MARKETING SCIENCE INSTITUTE

MSI Reports

A Meta-analysis of Personal Selling Elasticities (08-100)

Sönke Albers, Murali K. Mantrala, and Shrihari Sridhar

Building with Bricks and Mortar: The Revenue Impact of Opening Physical Stores in a Multichannel Environment (08-101)

Koen Pauwels and Scott A. Neslin

Feeling Superior: The Impact of Loyalty Program Structure on Customers' Perceptions of Status (08-102)

Joseph C. Nunes and Xavier Drèze

A New Approach to Modeling the Adoption of New Products: Aggregated Diffusion Models (08-103)

Olivier Toubia, Jacob Goldenberg, and Rosanna Garcia

Getting Marketing Back in the Boardroom: Understanding the Drivers of Marketing's Influence within the Firm (08-104)

Peter C. Verhoef and Peter S.H. Leeflang

Online User Comments versus Professional Reviews: Differential Influences on Pre-release Movie Evaluation (08-105)

Anindita Chakravarty, Yong Liu, and Tridib Mazumdar

2008

WORKING PAPER SERIES

ISSUE ONE

NO. 08-001

MARKETING SCIENCE INSTITUTE

MSI Reports

2008

WORKING PAPER SERIES

ISSUE ONE

NO. 08-001

The Marketing Science Institute supports academic research for the development—and practical translation—of leading-edge marketing knowledge on issues of importance to business performance. Topics are identified by the Board of Trustees, which represents MSI member corporations and the academic community. MSI supports academic studies on these issues and disseminates findings through conferences and workshops, as well as through its publications series.

Marketing Science Institute
1000 Massachusetts Avenue
Cambridge, MA USA
02138-5396

Phone: 617.491.2060
Fax: 617.491.2065
www.msi.org

MSI Reports (ISSN 1545-5041) is published quarterly by the Marketing Science Institute.

The views expressed here are those of the authors.

Working Paper Series
The articles that appear in *MSI Reports* have not undergone a formal academic review. They are released as part of the MSI Working Paper Series, and are distributed for the benefit of MSI corporate and academic members and the general public.

Subscriptions
Annual subscriptions to *MSI Reports* can be placed online at www.msi.org. Questions regarding subscriptions may be directed to pubs@msi.org.

Single reports
Articles in *MSI Reports* are available in downloadable (PDF) format at www.msi.org.

Past reports
MSI working papers published before 2003 are available as individual hard-copy reports; many are also available in downloadable (PDF) format. To order, go to www.msi.org.

Corporate members
MSI member company personnel receive all MSI reports (PDF and print versions) free of charge.

Academic members
Academics may qualify for free access to PDF (downloadable) versions of MSI reports and for special rates on other MSI print publications. For more information and to apply, go to "Apply for academic membership" on www.msi.org.

Classroom use
Upon written request, MSI working papers may be copied for one-time classroom use free of charge. Please contact MSI to obtain permission.

Search for publications
See the searchable publications database at www.msi.org.

Submissions
MSI will consider a paper for inclusion in *MSI Reports*, even if the research was not originally supported by MSI, if the paper deals with a priority subject, represents a significant advance over existing literature, and has not been widely disseminated elsewhere. Only submissions from faculty members or doctoral students working with faculty advisors will be considered. "MSI Working Paper Guidelines" and MSI's current research priorities are available in the Research section of www.msi.org.

Publication announcements
To sign up to receive MSI's electronic newsletter, go to www.msi.org.

Change of address
Send old and new address to pubs@msi.org.

Building with Bricks and Mortar: The Revenue Impact of Opening Physical Stores in a Multichannel Environment

Koen Pauwels and Scott A. Neslin

What is the impact of adding physical stores to a firm's existing catalog and Internet channels? In this study, revenues increased by 20%, catalog sales were cannibalized, and the Internet channel was unaffected. Overall, the firm benefited from more customer–firm contacts, a form of improved customer retention.

Koen Pauwels is an Associate Professor and **Scott A. Neslin** is the Albert Wesley Frey Professor of Marketing, both at the Tuck School of Business Administration at Dartmouth College.

Report Summary

A crucial decision firms face today is which channels they should make available to customers for sales transactions. Here, Koen Pauwels and Scott Neslin assess the revenue impact of adding bricks-and-mortar stores to a firm's already existing repertoire of catalog and Internet channels. They seek to advance knowledge on the impact of channel addition in four ways: first, by examining specifically how the addition affects the frequency and size of purchases, returns, exchanges, and customer acquisition; second, by turning attention on the store channel as opposed to the currently more widely studied Internet channel; third, by investigating the role a firm's marketing efforts play in producing this impact; and fourth, by using a multivariate baseline approach to quantify the impact.

