuring and/or advertising substantially increase sales of the promoted products (at the reduced prices) in the short term and lift store traffic, but they also decrease reference prices and increase price sensitivity (Blattberg, Briesch & Fox 1995; Nijs et al. 2001; Van Heerde, Leeflang & Wittink 2001; Van Heerde et al. 2004). Thus, we expect the effects of offline promotions on offline buying behavior to be similar to those found in numerous previous studies.

Offline promotions also may increase online search behavior. Customers might be triggered by offline promotions to use the informational Web site to find out more about promotions and determine if they are worth a trip to the store. However, if offline promotions provide customers with sufficient information, a visit to the Web site might become redundant, which would decrease the average number of site visits.

In this study, we are interested how online marketing efforts influence offline buying. We therefore formulate our hypotheses to pertain to the immediate effects of marketing efforts in the online channel on buying behavior in the offline channel.

Ansari et al. (2006) indicate that marketing efforts (both online and offline) have a positive effect on purchase volume, but mainly drive customers to the same channel; that is, these authors mostly report same-channel effects. We argue that the effects of online promotions may differ from those found for offline promotions, possibly as a result of the associated level of customer consciousness. Customers online tend to search more actively for specific information and therefore likely are more efficient. In turn, the Web site can facilitate less effort or time on their part, as well as fewer shopping trips, to fulfill their goals (Mick & Fournier 1998). We therefore formulate the following hypothesis for the immediate effect of online promotions.

H1. Online promotions decrease money spent per product, increase products purchased, decrease trips taken and increase the number of customers of the retailer.

In contrast to promotions, communications reduce price sensitivity (Kaul & Wittink 1995) because they are geared toward communicating unique brand or product features. Because online customers actively search for particular information, online communications likely increase the money they spend per product or lead them to upgrade to higher-margin products (Chandon et al. 2000). However, just as we hypothesized for online promotions, communications can facilitate consumer efficiency and thereby reduce the number of shopping trips they make (Mick & Fournier 1998).

That is, we expect online communications to increase the money spent, the products purchased, and the number of customers but decrease trips taken. Just introducing the focal site should have a similar effect to general online communications because of its theme orientation and general focus on communication. We formulate the following hypothesis for the immediate effect of online communications:

H2. Online communications and the site introduction increase money spent per product, products purchased, and number of customers but decrease trips taken.

Table 4-1 provides an overview of these hypotheses.

TABLE 4-1 OVERVIEW OF FORMULATED HYPOTHESES REGARDING MARKETING EFFORTS

From	To	Literature	Expectation
Online promotions (H1)	Money per product	-	-
	Products per trip	+	+
	Number of trips	+	-
	Customers	+	+
Online communications & site introduction (H2)	Money per product	+	+
	Products per trip	+	+
	Number of trips	+	-
	Customers	+	+

4.4 PROPOSED METHODOLOGY

We describe the persistence modeling approach for estimating long-term marketing and feedback effects.

4.4.1 Decomposition of Behavior

We decompose both offline buying and online search behavior into various relevant components, as follows:

$$(1)\ \ \textit{Offline behavior}_t = \textit{Total money}_t = \frac{\tilde{M}_t}{\tilde{P}_t} * \frac{\tilde{P}_t}{\tilde{T}r_t} * \frac{\tilde{T}r_t}{C_t} * C_t\,,$$

where
$\tilde{M}_t$ = the monetary value spent in period t,
$\tilde{P}_t$ = the total number of products purchased in period t,
$\tilde{T}r_t$ = the total number of shopping trips in period t, and
C_t = total number of customers in period t.

$$(2)\ \ \textit{Online behavior}_t = \textit{Total time}_t = \frac{\tilde{T}i_t}{\tilde{P}a_t} * \frac{\tilde{P}a_t}{\tilde{V}s_t} * \frac{\tilde{V}s_t}{Vrs_t} * Vrs_t\,,$$

where
$\tilde{T}i_t$ = the total amount of time spent online in period t,
$\tilde{P}a_t$ = the total number of pages seen in period t,
$\tilde{V}s_t$ = the total number of online visits in period t, and
Vrs_t = total number of Web visitors in period t.

In Appendix VIII, we provide a more precise description of the series. In the rest of this chapter, we will refer to $\frac{\tilde{M}_t}{\tilde{P}_t}$ as money (M_t), $\frac{\tilde{P}_t}{\tilde{T}r_t}$ as products (P_t), $\frac{\tilde{T}r_t}{C_t}$ as trips (Tr_t) and C_t as customers in terms of offline buying behavior. For the online search behavior, we refer to $\frac{\tilde{T}i_t}{\tilde{P}a_t}$ as time (Ti_t), $\frac{\tilde{P}a_t}{\tilde{V}s_t}$ as pages (Pa_t), $\frac{\tilde{V}s_t}{Vrs_t}$ as visits (Vs_t) and Vrs_t as visitors.

4.4.2 Dynamics

To test our hypotheses, we need a flexible model that can uncover dynamic marketing effects and feedback loops. Because we have little a priori knowledge about the signs and dynamics of those effects, we employ a persistence modeling framework (Dekimpe & Hanssens 1999) and specify a VAR model to uncover important interrelationships among the series instead of determining them a priori (Sims 1980; Enders 1995). Equation (3) represents the VAR model:

$$
(3)\quad
\begin{bmatrix} M_t \\ P_t \\ Tr_t \\ C_t \\ Ti_t \\ Pa_t \\ Vs_t \\ Vrs_t \end{bmatrix}
=
\begin{bmatrix}
a_{0,M} + \Sigma_{y=1}^{4} a_{y,M} YD_{y,t} + \Sigma_{s=1}^{2} a_{s,M} SD_{s,t} + \partial_M t \\
a_{0,P} + \Sigma_{y=1}^{4} a_{y,P} YD_{y,t} + \Sigma_{s=1}^{2} a_{s,P} SD_{s,t} + \partial_P t \\
a_{0,Tr} + \Sigma_{y=1}^{4} a_{y,Tr} YD_{y,t} + \Sigma_{s=1}^{2} a_{s,Tr} SD_{s,t} + \partial_{Tr} t \\
a_{0,C} + \Sigma_{y=1}^{4} a_{y,C} YD_{y,t} + \Sigma_{s=1}^{2} a_{s,C} SD_{s,t} + \partial_C t \\
a_{0,Ti} + \Sigma_{y=1}^{4} a_{y,Ti} YD_{y,t} + \Sigma_{s=1}^{2} a_{s,Ti} SD_{s,t} + \partial_{Ti} t \\
a_{0,Pa} + \Sigma_{y=1}^{4} a_{y,Pa} YD_{y,t} + \Sigma_{s=1}^{2} a_{s,Pa} SD_{s,t} + \partial_{Pa} t \\
a_{0,Vs} + \Sigma_{y=1}^{4} a_{y,Vs} YD_{y,t} + \Sigma_{s=1}^{2} a_{s,Vs} SD_{s,t} + \partial_{Vs} t \\
a_{0,Vrs} + \Sigma_{y=1}^{4} a_{y,Vrs} YD_{y,t} + \Sigma_{s=1}^{2} a_{s,Vrs} SD_{s,t} + \partial_{Vrs} t
\end{bmatrix}
+ \sum_{i=1}^{K}
\begin{bmatrix}
\beta_{1,1}^{i} \cdots \beta_{1,8}^{i} \\
\beta_{2,1}^{i} \cdots \beta_{2,8}^{i} \\
\beta_{3,1}^{i} \cdots \beta_{3,8}^{i} \\
\beta_{4,1}^{i} \cdots \beta_{4,8}^{i} \\
\beta_{5,1}^{i} \cdots \beta_{5,8}^{i} \\
\beta_{6,1}^{i} \cdots \beta_{6,8}^{i} \\
\beta_{7,1}^{i} \cdots \beta_{7,8}^{i} \\
\beta_{8,1}^{i} \cdots \beta_{8,8}^{i}
\end{bmatrix}
\begin{bmatrix} M_{t-i} \\ P_{t-i} \\ Tr_{t-i} \\ C_{t-i} \\ Ti_{t-i} \\ Pa_{t-i} \\ Vs_{t-i} \\ Vrs_{t-i} \end{bmatrix}
+
$$

$$
\begin{bmatrix}
\gamma_{1,1} \cdots \gamma_{1,4} \\
\gamma_{2,1} \cdots \gamma_{2,4} \\
\gamma_{3,1} \cdots \gamma_{3,4} \\
\gamma_{4,1} \cdots \gamma_{4,4} \\
\gamma_{5,1} \cdots \gamma_{5,4} \\
\gamma_{6,1} \cdots \gamma_{6,4} \\
\gamma_{7,1} \cdots \gamma_{7,4} \\
\gamma_{8,1} \cdots \gamma_{8,4}
\end{bmatrix}
\begin{bmatrix} OP_{1,t} \\ OP_{2,t} \\ OC_t \\ SI_t \end{bmatrix}
+
\begin{bmatrix} \varepsilon_{M,t} \\ \varepsilon_{P,t} \\ \varepsilon_{Tr,t} \\ \varepsilon_{C,t} \\ \varepsilon_{Ti,t} \\ \varepsilon_{Pa,t} \\ \varepsilon_{Vs,t} \\ \varepsilon_{Vrs,t} \end{bmatrix}
$$

We face an important decision regarding which series to include in the VAR estimation and whether to treat these series as endogenous or exogenous. The vector of endogenous series includes the components of offline buying and online search, defined by the decomposition. The endogenous series relate to their own past and thereby allow for complex, dynamic interactions.

The first vector of exogenous series includes (1) an intercept *a* (2) four half year dummies ($YD_{y,t}$) to account for trends of time, (3) two seasonal dummies (high and low) ($SD_{s,t}$), and (4) a deterministic-trend variable *t*. The high and low seasonal dummies control for peaks and dips that cannot be explained by the marketing efforts. The marketing efforts, measured as dummies, constitute the second set of exogenous series: (1) offline promotions ($OP_{1,t}$), (2) online promotions ($OP_{2,t}$), (3) online communications (OC_t), and (4) site introduction (SI_t).

In our estimation, we choose the number of lags on the basis of the Schwarz information criterion (SC). We do not interpret the coefficients of cross-channel behavior in the VAR model directly but focus our attention on the impulse response functions (IRF), which simulate the over-time impact of a change (compared with a baseline) in one variable on the full dynamic system. For the cross-channel effect, recall that we consider the cumulative (over 26 weeks) effect of the IRF (Pauwels et al. 2002), whereas for the marketing efforts, we are interested in the immediate (i.e., same week) effects. We interpret the coefficients for the marketing efforts of the VAR model instead of the IRFs.

4.4.3 Model Calibration Steps

We start by inspecting the series graphs plotted against time to obtain general insights into the series' behavior (graphs not shown here). To assess the temporal behavior (evolution/stationarity) of offline buying and online search, we perform unit root tests (Enders 1995; Maddala & Kim 1996, Dekimpe & Hanssens 1999 for marketing applications). Then, we remove the deterministic component from the series through seasonality dummies. That is, we inspect the series for specific seasonality peaks and dips that the marketing mix instruments cannot explain. Next, we relate all the series to one another with a correlation matrix and remove those series that cause multicollinearity. Finally, we perform Granger causality tests to determine which series of interest in period t causes changes in other series in future periods, which enables us to interpret the results of the subsequent VAR models and IRFs. We make only causal inferences for the impulse series that the Granger test considers to cause the response series.

4.4.4 Unit Root Testing Procedure

Unit root testing determines whether a series is stationary over time, that is, whether it reverts to its stationary mean or trend. If a series is stationary, there are no permanent effects, and we estimate a VAR model in levels.

Generally, the Augmented Dicky Fuller (ADF) method serves to test for a unit root. The ADF contains the null hypothesis that all series have a unit root (i.e., are nonstationary). Other tests are available as well, including the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test, whose null hypothesis states that the series is stationary. For unit root testing, we must choose whether:

- the test specification includes a deterministic time trend, and
- on which null hypothesis— unit root (e.g., ADF) versus stationarity (e.g., KPSS)—it should be based.

For the unit root test specification, we follow Enders (1995, p. 257) procedure, which requires that we test in both the presence and the absence of a deterministic time trend. When the first test specification indicates the absence of a unit root, the series is classified as trend stationary. If the second test specification indicates the absence of a unit root, the series is classified as mean stationary. When both specifications indicate a unit root, we classify the series as evolving.

Regarding our second choice, we perform a confirmatory analysis, as suggested by Madalla and Kim (1996, p. 126). With a confirmatory analysis, we can use a test with stationarity as the null hypothesis to confirm the conclusions about the unit root (i.e., compared with the test that uses unit root as the null hypothesis). The confirmatory analyses, rather than just the ADF test, highlight concerns about conventional unit root tests, such as their low power (see e.g., Madalla & Kim 1996). Confirmatory analysis uses two different tests, namely ADF (H0: series is nonstationary) and KPSS (H0: series is stationary). When these test results converge, we obtain greater reliability in terms of the series' classification. Table 4-2 provides an overview of the unit root testing procedure.