The study uses data from a retailer of durables and apparel that hitherto has sold predominantly through catalogs and, increasingly, through the Internet. The authors observe the orders, returns, exchanges, and catalogs and e-mails received for customers living within 50 miles of at least one of the three newly opened stores, for the period from January 1997 through November 2002, a total of 309 weeks. Their analysis reveals that returns and exchanges shifted to the store channel and increased, with the increase in extra sales that occur when customers come in to make exchanges offsetting the loss from increased returns.

The net impact of adding the store channel was to increase revenues by 20%, with the majority of this increase being attributable to higher purchase frequency. As hypothesized, catalog sales were cannibalized and the Internet channel was unaffected. From a customer management perspective, adding the new channel benefited the retailer through increased customer retention, manifested in more frequent customer–firm contacts. These findings yield a deeper understanding of the revenue relation between channels, of how new channels affect the customer's relationship with the firm, and of the cross-channel effects of marketing actions. ■

Introduction

Spurred by precipitous growth in the number and variety of sales outlets through which consumers can purchase products, multichannel customer management has become both a challenge and opportunity for firms (Neslin et al. 2006; Rangaswamy and van Bruggen 2005). A key question in this area is, "If the firm were to add a channel, what impact would it have on revenues?" (Neslin et al. 2006). This paper addresses that question from a multichannel customer management perspective. In particular, we examine the revenue impact of opening a physical store through its effect on the frequency and size of customer purchases, returns, and exchanges across all the firm's channels, as well as the impact on customer acquisition.

Due to the rise of the Internet, researchers have begun to investigate whether adding this channel enhances or cannibalizes existing sales. Deleersnyder et al. (2002) analyzed the circulation of 67 newspapers that added an Internet version of their offline newspaper. They found the impact was most often insignificant, but when significant, likely to be positive. Biyalogorsky and Naik (2003) examined the impact that adding an Internet channel had on sales in a bricks-and-mortar store. They found the impact to be directionally negative but not statistically significant.

The evidence above suggests that adding an Internet channel does not seriously cannibalize offline sales. However, the focus of those studies is the Internet. Retailers may contemplate adding a different channel, such as physical stores, catalog, etc. There is reason to believe the impact of adding a channel differs depending on the channel because channels themselves differ in the customers that use them, in the value proposition they offer, and in what they require of customers. In fact, based on these factors, we propose that the introduction of a physical store should not cannibalize the Internet, but will cannibalize catalog sales. Our main goal is to understand the effects of the addition of different channel types because there is reason to believe they could be different. Table 1 places our work in this nascent area of research.

The research cited above investigates the net impact on overall performance, but does not identify the source of the impact. From a customer management perspective, we need to understand whether that impact is due to attracting new customers, altering the frequency of customer transactions, or changing the dollar value of these transactions. In a retail setting, there are three types of transactions that directly affect revenues—purchases, returns, and exchanges. Multichannel retailers are particularly concerned with returns, which amount to between 18-35% of products purchased by catalog (Rogers and Tibben-Lembke 1998), and with exchanges; i.e., customers returning an item but purchasing another item in its place. Adding a channel that permits easy returns and exchanges, such as the physical store channel, may increase purchase orders, but also the frequency and size of returns and exchanges.

Finally, a key issue not addressed by the previous work is the role of marketing. Neslin et al. (2006) posit that marketing plays a key role in multichannel customer management, and to fully understand the impact that adding a channel has on total firm performance, one must factor in the role of the firm's marketing efforts.

Methodologically, our work extends the baseline analysis approach used in the evaluation of sales promotions (Abraham and Lodish 1993). This approach extrapolates a single variable—the baseline sales level—to evaluate the performance of a promotion. Our interest, however, is in several variables—customer acquisition, purchase frequency, order size, etc. Therefore, we need to extrapolate several variables into the store introduction period. Accordingly, we employ a multivariate vector

Table 1
The Multichannel Cross-Elasticity Matrix: The Role of This Paper

		Impact on:		
		Store	**Catalog**	**Internet**
Channel Introduced	**Store**		This paper	This paper
	Catalog	?		?
	Internet	Biyalogorsky and Naik (2003) Deleersnyder et al. (2002)	?	

autoregression model to develop a multivariate baseline, from which we calculate the impact of adding the physical store channel.

Our analysis is at the weekly level, aggregated across customers. This is for three reasons. First, we examine nine endogenous variables (customer purchase frequency, average order size, customer acquisition, etc.). A customer-level model with nine endogenous variables would be extremely complex, and it isn't even clear how variables such as customer acquisition would be handled. Second, we aim to propose a general methodology that may be applied in the many situations in which only aggregate data are available. Finally, the nine aggregate variables we examine are relevant metrics of direct interest to managers evaluating the addition of a new channel.