TABLE 4-2 UNIT ROOT TESTING PROCEDURE

Test	Specification	Result	Conclusion
1. ADF	With intercept and trend (*t*)	H0[a] rejected *t* significant	Trend stationary
		H0 not rejected *t* significant	Unit root
2. KPSS	With intercept and trend (*t*)	H0[b] not rejected *t* significant	Trend stationary
		H0 rejected *t* significant	Unit root
	If trend variable t is insignificant		
3. ADF	With intercept	H0 rejected	Mean stationary
		H0 not rejected	Unit root
4. KPSS	With intercept	H0 not rejected	Mean stationary
		H0 rejected	Unit root

a. H0 states that the variable has a unit root
b. H0 states that the variable is stationary

In the confirmatory analysis, the level of confirmation between the ADF and KPSS tests depends on the strictness of the classification. Exact confirmation occurs if test 1 and 2 (or 3 and 4) from Table 4-2 result in the same conclusion, namely, trend stationary or mean stationary. We obtain a less strict confirmation if we consider only the evolving versus stationary classification (Enders 1995).

In addition to the unit root test procedure, we test the offline buying series for a structural change with a known breakpoint, namely, the first week after the introduction of the Web site (Madalla & Kim 1996). Specifically, we use the Chow breakpoint test to uncover any significant differences in the estimated equations before and after the site introduction. We do not elaborate on the test results when they confirm the previous unit root test results.

4.4.5 Moderation

In linear regression, moderation can be easily tested with an interaction term. With our VAR model, including 8 endogenous variables, adding an interaction would imply another 8 endogenous variables. Each equation would then be estimated with at least 28 exogenous variables (i.e. in case of one lag). Assuming five observations are needed per parameter, our data would not be sufficient. Moreover, introducing these interactions terms might also cause multicollinearity problems. Hence, to determine the influence of the context characteristics, we follow Lim, Currim and Andrews (2005) by estimating the VAR models for each high versus low group (i.e., product type, experience of online flow, frequency of Web site visits). Comparing the Granger causality and dynamic performance impact through the IRF's indicates whether there are differences across the groups.

Several studies have classified products as sensory versus nonsensory goods and we draw on these to determine how the products should be classified. Table 4-3 depicts the classification we assigned and in which studies this classification has been used previously.

TABLE 4-3 CLASSIFICATION OF PRODUCT TYPE

	Classification	Example study
Consumer electronics	Nonsensory	Burke 2002, Citrin et al. 2003
Cd's, book's, DVD's	Nonsensory	Burke 2002, Citrin et al. 2003
Computer hard- and software	Nonsensory	Peterson et al. 1997, Van Baal & Dach 2005
Toys	Nonsensory	Van Baal & Dach 2005
Clothing	Sensory	Citrin et al. 2003, Van Baal & Dach 2005
Shoes & accessories	Sensory	Peterson et al. 1997, Citrin et al. 2003
Cosmetics	Sensory	Van Baal & Dach 2005
Furniture	Sensory	Van Baal & Dach 2005

4.5 Empirical Setting

We use the same empirical data as discussed in Section 1.6.

4.5.1 Data

The data used in this chapter pertain to the behavior of 6,594 customers who started using the Web site after its introduction. The data include these customers' offline buying behavior for 127 weeks. Of the 127 weeks, 60 weeks of buying behavior occur before the introduction of the Web site, and we collect online search behavior for the 67 weeks after the site introduction.

The sample sizes for the analyses differ due to the availability of information about the moderators. We estimate a VAR model at the aggregate level for 6,594 customers. For the product type median split, we use the data from 6,594 customers; for the flow median split, the sample sizes are 2,900 for low flow and 3,481 for high flow; and for the median split of the frequency of site visits, the sample sizes are 3,651 for low frequency and 2,623 for high frequency.

In our median split approach, we use attitudinal and customer behavior data. The attitudinal data, i.e. the experience of online flow, of visitors to the Web site are gathered through two online questionnaires, conducted three months after the introduction of the Web site in May 2001 and one year later in May 2002. Flow is a construct represented by the mean of responses to questions in both questionnaires. All questions use a five-point scale. We measure the frequency of Web visits as the number of site visits a customer makes during the data collection period. On the basis of the median level, we split the customer panel into two segments. Appendix IX provides the items or descriptions of the variables used in the moderation approach, the reliability of these variables, and descriptive statistics[13].

4.6 Aggregate Level Findings

This section details the results of the VAR model at the aggregate level. We first discuss multichannel behavior, followed by the effects of marketing efforts.

[13] Descriptives for product types are not provided, because there is no median product type; rather products are classified solely as sensory or nonsensory.

4.6.1 Multichannel Behavior

Preliminary data inspection. A visual inspection of the series suggests sufficient variability in the data to designate two important seasons: summer and winter. We check the data for seasonality and inspect the residuals after correcting for known marketing efforts. We include a low dummy, a high dummy (the two seasonal dummies), and four half-year dummies in the VAR model.

The correlation between the offline buying series varies from .05 to .30. For online search series, the correlation varies from -.32 to .69. In other words, though the series are correlated, we do not anticipate any important multicollinearity issues.

Unit root testing. The test results in Table 4-4 show that all series are (mean or trend) stationary, according to the ADF test. In the ADF, the test value (*tv*) must be greater than the critical value (*cv*) to reject the null hypothesis of a unit root, whereas with KPSS, the test value must be less than the critical value to accept the null hypothesis of stationarity.

We find exact confirmation (i.e., both the AFD and KPSS tests indicate trend or mean stationarity) for five of the eight series. When we consider only whether the series is classified as stationary versus evolving, we confirm that all series are stationary. Compared with Madalla and Kim (p. 128, 1996), who report little convergence for the macroeconomic series they tested, we find more promising results through our confirmatory analysis of these marketing series.

The structural break Chow test indicates a significant structural break in week 61 in the number of trips (F = 6.32 Prob. = .00; Chi-squared log likelihood ratio = 24.45 Prob. = .00) (Madalla & Kim 1996). The unit root tests, of the periods before (weeks 1-60) and after (weeks 62-127) the structural break caused by the Web site introduction in week 61, indicate stationarity (ADF trend significant, t = -8.88 for weeks 1-60, t = -4.93 for weeks 62-127). By allowing for the structural break in the VAR model with a dummy for the site introduction, we estimate the VAR in levels (Kornelis 2002; p. 49).