In summary, our goal is to measure the revenue impact of adding a bricks-and-mortar store to an existing channel structure. Our work contributes in four ways: (1) decomposing the impact into components pertaining to the frequency and size of purchases, returns, exchanges, and to customer acquisition, (2) investigating the store channel rather than the Internet, (3) investigating the role of the firm's marketing efforts in producing this impact, and (4) using a multivariate baseline approach to quantify the impact.

Revenue Components and the Impact of Adding Physical Stores

Figure 1 proposes a framework for analyzing the revenue contribution of a new channel. Revenues depend on the size of the customer base, multiplied by the per-customer frequency and by the transaction size in each channel. Transactions can take the form of purchases, returns, or exchanges. An additional channel can affect each of these components. More customers might be acquired because the firm's products become available to a new set of customers. Purchase frequency and size can increase due not only to availability, but also to higher customer satisfaction. For example, catalogs offer superior image and portability of information, while the Web offers convenience, customer reviews, and quick updates on pricing and promotions (Grewal, Iyer, and Levy 2004). Physical stores allow prepurchase handling and trial, personalized attention, and instant gratification (Grosso, McPherson, and Shi 2005). Moreover, consumers find it easy to return or exchange items when a local store is available (Kushawaha 2005).

We want to translate the framework in Figure 1 into an equation for revenues that we can in turn use to calculate the impact of adding a new channel. In our case, customers can order through all three channels, but returns and exchanges (of items bought through any channel) can be made only through the store or via mail (which we refer to as catalog returns and exchanges). As a result, total revenue for the company in week t can be expressed as:

$$TR_t = NCUST_t \times \left\{ \sum_{j=1}^{3} FREQ_{jot} SIZE_{jot} - \sum_{j=1}^{2} FREQ_{jrt} SIZE_{jrt} + \sum_{j=1}^{2} FREQ_{jet} SIZE_{jet} \right\} \quad (1)$$

where:
TR_t = total revenues in period t.

Figure 1

A Multichannel Customer Management Framework for Analyzing the Revenue Impact of Adding the Physical Store Channel

Number of Customers	×	Transaction Frequency	×	$ Size per Transaction	=	Revenues
		• purchases - store - catalog - Internet • returns - store - catalog • exchanges - store - catalog		• purchases - store - catalog - Internet • returns - store - catalog • exchanges - store - catalog		

$NCUST_t$ = size of the customer base in period t.
j = channel 1, 2, 3, indexing the retail store, catalog, and Internet, respectively.
o, r, e = indexes orders, returns, and exchanges, respectively.
$FREQ_{jot}$ = number of purchases (orders) through channel j in period t.
$FREQ_{jrt}$ = number of returns through channel j in period t.
$FREQ_{jet}$ = number of exchanges through channel j in period t.
$SIZE_{jot}$ = average order size through channel j in period t.
$SIZE_{jrt}$ = average return size through channel j in period t.
$SIZE_{jet}$ = average exchange size through channel j in period t.

The interplay among the variables in Equation 1 is very rich and is further directed by marketing activities. For example, a mailed catalog may induce a customer to order a coat through the catalog because the catalog is convenient. However, upon receiving the garment, the customer discovers that it does not fit. Rather than returning the garment through the mail, the customer now goes to the store and exchanges the garment for one in the right size, and purchases a scarf to match. The customer is more satisfied with the overall experience, and therefore more receptive in the future to buy through any of the firm's channels. This example illustrates how channels, purchases, returns, exchanges, and marketing efforts interact with each other over time. If we are to quantify the net result of the introduction of a new channel, we need a statistical method that handles these dynamics. This is why we employ a multivariate baseline approach, in which we predict the performance variables using only the information set available to managers before they introduced the physical store channel. In the words of Swanson and White (1997): "Using only data which were available prior to period t allows us to guard against future information creeping in to our econometric specifications, and thus, our forecasts" (p. 441).

We have several expectations regarding the impact of store introduction, summarized in Table 2. Permeating many of these is the availability effect (Neslin et al. 2006; see also Kumar and Venkatesan 2005). The availability effect is simply that more channels decrease the effort required for the customer to interact with the firm, resulting in more transactions—much in the way that more soda outlets (vending machines, supermarkets, etc.) increase soda sales.

Purchases

Due to the availability effect, we expect more total purchases, i.e., higher purchase frequency. However, the introduction of stores may also

Table 2

Expected Impact of Store Introduction

(+ = Increase; – = Decrease; 0 = No Change; na = Not Applicable; ? = Unsure)

	Purchases				Returns				Exchanges			
	store	catalog	Internet	net	store	catalog	Internet	net	store	catalog	Internet	net
Number of transactions	+	–	0	+	+	–	na	+	+	–	na	+
Size/Transaction	?	?	0	?	–	?	na	–	+	?	na	+

Note: The number of purchase, return, and exchange transactions for the store must increase since this is the new channel.

cannibalize purchases from a similar channel. In particular, we expect a decline in the number of catalog (but not Internet) purchases for two main reasons. First, catalogs and stores are popular with the same customer segment. For example, Alreck and Settle (2002) found that women had more positive attitudes toward stores and catalogs than did men, whereas men had more positive attitudes toward the Internet than did women. Likewise, Kushawaha (2005) finds that online-only customers are typically male, while female customers typically purchase both offline and online. Second, Ward (2001) argues that channels are more likely to be substitutes if they require similar human resources (time, browsing ability, education, etc.). He finds evidence based on an analysis of regression residuals that these resources are more similar for the store and catalog than for the store and Internet.

Third, catalog and store shopping both involve an aesthetic component (the experience itself), whereas the Internet is more transactional. That aesthetics and recreational aspects are important drivers of store shopping is well documented (e.g., Dholakia 1999; Jarratt 1996). The literature suggests that catalogs are similar to stores in this respect. For example, Mathwick, Malhotra, and Rigdon (2001) find that aesthetics affect catalog shoppers but not Internet shoppers. Forsythe et al. (2006) find that enjoyment did not differentiate heavy versus light Internet users, whereas convenience and product selection did.[1]

The above arguments involve purchase frequency. We do not advance expectations for the dollar size per purchase through the catalog or the store. It is possible that dollar size could decrease if catalog customers spread their purchase across the catalog and store. On the other hand, size could be lower or higher in either channel, depending on whether the heavy or light user is diverted to the store. In the case of the Internet, however, our expectation that the store and Internet are not close substitutes implies that both frequency and volume per purchase on the Internet will be unaffected.

Returns

We expect the store introduction to divert returns from the catalog to the store, plus increase the number of returns in total. This is largely a matter of availability and convenience: consumers find it easier to return merchandise to the store than to mail it back to the retailer. For example, some clicks-and-bricks retailers report that half of all items returned to their stores were purchased online. Richard Thalheimer, CEO of Sharper Image, calls store returns “a serious problem,” amounting to up to 20% of the company’s sales (Kushawasha 2005). At the same time, though, Shulman, Coughlan, and Savaskan (2005) note that the ease of returns helps customers make the purchase in the first place, especially for high-risk experience goods. This explains why returns are typically free for apparel (our empirical application context): reducing returns would reduce profits

(Shulman, Coughlan, and Savaskan 2005). With respect to the dollar size per return, we expect the marginal incremental return will probably be of lower dollar size—the unsatisfactory but low-cost purchase previously might not have been worth the hassle to return via mail, but with a more convenient return channel, more low-dollar value returns will be made. This suggests the mean dollar size of returns should be lower in the store than through the catalog, and the overall mean size per return should decrease as well.

Exchanges

As with returns, availability and convenience should increase the number of exchanges while diverting them from the catalog to the store. In fact, the store may convert catalog returns into exchanges, and this could override our expectation stated above that total return frequency should increase. We expect the dollar size per store exchange to be more positive than a catalog exchange. A catalog exchange decouples exchanging from shopping since the exchange is through the mail. However, a store exchange invites the opportunity for more shopping, as in the example above. This, plus the selling skills of store personnel, suggests that the net dollar size per exchange should be more positive for the store than the catalog, and more positive overall.

Total revenue

Total revenue should increase with the introduction of the store. First, we expect store introductions will increase the customer base, i.e., increase customer acquisition. Second, we expect higher total purchase frequency and more frequent and more positive dollar-size exchanges. Third, while we do not specify an expectation regarding dollar size per purchase, it is difficult to see how total volume could decrease. Even in the worse case that customers simply buy the same volume as before but spread their purchases across more purchase occasions, total volume per customer would remain the same, but the acquisition of more customers would increase total revenues. Perhaps the one route by which revenues would decrease is if the number of returns increased dramatically. This could offset the other positive effects we hypothesize. However, we think this is unlikely: there are more forces pointing to increasing revenues than to the potential problem—returns—that could decrease them.

Methodology

Multivariate baseline analysis

Our goal is to measure how the elements of Equation 1 (size of customer base; frequency of orders, returns, and exchanges; size of orders, returns, and exchanges) are influenced by the introduction of the physical store channel. That is, we wish to measure the impact of store introduction on a multivariate vector. The task is challenging because the store introduction sets in motion a chain of dynamic interactions among the store, catalog, and Internet that are difficult to disentangle analytically. In addition, marketing activities such as catalog mailings and e-mails shape this interplay. We therefore adopt baseline analysis as our analysis strategy. Baseline analysis projects the several interacting variables from a preperiod (before the store was introduced) into a postperiod (after the store was introduced). For each variable, the difference between its actual postperiod value and its postperiod baseline value is assumed due to the impact of the store. This being said, we verify whether this assumption holds up by analyzing alternative explanations for revenue component changes, due to factors both external and internal to the company.