TABLE 4-4 RESULTS FOR THE CONFIRMATORY UNIT ROOT ANALYSIS

	ADF				*KPSS*			
	T(rend)	*tv*	*Cv*	*Result*	*T(rend)*	*tv*	*cv*	*Result*
Money	0.00	-4.44	-4.03	mean	0.00	0.11	0.22	mean
		-4.47	-3.48			0.15	0.74	
Products	-0.002	-11.91	-4.03	mean	**-0.003**	0.16	0.22	trend
		-11.65	-3.48			0.44	0.74	
Trips	**-0.001**	-5.22	-4.03	trend	**-0.001**	0.26	0.22	mean
		-4.77	-3.48			0.52	0.74	
Customers	**2.50**	-9.09	-4.03	trend	**2.97**	0.14	0.22	trend
		-8.47	-3.48			0.59	0.74	
	ADF				*KPSS*			
	t	*tv*	*Cv*	*Result*	*t*	*tv*	*cv*	*Result*
Time	-0.03	-7.05	-4.10	mean	-0.02	0.10	0.22	mean
		-7.11	-3.53			0.11	0.74	
Pages	**-0.08**	-6.05	-4.10	trend	**-0.11**	0.24	0.22	mean
		-4.70	-3.53			0.53	0.74	
Visits	**-0.002**	-23.83	-4.10	trend	**-0.003**	0.19	0.22	trend
		-18.86	-3.53			0.74	0.74	
Visitors	**-6.66**	-8.19	-4.10	trend	**-6.73**	0.18	0.22	trend
		-6.28	-3.53			0.87	0.74	

Notes: t(rend) = trend variable, *tv* = test value, *cv* = critical value. Coefficients for the trend variable in bold are significant at the .05 level.

Granger causality. To make causal inferences based on the results of the VAR model and IRFs, we test for Granger causality at lags 1-6 between the online search and offline buying behavior and vice versa.[14] The results show that at the aggregate level, only a few Granger-caused cross-channel relationships occur. For online search, only "visitors" Granger-cause trips. Thus, if more unique visitors go online in week *t*, in week *t+1*, the average number of shopping trips per customer changes. With regard to the offline buying components, "trips" and "customers" Granger-cause an online search component: "visitors".

VAR Model. We determine the number of lags through the SC and the SC with the lowest value of 37.14 indicated a VAR with one lag. The VAR with one lag shows an acceptable in-sample model fit (the adjusted

[14] We do not expect online search to Granger-cause offline buying or vice versa beyond a period of six weeks.

R^2 ranges from .29 to .95, and the F-statistic ranges from 3.54 to 132.7). The Lagrange-multiplier (LM) test shows residual correlation at lag order 2 (LM-stat = 94.37; Prob. = .008), but none at lag order 3 (LM-stat = 58.63; Prob. = .66) or lag order 4 (LM-stat = 76.82; Prob. = .13).

Considering the large amount of results a VAR model provides, we interpret only the relations of interest that show Granger causality in at least one test specification. Table 4-5 offers the cumulative IRF results.

TABLE 4-5 CUMULATIVE RESULTS OF THE IRFS FOR MULTICHANNEL BEHAVIOR AT THE AGGREGATE LEVEL

From ↓ to →	*M*	*P*	*Tr*	*C*	*Ti*	*Pa*	*Vs*	*Vrs*
		A				*B*		
Time (Ti)	-0.11	0.04	0.00	-64.0	10.76	**2.03**	0.23	**72.0**
Page (Pa)	0.19	0.00	0.01	0.0	**-2.63**	2.20	**0.00**	**0.00**
Visits (Vs)	0.14	-0.03	-0.04	-56.6	**13.17**	**8.50**	0.62	**150.1**
Visitors (Vrs)	0.00	-0.07	**0.03**	55.4	0.53	**0.25**	**-0.02**	139.3
		C				*D*		
Money (M)	1.85	**-0.17**	-0.03	**-23.6**	1.97	1.81	0.14	40.9
Products (P)	**0.27**	0.31	0.00	**145.5**	-1.89	-1.29	-0.08	-48.6
Trips (Tr)	-0.50	**0.05**	0.06	**193.1**	0.41	0.19	0.00	**22.4**
Customers (C)	0.37	**0.09**	**0.04**	316.2	-2.24	-1.62	-0.11	**-33.7**

Notes: Bold parameter estimates indicate Granger causality.

Panel A includes the cross-channel effects from online search in week t on offline buying in weeks $t + n$, where n can reach a maximum of 26 weeks. Panel B shows the same-channel effects from online search in week t on online search in weeks $t + n$. Panel C provides the same-channel effects of offline buying in week t on offline buying in weeks $t + n$. Finally, Panel D includes the cross-channel effects of offline buying in week t on online search in weeks $t + n$.

Panel A. We find a limited number of cross-channel effects. The only cross-channel behavior effect from online to offline, which is Granger caused, is from visitors to trips. If more customers visit the Web site in week t, the average number of trips to the store by Panel A in weeks $t + n$ increases. The increase in unique visitors online most likely reflects customers with a higher shopping trip baseline.

Panel D. For the cross-channel behavior from offline to online, we find that an increase in trips in week t increases the number of visitors online in weeks $t + n$. Moreover, an increase in customers in week t, decreases online visitors in weeks $t + n$. Overall, an increase in offline buying negatively influences online search.

Panel C. Considering the same-channel effects of offline buying, we find among other effects that

- If money per product increases, over time, customers buy fewer products per trip;
- If products per trip increase, over time, customers spend more money per product; and
- If trips increase, over time, customers buy more products per trip.

Panel B. For the same-channel effects from online search, we find among other effects that

- If time per page increases, over time, customers view more pages per visit and visit more often;
- If pages per visit increase, customers spent less time per page; and
- If visits increase, customers spent more time per page and view more pages per visit.

The cumulative cross-channel results indicate that in the long-run the Web site complements the offline store, shown by the increase in the number of shopping trips. However, the offline store retains customers in the offline channel.

4.6.2 Cross-Channel Marketing Efforts

Table 4-6 provides the effects, that is, the VAR coefficients, of marketing efforts on both online and offline behavior. We focus our attention on the immediate effects of online marketing efforts (i.e., promotions and communications) on offline buying and of offline promotions on online search. For benchmark purposes, we also provide the same-channel effects.

The results indicate that offline promotions, online communications, and the site introduction increase one or more components of offline buying. In addition, online promotions, online communications, and site introduction have an effect on online search. The effect of the site introduction on online behavior reflects the average online behavior in the first week of Web site use. We notice that online promotions decreases time spent per page, indicating that online promotions make users browse through the web pages faster.