Baseline analysis has been used successfully—and commercialized—in the sales promotion field (Abraham and Lodish 1993). However, those applications have involved only a single target variable: brand sales. Our problem is more challenging because we have several target variables that feed back on each other over time. We therefore need a dynamic multivariate model to estimate the baseline. We adopt a vector autoregressive (VARX) model based on three properties desirable for our purpose. First, the VARX model estimates dynamic relationships among several variables, thus predicting a multivariate baseline. Second, impulse response functions based on VARX models allow us to estimate the long-term effects of marketing actions on the revenue components and thus to investigate the role of those marketing actions in the net revenue impact of the store channel introduction. Finally, VARX models include variables in levels or differences, based on the outcome of unit root and cointegration tests. This treatment guards against spurious relationships among variables (Granger and Newbold 1986) and allows for permanent effects of marketing actions. While permanent revenue effects of tactical marketing actions are unlikely for established brands (Slotegraaf and Pauwels in press), they are observed for more strategic marketing actions, such as the introduction of new products (Pauwels et al. 2004), and thus may well result from new channel introductions. As a result of these properties, VARX models are popular within econometrics and marketing (Dekimpe and Hanssens 1999; Franses 2004) for forecasting applications involving several endogenous variables.

Unit root and cointegration tests

As a first step in our analysis (e.g., Dekimpe and Hanssens 1999), we conduct unit root tests to determine whether the variables in our model are stationary or evolving, using both the augmented Dickey-Fuller test procedure recommended in Enders (2003) and the Kwiatkowski-Phillips-Schmidt-Shin test (1992). Each test is conducted with and without a deterministic time trend. To the extent these tests converge, we are more confident in whether to classify a variable as stationary or evolving (Maddala and Kim 1998). Next, we examine the robustness of our unit root tests with repect to structural breaks (Bai and Perron 1998), with the store openings as obvious choices for break points. Finally, the cointegration test of Johansen, Mosconi, and Nielsen (2000) verifies whether any combination of evolving variables are in long-run equilibrium, allowing for structural breaks in these variables.

The baseline model (VARX1)

We model the revenue components of Equation 1 as endogenous, i.e., they are explained by their own past and the past of the other endogenous variables. We expect the revenue components to influence each other due to consumer learning and experience over time (e.g., see Ansari, Mela, and Neslin 2008). Moreover, “catalogs sent” and “e-mails sent” are expected to be endogenous as the company uses recency, frequency, and monetary variables (RFM variables) to target catalogs and gather e-mail addresses when purchases are made. As a result, increases in the revenue components of Equation 1 affect these marketing activities. This is called “performance feedback” in Dekimpe and Hanssens (1999). Empirically, we verify our endogeneity assumptions using Granger causality tests (Granger 1969).

The VARX1 baseline model includes 11 endogenous variables: number of customers, frequency of orders via catalogs and the Internet, frequency of returns via catalog, frequency of exchanges via catalog, order size via catalog and the Internet, return size via catalog, exchange size via catalog, and the marketing actions “catalogs sent” ($CATALOGS_t$) and e-mails sent ($EMAILS_t$). Note that none of these is store related. This is because the baseline model is estimated on the prestore introduction period. We represent lags by B^k, a (11×11) matrix of coefficients, and U_t is a (11×1) vector of errors ($U_t = [u_{Cust,t}, \ldots, u_{Email,t}]' \sim N(0, \Sigma_u)$). We also include an intercept α, a time trend t, and 12 four-weekly seasonal dummies SD (using the first 4 weeks of the year as the benchmark). Equation 2 displays the VARX1 model in its general specification (variables are included in levels or first differences, depending on whether the unit root tests classify the variable as stationary or evolving):