The results for the online and offline promotions confirm previous results summarized by Ansari et al. (2006): Promotions mainly cause same-channel effects. The results pertaining to the online communications and site introduction suggest that these types of marketing efforts have cross-channel effects.

TABLE 4-6 EFFECTS OF MARKETING EFFORTS ON OFFLINE AND ONLINE BEHAVIOR AT THE AGGREGATE LEVEL

	Offline Behavior			
	Money	*Products*	*Trips*	*Customers*
Offline promotions	-0.03	-0.04	**0.07**	**380.68**
Online promotions	0.28	0.13	0.01	67.44
Online communications	0.54	**0.54**	0.01	199.52
Site introduction	**3.04**	**1.20**	-0.06	**1218.74**
	Online Behavior			
	Time	*Pages*	*Visits*	*Visitors*
Offline promotions	0.67	0.3	-0.02	-19.18
Online promotions	**-3.55**	0.75	-0.01	-10.34
Online communications	-1.98	-0.37	-0.01	**129.21**
Site introduction	**48.46**	**21.50**	**1.27**	**1571.58**

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

Table 4-7 summarizes the results and formulated hypotheses. In H1, we posit that online promotions decrease money spent, increase products purchased, decrease trips taken, and increase the number of customers. We cannot confirm this hypothesis because the results indicate insignificant relationships. However, we can confirm, as we suggest in H2, that online communications and the site introduction increase money spent, products purchased, and number of customers, but we cannot support our claim that they decrease the trips taken. We do note that the Web site causes a structural break in the number of store trips. After the introduction the number of store trips decreases significantly. This effect, however, is not found for the online communications.

Overall, we find limited cross-channel effects at the aggregate level and show that marketing efforts mainly trigger behavior in the same channel. Moreover, we find that online marketing efforts are more effective if they communicate brand or product features instead of price.

Besides the aggregate VAR, we also performed an exploratory segmentation through cluster analysis. The VAR model is estimated for each segment. The results of this exploratory analysis show differences across segments. However, the segmentation approach does not provide additional insights.

TABLE 4-7 REVIEW OF HYPOTHESES ABOUT MARKETING EFFORTS

From	To	Lit.	Exp.	Result
Online promotions (H1)	Money	-	-	Not confirmed
	Products	+	+	Not confirmed
	Trips	+	-	Not confirmed
	Customers	+	+	Not confirmed
Online communications & site introduction (H2)	Money	+	+	Confirmed
	Products	+	+	Confirmed
	Trips	+	-	Not confirmed
	Customers	+	+	Confirmed

Notes: *Lit.* = literature, *Exp.* = expectation.

4.7 MEDIAN SPLIT FINDINGS

Our approach to determine the moderating impact of context characteristics (i.e., product type, flow, frequency of site visits) on cross-channel behavior requires us to divide the customer panel by a median split and estimate the persistence modeling framework for each condition (i.e., low versus high). Because not all data are available for all customers, the sample sizes for the median splits vary (see Section 4.5.1). We focus on determining whether context characteristics moderate cross-channel behavior and therefore report only cross-channel effects (Panels A and D in Table 4-6). We focus on the long-term impact that is the total change in behavior over a period of 26 weeks. Moreover, we consider only those relationships that are Granger-caused. For our interpretation of the marketing efforts, we focus on the coefficients from the VAR model.

Preliminary data inspection. For all median splits, we conclude there is sufficient variability in the data and find the same seasons as in the aggregate data.

The correlations for product type vary between -.25 and .52 for offline buying and between -.37 and .78 for online search. For flow, the correlations with offline buying vary between -.13 and .50 and those with online search between -.04 and .60. With regard to the frequency of Web visits, we find correlations with offline buying that vary between -.16 and .52 and with online search that vary between -.20 and .81.

Unit root testing. For all median splits, we perform the confirmatory analysis (Madalla & Kim 1996) and, for the majority of series, find confirmation of the tests, just as we did with the aggregate level tests. A structural break for the site introduction exists for products and trips in most median splits. Both series in all median splits may be classified as stationary, after we allow for the break. As a result of the unit root testing, we consider all variables stationary and therefore include them in the levels for the VAR models.

4.7.1 Product Type

Cross-channel behavior. We may choose a first- or second-order VAR according to the lag length criterion, but on the basis of a comparison of other the fit measures (i.e., adjusted R^2, LM, normality, and heteroskedasticity), we use a second-order VAR. The VAR with two lags shows an acceptable in-sample model fit (for sensory products, adjusted R^2 ranges from .28 to .99, F-statistic ranges from 3.5 to 1006.85; for nonsensory products, adjusted R^2 ranges from .22 to .95, F-statistic ranges from 2.5 to 979.62). The LM test shows no residual correlations for the nonsensory products but some residual correlation for the sensory products.

Table 4-8 provides the cumulative changes in the response series of a one-unit shock in the impulse series for both median splits.

TABLE 4-8 CROSS-CHANNEL IRF RESULTS FOR SENSORY AND NONSENSORY PRODUCTS

	Money		*Products*		*Trips*		*Customers*	
	NS	*S*	*NS*	*S*	*NS*	*S*	*NS*	*S*
Time	**-0.20**	**0.76**	**0.00**	0.00	0.00	**0.00**	-6.84	0.00
Pages	-0.06	-0.37	0.02	0.01	0.01	0.01	0.00	8.92
Visits	1.54	0.00	0.00	0.00	-0.03	**0.00**	-70.40	0.00
Visitors	-0.42	**-0.22**	**0.06**	-0.01	0.06	-0.02	86.09	38.71
	Time		*Pages*		*Visits*		*Visitors*	
	NS	*S*	*NS*	*S*	*NS*	*S*	*NS*	*S*
Money	5.28	-1.46	4.07	0.00	0.27	0.00	59.31	0.00
Products	0.00	0.00	**-0.14**	0.17	-0.01	0.00	-61.63	-14.38
Trips	0.00	0.00	0.39	0.00	0.00	0.00	5.29	0.00
Customers	-2.09	0.00	-2.35	0.00	-0.15	0.00	-38.63	0.00

Notes: *NS* = nonsensory products, *S* = sensory products. Bold parameter estimates indicate Granger causality.

For nonsensory products, shocking online search decreases money spent but increases products purchased, which implies greater consumer awareness of the price due to online search. A shock in offline buying leads to a decrease in online search in terms of pages viewed.