$$
\begin{bmatrix} NCUST_t \\ FREQ_{2ot} \\ FREQ_{3ot} \\ SIZE_{2ot} \\ SIZE_{3ot} \\ FREQ_{2rt} \\ SIZE_{2rt} \\ FREQ_{2et} \\ SIZE_{2et} \\ CATALOGS_t \\ EMAILS_t \end{bmatrix}
=
\begin{bmatrix} \alpha_1 + \delta_1 t + \Sigma\chi_{1m} SD_{mt} \\ \alpha_2 + \delta_2 t + \Sigma\chi_{2m} SD_{mt} \\ \alpha_3 + \delta_3 t + \Sigma\chi_{3m} SD_{mt} \\ \alpha_4 + \delta_4 t + \Sigma\chi_{4m} SD_{mt} \\ \alpha_5 + \delta_5 t + \Sigma\chi_{5m} SD_{mt} \\ \alpha_6 + \delta_6 t + \Sigma\chi_{6m} SD_{mt} \\ \alpha_7 + \delta_7 t + \Sigma\chi_{7m} SD_{mt} \\ \alpha_8 + \delta_8 t + \Sigma\chi_{8m} SD_{mt} \\ \alpha_9 + \delta_9 t + \Sigma\chi_{9m} SD_{mt} \\ \alpha_{10} + \delta_{10} t + \Sigma\chi_{10m} SD_{mt} \\ \alpha_{11} + \delta_{11} t + \Sigma\chi_{11m} SD_{mt} \end{bmatrix}
+ \sum_{k=1}^{K} B^k \times
\begin{bmatrix} NCUST_{t-k} \\ FREQ_{2o,t-k} \\ FREQ_{3o,t-k} \\ SIZE_{2o,t-k} \\ SIZE_{3o,t-k} \\ FREQ_{2r,t-k} \\ SIZE_{2r,t-k} \\ FREQ_{2e,t-k} \\ SIZE_{2e,t-k} \\ CATALOGS_{t-k} \\ EMAILS_{t-k} \end{bmatrix}
+ U_t \qquad (2)
$$

Equation 2 provides the means to project the 11 endogenous variables from the preintroduction to postintroduction periods and provides the main vehicle for our analysis. We decide on the number of lags (K) based on the Bayesian information criterion (BIC), which is a consistent estimator of lag length (Lütkepohl 1993), and test whether we should add lags to implement the diagnostic tests on residual autocorrelation described in Franses (2005).

The postintroduction model (VARX2)

An additional goal of our analysis is to assess the role that marketing decisions played in the total impact of the store introduction on other channels. To this end, we employ a second VARX model (VARX2), estimated over the post–store introduction period. VARX2 adds six endogenous store revenue components: frequency of store orders, returns, and exchanges; and size of store orders, returns, and exchanges. Moreover, the stores employed direct mail promotions ($Prom_t$) and media advertising (Adv_t), which we consider endogenous to the store openings. The data include three store openings, so we operationalize these as three dummy variables ($Open_{st}$, s = 1, 2, 3 indexing each store). The control variables are the same as those in Equation 2 (intercept, trend, and seasonal dummies). Equation 3 displays the model:

$$
\begin{bmatrix} NCUST_t \\ FREQ_{1ot} \\ FREQ_{2ot} \\ FREQ_{3ot} \\ SIZE_{1ot} \\ SIZE_{2ot} \\ SIZE_{3ot} \\ FREQ_{1rt} \\ FREQ_{2rt} \\ SIZE_{1rt} \\ SIZE_{2rt} \\ FREQ_{1et} \\ FREQ_{2et} \\ SIZE_{1et} \\ SIZE_{2et} \\ CATALOGS_t \\ EMAILS_t \\ PROM_t \\ ADV_t \end{bmatrix}
= A_t + \sum_{k=1}^{K} B^k \times
\begin{bmatrix} NCUST_{t-k} \\ FREQ_{1o,t-k} \\ FREQ_{2o,t-k} \\ FREQ_{3o,t-k} \\ SIZE_{1o,t-k} \\ SIZE_{2o,t-k} \\ SIZE_{3o,t-k} \\ FREQ_{1r,t-k} \\ FREQ_{2r,t-k} \\ SIZE_{1r,t-k} \\ SIZE_{2r,t-k} \\ FREQ_{1e,t-k} \\ FREQ_{2e,t-k} \\ SIZE_{1e,t-k} \\ SIZE_{2e,t-k} \\ CATALOGS_{t-k} \\ EMAILS_{t-k} \\ PROM_{t-k} \\ ADV_{t-k} \end{bmatrix}
+ \sum_{l=0}^{L}
\begin{bmatrix} \Sigma\lambda_{1l} Open_{s,t-l} \\ \Sigma\lambda_{2l} Open_{s,t-l} \\ \Sigma\lambda_{3l} Open_{s,t-l} \\ \Sigma\lambda_{4l} Open_{s,t-l} \\ \Sigma\lambda_{5l} Open_{s,t-l} \\ \Sigma\lambda_{6l} Open_{s,t-l} \\ \Sigma\lambda_{7l} Open_{s,t-l} \\ \Sigma\lambda_{8l} Open_{s,t-l} \\ \Sigma\lambda_{9l} Open_{s,t-l} \\ \Sigma\lambda_{10l} Open_{s,t-l} \\ \Sigma\lambda_{11l} Open_{s,t-l} \\ \Sigma\lambda_{12l} Open_{s,t-l} \\ \Sigma\lambda_{13l} Open_{s,t-l} \\ \Sigma\lambda_{14l} Open_{s,t-l} \\ \Sigma\lambda_{15l} Open_{s,t-l} \\ \Sigma\lambda_{16l} Open_{s,t-l} \\ \Sigma\lambda_{17l} Open_{s,t-l} \end{bmatrix}
+ U_t \qquad (3)
$$

A_t is the (19×14) matrix of control variables (see Equation 2); K is the number of lags selected for the endogenous variables; B^k is the (19×19) matrix of dynamic coefficients; L is the number of lags selected for the exogenous store opening variables; and $U_t = [u_{Cust,t}, \ldots, u_{Adv,t}]' \sim N(0, \Sigma_u)$.

Impulse response functions

We make use of impulse response functions to gauge the role of marketing actions on the revenue components. We adopt the generalized, simultaneous-shocking approach (Pesaran and Shin 1998), which uses the information in the residual variance-covariance matrix of the VAR model instead of requiring the researcher to impose a causal ordering among the endogenous variable (Dekimpe and Hanssens 1999). We assess the statistical significance of each impulse-response value by applying a one-standard-error band, as motivated in Pesaran, Pierse, and Lee (1993) and Sims and Zha (1999).

Assessing the assumptions of multivariate baseline analysis

Baseline analyses assume that projections into the post-store introduction period represent what would have happened had the stores not been introduced. However, events may occur in the post-store introduction period that are not explicitly included in the baseline VAR model. These events can be external to the company or internal. An example of an external event would be an unexpected increase in retail market growth. This would result in our baseline being too pessimistic and thus would overstate the revenue impact of the store channel introduction. An example of an internal event might be a change in marketing expenditures not predictable by the trend in marketing expenditures in the baseline period. For example, a sudden decision to depart from the historical patterns and decrease catalogs sent would result in baseline purchase frequency that is overly optimistic, because it would be predicated on a higher level of marketing expenditures than actually occurred.

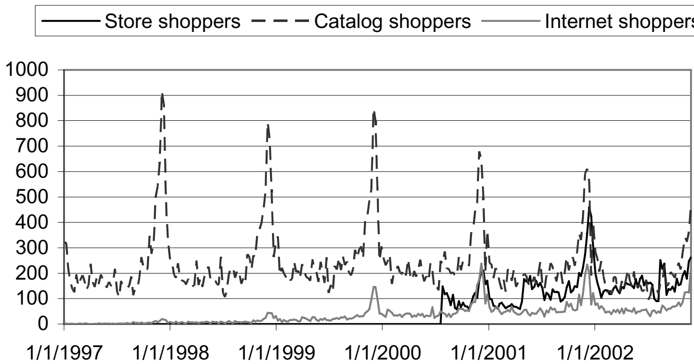
How can we check for these exogenous events? First, company-external effects such as industry-level sales may be added to the VARX models as exogenous variables. To the extent that they add explanatory power over the existing variables (including trend and seasonality), their revenue effects should be incorporated in the baseline. Second, the VARX1 model also provides a baseline of the company's existing marketing actions, such as catalogs and e-mails sent. After store channel introduction, we can thus compare this projected level of marketing with actual levels. Substantial deviations may then be incorporated in an adjusted baseline, which projects the revenue components based on the actual level of postintroduction marketing activity (using the VARX1 estimates of the marketing effects on these revenue components).

Note that the baseline only need be adjusted if something occurs that is not included in the baseline model *and* is exogenous (unrelated) to the store introduction. If the store introduction causes an event, such as competitive response, this will be reflected in the actual level of sales in the postintroduction period. The baseline need not be adjusted because the baseline should reflect what would have happened had the stores not been introduced, and the competitive response would not have happened had the stores not been introduced. However, if an exogenous event occurs, e.g., unexpectedly low sales due to an economic recession, this needs to be incorporated in the baseline.

In summary, VARX1 (Equation 2) is our baseline model. It is estimated on the prestore introduction period and forecasts the values of the revenue components into the postintroduction period assuming no stores were introduced. We also calculate an adjusted baseline by considering unanticipated changes to company-external and company-internal factors. By subtracting the actual values of the postintroduction revenue components from their baseline predictions, we infer the impact of the store introduction. VARX2 (Equation 3) is

Figure 2

Weekly Shoppers in the Store, Catalog, and Internet Channels



estimated over the postintroduction period so we can gauge the effectiveness of marketing activities during this period. VARX2 includes store-related endogenous variables (frequency and order size) that become relevant in the postintroduction period, as well as the marketing (store promotions and advertising) introduced in that period.

Data Description

The data provider sells durables and apparel in mature categories predominantly through catalogs and increasingly through the Internet. As with most catalogers, its house list of customers is carefully maintained and provides the means for the company to target marketing efforts. As this customer management is the lifeblood of the company, we consider a customer to be acquired only if the company could be identified and added to the house list.