For sensory products, we find that more time per page increases money spent, but an increase in the number of unique visitors online, decreases it. Offline buying does not Granger-cause online search for sensory products. The number of cross-channel effects is similar in both conditions, and the direction of the impact varies across the median splits. For nonsensory products, online search mainly decreases money spent per product, whereas for sensory products, online search mainly increases money spent per product. This indicates that customers search for the cheapest alternative in case of non-sensory products. For sensory products, the findings indicate the customers upgrade to more expensive products.

When reviewing the graphs of offline behavior[15] and the R^2 adjusted for both sensory and nonsensory products, the differences make more sense. Figure 4-1 shows the money spent per product for sensory and non-sensory products as an example of the difference between both conditions.

We notice that the graphs for the number of customers for both product types roughly show similar patterns. For the other three offline behavior variables, the graphs show very different patterns. Money spent per product has a more volatile pattern for nonsensory products, whereas products and trips are more volatile for sensory products. Second, we see that the variation explained is higher for money spent per product for sensory products (sensory products: money $R^2_a = .59$; nonsensory products: money $R^2_a = .25$) and products per trip for nonsensory products (sensory products: products $R^2_a = .29$; nonsensory products: products $R^2_a = .59$).

The cross-channel effects from online to offline are stronger for sensory products. Regarding the direction of the relationship, we find that an informational Web site benefits money spent in case of sensory products. However, for nonsensory products, the cross-channel effects from offline to online are stronger but negative, especially for the number of products per shopping trip.

[15] We do not inspect the graphs for online behavior because the online behavior is equal in the case of this median split.

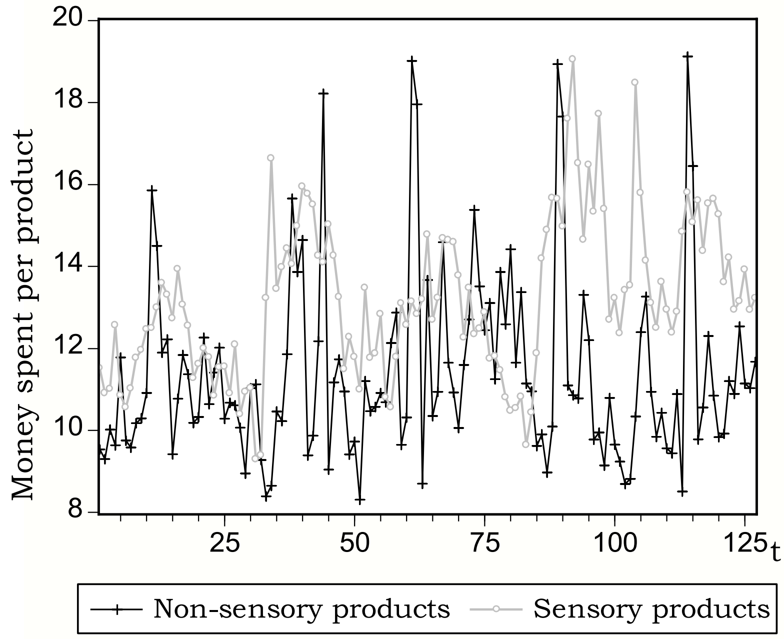

FIGURE 4-1 COMPARISON OF MONEY SPENT PER PRODUCT FOR SENSORY AND NON-SENSORY PRODUCTS

4.7.2 Flow Median Split

Cross-channel behavior. According to the lag length criterion, we could choose either a first- or a second-order VAR, but the second-order VAR provides a better in-sample model fit (for low flow, adjusted R^2 ranges from .25 to .97, F-statistic ranges from 2.5 to 148.02; for high flow, adjusted R^2 ranges from .16 to .99, F-statistic ranges from 1.8 to 676.58). The LM test shows no residual correlations for high flow but some for low flow.

Table 4-9 details the cross-channel IRF results. The number of Granger-caused relationships for low flow (17) is twice as many as for high flow (8). The effect on money spent for low flow is either positive or negative depending on which online search variable represents the shock. We observe that the effect for low flow is stronger than that for high flow. With low flow, an increase in online search increases money spent and decreases trips taken, whereas with high flow, an increase in online search decreases both money and trips.

For the high flow condition, we notice that offline behavior only effects online search if money spent per product or the number of products per trip is increased. An increase in money spent, increases the pages seen. An increase in products, decreases time spent per page. For the low flow condition, we notice a lot more effects from offline behavior on online search than in the high flow condition. An increase in money has a positive effect on online search, whereas an increase in products or trips seems to decrease online search.

TABLE 4-9 CROSS-CHANNEL IRF RESULTS FOR LOW AND HIGH FLOW EXPERIENCE

	Money		*Products*		*Trips*		*Customers*	
	L	*H*	*L*	*H*	*L*	*H*	*L*	*H*
Time	**0.43**	**0.00**	0.00	-0.08	**-0.05**	**-0.02**	0.00	-18.63
Pages	1.00	0.24	0.00	0.00	**-0.05**	**0.01**	**15.37**	16.16
Visits	**1.58**	0.25	0.00	-0.03	-0.10	**-0.03**	**-26.41**	0.00
Visitors	**-0.82**	**-1.15**	0.00	0.06	**-0.01**	0.01	20.80	18.43
	Time		*Pages*		*Visits*		*Visitors*	
	L	*H*	*L*	*H*	*L*	*H*	*L*	*H*
Money	**6.81**	-0.38	**5.38**	**1.66**	**0.34**	0.03	41.09	13.49
Products	0.00	**-0.55**	-0.28	0.00	**-0.01**	**0.00**	-12.22	-4.96
Trips	-0.55	0.00	**-1.20**	0.44	**-0.08**	0.00	**-1.28**	4.22
Customers	**0.00**	-0.42	**0.65**	0.22	-0.03	-0.01	0.00	0.00

Notes: *L* = low flow, *H* = high flow. Bold parameter estimates indicate Granger causality.

To explain some of the differences between low and high flow, we inspect the graphs (not shown here) and adjusted R^2 for offline and online behavior. For the offline behavior variables, we observe that the patterns in the graphs are similar. Considering the explained variance, for low flow the VAR explains more for money spent and trips taken when compared with high flow (for low flow, money R^2_a = .25, trips = .41; for high flow, money R^2_a = .16, trips = .32). Reviewing the online behavior graphs and the VAR adjusted R^2's, we find similar patterns. However, the pre-VAR calibration steps (see Section 4.4.3) indicate for high flow that lagged online behavior is a better predictor of online behavior than for low flow. This difference may cause a larger number of Granger-caused relationships for low flow.

In Section 4.2.1 we mentioned that one may expect that the cross-channel effects will be stronger for customers who have experienced low flow. Our findings indicate that in case of an informational Web site, the cross-channel effects are strongest, in terms of the number of Granger-caused relationships and the magnitude of the effects, for low flow. Those customers who experience higher flow integrate the channels less.

4.7.3 Frequency of Site Visits

Cross-channel behavior. The lag length criteria indicates we may choose a first- or second-order VAR, but again, the second-order VAR, shows a better in-sample model fit (for low visit frequency, adjusted R^2 ranges from .11 to .96, F-statistic ranges from 1.6 to 127.2; for high visit frequency, adjusted R^2 ranges from .34 to .99, F-statistic ranges from 3 to 652.4). Although, the LM test indicates residual correlations for the median split, we estimate a second-order VAR model.

Table 4-10 shows the cross-channel IRF results. Shocking online search increases offline buying, in terms of money spent and trips taken, among low frequency site visitors. For those who visit the site frequently, an increase in online search increases offline buying in terms of trips. For the low frequency of site visits, shocking offline buying mainly decreases online search, whereas for the high frequency of Web visits, shocking offline buying does not influence online search. Furthermore, among low frequency customers, we find more Granger-caused online search.

TABLE 4-10 CROSS-CHANNEL IRF RESULTS FOR LOW AND HIGH FREQUENCY OF SITE VISITS

	Money		*Products*		*Trips*		*Customers*	
	L	*H*	*L*	*H*	*L*	*H*	*L*	*H*
Time	**0.65**	-0.31	-0.01	0.00	-0.02	-0.02	10.53	-20.75
Pages	0.51	0.19	0.03	0.05	**0.01**	0.00	7.82	3.09
Visits	0.00	0.25	0.05	-0.16	-0.01	-0.06	-11.35	-6.61
Visitors	-0.17	-0.40	0.03	0.10	0.01	**0.03**	30.22	11.24
	Time		*Pages*		*Visits*		*Visitors*	
	L	*H*	*L*	*H*	*L*	*H*	*L*	*H*
Money	**-1.58**	-0.69	**0.04**	0.88	**-0.04**	0.00	4.03	39.26
Products	-2.24	-1.30	-0.76	-2.61	**-0.02**	-0.17	-2.64	-17.36
Trips	-7.06	-1.85	-3.18	-3.49	**-0.26**	-0.21	-26.94	-15.55
Customers	-2.14	-2.72	0.25	-2.97	-0.01	-0.18	5.64	-27.79

Notes: *L* = low frequency of site visits, *H* = high frequency of site visits. Bold parameter estimates indicate Granger causality.

Based on the offline behavior series, i.e. the graphs and the VAR R^2 adjusted, we do not see many differences between the splits. We notice that among customers who frequently visit, lagged money spent is a better predictor of money spent than for those who visit infrequently. With respect to the online behavior series, we observe more volatility in the graphs for low visits, especially for time per page and pages per visit. Besides that, lagged online behavior predicts online behavior better in the case of high visits (R^2 adjusted range from .34 to .75 in case of high visits and from .09 to .45 in case of low visits).

The literature (see Section 5.2.1) indicates that that the cross-channel effects are stronger for customers who engage in a low frequency of Web visits, and our findings enable us to confirm this expectation. For customers with a low frequency of visits, we find more cross-channel effects, especially from offline to online.

Investigating the differences across the median splits, we find that the data aggregation creates varying patterns. Comparing our median split results to the aggregate level results, we find some differences and similarities. At the aggregate level, visitors do not have an effect on money spent but for both low and high flow, we find a negative significant effect. Visitors at the aggregate level do increase trips, which we also find in case of a high frequency of Web site visits. Two possible reasons may cause the differences: aggregation bias over units, and different sample sizes. The differences in the graphs and explanatory behavior of lagged (own series) behavior, indicate a likelihood of parameter heterogeneity across customers for the aggregate level VAR (Leeflang et al. 2000 p. 268).

4.7.4 Cross-Channel Marketing Efforts for Median Splits

Appendix X summarizes the results of online marketing efforts' effects on offline buying for each of the median splits.

For nonsensory products, only the site introduction significantly increases money spent and the number of customers. A significant structural break in the shopping trips is found for nonsensory products. After the introduction, the number of shopping trips for nonsensory products decreases significantly.

For sensory products, the site introduction increases products purchased, trips taken, and number of customers, and online promotions increase trips. No structural break due to the introduction of the Web site is found in case of sensory products. For sensory products, online promotions influence behavior in the opposite channel.

The effects of the marketing efforts are small and similar for the median split of flow. Only the site introduction has a significant influence on offline buying. For both low and high flow a structural break in the number of shopping trips and products purchased is found. In the case of high flow, the site introduction has a positive immediate influence on both products and customers, whereas with low flow, it only influences the number of customers. For both conditions the long term impact of the site introduction is negative for the number of shopping trips and products bought per shopping trip.

For a low frequency of site visits, the site introduction has a significant impact on offline buying. More frequent visits means the site introduction significantly increases money, products, and customers. Online promotions also significantly increase products purchased among customers who visit more frequently. For both conditions, a structural break caused by the Web site introduction is found for the number of shopping trips and the number of products bought per trip. Both offline buying components diminish after the site introduction.

Compared with the aggregate level results, the median split results tell a different story with respect to the effect on trips taken and the influence of online promotions. At the aggregate level, we find no significant results regarding the number of trips, and for sensory products, we find that online promotions and the site introduction increase the number of shopping trips. The informational Web site does not make customers more efficient but instead causes them shop more often offline in the case of sensory products. In contrast with the aggregate level, for customers who engage in more frequent site visits, we find that online promotions increase the number of products they purchase. The structural breaks found for all conditions, except for sensory products, are in line with the aggregate results. The results indicate that in case of sensory products an informational web site has more positive effects compared to non-sensory products.

4.8 DISCUSSION

In this chapter, we investigate cross-channel effects in an informational Web site/offline store setting. We focus our attention on cross-channel behavior, or how online search affects offline buying and vice versa. We develop an approach to determine cross-channel effects and specify different VAR-models that capture the relationships among different components of offline and online behavior. We also determine how marketing efforts in channel *a* affect behavior in channel *b*; and how context characteristics moderate cross-channel behavior and marketing efforts. We discuss our findings in the context of existing multichannel literature.

4.8.1 Cross-Channel Behavior

At the aggregate level, we find limited cross-channel behavior. the results seem to indicate that over time behavior in a particular channel is best explained by past behavior in the same channel. In case of the traditional channel (i.e. the offline channel), offline behavior keeps customers in the offline channel. The online channel complements the offline channel in the long-term.

Compared with these results however, we find more cross-channel effects for the median splits. It appears that aggregation across individuals customers in the panel limits the results at the aggregate level. The differences between the aggregate-level VAR and the median split VARs likely result from heterogeneity in the parameters across customers (Leeflang et al. 2000 p. 268). That is, customers in each median split likely react more similar, which results in parameter homogeneity across customers.

In some of the median-split results, we find that online behavior decreases money spent per product, a result that reinforces our findings from chapter 3 that the majority of individuals, though not all, experience a negative effect. In addition based on the structural break Chow tests, we find that online search generally decreases the number of shopping trips, which may indicate that customers free-ride on the information provided (see e.g. Van Baal & Dach 2005), become more efficient in their decision-making process (see e.g., Alba & Lynch 1997) or become less loyal over time (see e.g., Gensler et al. 2007).

Overall, our results, especially for the median-splits, indicate that behavior in channel *a* influences behavior in channel *b* and vice versa. These influences, however, are not necessarily positive. The cross-channel synergies are apparent in the case of money spent per product in some cases, but we cannibalization occurs in the number of shopping trips.

4.8.2 Cross-Channel Marketing Efforts

We find that offline marketing efforts mainly drive behavior in the offline channel, in line with Ansari et al. (2006), who show that promotions cause same-channel effects. However, online marketing efforts also create cross-channel effects. The setting of our study —an informational online channel instead of an online transactional channel—may explain this effect. With an online informational channel, buying behavior can only take place offline.

Reviewing our results across the different data aggregations, we find that the effects of marketing efforts are reasonably consistent. The different type of coefficients likely causes this greater consistency, in that we measure marketing efforts as immediate effects on behavior variables, whereas we measure cross-channel effects with Granger-caused IRFs (i.e., cumulative effects).

Overall, our results show that of the online marketing efforts the site introduction has the strongest impact, with positive immediate effects on money spent per product, products bought per shopping trips, and the number of customers in the store. Although the site introduction does not have an immediate effect on the number of shopping trips, the site introduction also entails a structural break for this component. The results of the structural break test show that due to the site introduction, customers reduce their average number of shopping trips per week over time.

4.8.3 Context Characteristics

We investigated moderator effects of product type, flow during Web visits and frequency of Web visits and find that for sensory products, online search improves offline buying. This result is surprising, because previous studies indicate that prepurchase decisions about sensory products rely heavily on consumers' ability to touch, smell and taste (Degeratu et al. 2000). However, Gupta et al. (2004) also show that the search effort associated with sensory products is significantly higher than that for nonsensory products, and our results confirm this claim. To generate ideas or a consideration set, online information demands less effort than does retrieving the same information offline. Our results confirm the higher search effort required but also show that an informational Web site provides customers with a more efficient way to retrieve initial information about sensory products.

We confirm our expectation that a lower level of flow strengthens the cross-channel effects. This finding might be the results of several reasons. First, customers who experience high flow lose their self-consciousness and a sense of their surroundings (e.g., Hoffman & Novak 1996). Therefore, customers with high flow might not perceive the channels as integrated or may consider the online experience satisfactory to fulfill their need to shop. Second, previous research shows that the experience of flow during a site visit improves customers' attitudes and behavior toward the online channel (see e.g., Hoffman & Novak 1996, Mathwick & Rigdon 2004) but not toward the offline channel. Our results indicate that a high state of flow, though intrinsically enjoyable to the customer, does not enhance offline behavior. Rather, customers who experience low flow tend to exhibit more cross-channel behavior and are more receptive to marketing efforts.

With regard to transactional Web sites, previous research shows that greater visiting frequency improves conversion rates and indicates stronger loyalty or preference for the online channel (see e.g., Shankar et al. 2003; Moe & Fader 2004). Our results confirm that customers who visit the site more frequently prefer the online channel; we find no significant relationships between offline buying and online search. We also show for an informational Web site that customers who visit less frequently exhibit stronger cross-channel behavior and are more receptive to marketing efforts.

4.9 Conclusions

The objective of this study is to determine to what extent cross-channel behavior takes place when online search is the only option. We estimate a VAR model and thereby capture the relationships among the different types of offline and online customer behavior. We also determine how marketing efforts in channel *a* influence behavior in channel *b*. The VAR model estimated for each median split provides insight into cross-channel customer behavior and the effects of marketing efforts given a specific moderator.

Our research also shows that aggregate-level estimations of cross-channel behavior are limited. With median splits, we demonstrate that introducing an informational Web site benefits the organization most with regard to sensory products, low flow during Web visits and a low frequency of Web visits. An increase in online search leads to an increase in offline buying of sensory products. Online search leads to increased money per product, but less shopping trips for those customers who experience less flow during their Web visits. An increase in online search leads to an increase in money and trips for those customers who visit the site less frequently.

Prior research also indicates that marketing efforts influence customers to use a particular channel (Burke 2002; Ansari et al. 2006). It would be reasonable to expect that offline promotions would lead customers to the store and online promotions would lead customers to the Web site. However, in the case of informational Web sites, promotions, whether offline or online, influence customers' use of the offline channel, in which they may buy products. Customers who experience a high state of flow and engage in frequent Web visits are more receptive to online marketing efforts. The marketing efforts also benefit the organization more in the case of sensory products.

Although our research provides a plethora of new insights, as is any research, it is limited to the variables to which we have access. Most of the variables we collected pertain to individual customer behavior in either channel. For example, with regard to the marketing efforts, we cannot determine how the effects of offline communications influence online search. Our median-split approach shows that customers in our panel do not react in a similar manner. Thus, even though our median-splits allow for deeper insight, more conclusive answers may be possible through latent-class VAR modeling. Furthermore, most insights into the moderators of cross-channel behavior pertain to multiple transactional channels, and because our results differ from prior expectations, further research is needed to uncover the determinants of these differences.

Any organization is subject to competitors, about which we unfortunately have no information. Additional research might 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.

In conclusion, our study provides some initial insights into cross-channel behavior for online search and offline buying. Online search positively may influence the money spent per product but lowers the average number of shopping trips customers make. An increase in offline behavior mainly translates into an increase in online, which indicate increased overall behavioral loyalty to the store. Cross-channel behavior also is moderated by context characteristics in a manner that conflicts with previous research. Among customers who experience low flow online, visit the site less frequently, and are interested in sensory products, cross-channel behavior is stronger. Therefore, for an informational Web site, our results show that online marketing efforts drive offline buying.