The introduction of bricks-and-mortar stores means the firm may no longer be able to maintain a 360-degree view of each of its customers: it is inherently difficult to link store purchases back to the firm's database. This is a classic problem in multichannel marketing (Neslin et al. 2006). The match-back rate in our data, i.e., the percentage of store purchases for which the customer can be identified, varies over time, centered at around 55%, and we control for this with a "match-back rate" variable in our models. A major reason for the absence of full match-back is that some customers purchase with cash and fail to give identifying information.

We select customers living within 50 miles of at least one of the three stores to construct our data set. This avoids random noise from customers who live too far away to be influenced by the channel addition. For the selected customers, we observe their orders, returns, exchanges, catalogs received, and e-mails received.[2] We aggregate this transaction-level information into a weekly data set, from January 1, 1997 to November 27, 2002, a total of 309 weeks.[3] The three stores opened on July 26, 2000, May 2, 2001, and August 14, 2002. Figure 2 displays the weekly number of customers in our database that purchase via the store, catalog, and Internet. Figures 3 and 4 display the weekly number of customers making returns and exchanges via the store and the catalog. Note that the store channel quickly becomes as important as the catalog channel as a medium for returning items, and even more so for exchanging items.

Table 3 presents the means of the revenue components before and after the introduction of the first store. The stores have clearly been successful in generating their own purchases. At the same time, catalog order frequency decreased, Internet order frequency increased, catalog return frequency decreased, and e-mails increased. Table 3 cannot tell us which changes represent a true impact of the store channel addition, nor can it prioritize the reasons why the key variables change. To this end, we proceed with our analysis.

Results

Final model specification based on unit root and Granger causality tests

The unit root analysis classified Internet order frequency and size as stationary in all tests.

Figure 3

Weekly Shoppers Returning Merchandise to the Store and to the Catalog Channels

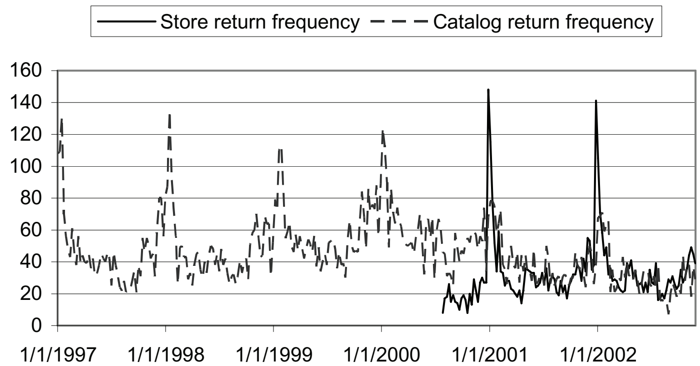
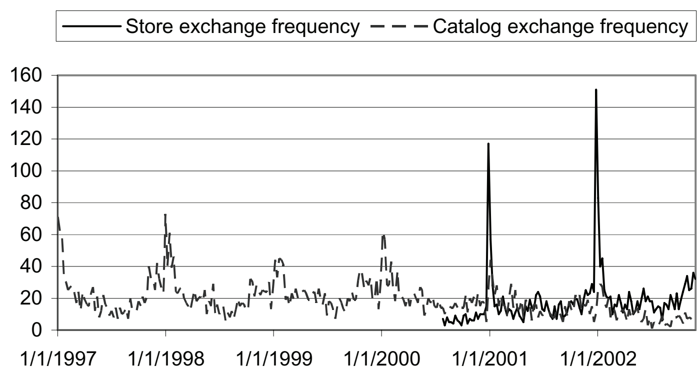


Figure 4

Weekly Shoppers Exchanging Merchandise in the Store and Catalog Channels



This provides initial confirmation of our expectation that the Internet channel was unaffected by the introduction of physical stores. Other variables were classified as evolving in at least one test, and accounting for structural breaks at store openings does not change this classification. In order to avoid spurious results (Granger and Newbold 1986), we therefore include them as first differences in the VARX models.[4]

The Granger causality tests confirm that all revenue components, catalogs, and e-mails are caused by other variables, confirming our specification of these variables as endogenous. The lag order for both the endogenous and exogenous variables (K in Equation 2; K and L in Equation 3) is 1, as selected by BIC and confirmed by the Hannan-Quinn information criterion. We verified that all substantive results hold up if lag = 2 is specified, as selected by the Akaike information criterion (and final prediction error).

Both VARX models fit the data rather well, explaining over 80% of the weekly variation in all frequency variables and over 60% of the weekly variation in order sizes and customer growth. As usual, the VARX models have a harder time explaining marketing actions such as catalogs sent (R^2 = 41% in VARX-2), store advertising (R^2 = 20%), and store promotions (R^2 = 38%). The one exception is e-mails sent (73%), which hardly deviates from a linear trend upwards.

Initial baseline projections versus actual sales

Figures 5-7 compare actual values of weekly customer growth, catalog, and Internet purchase frequency with their baselines as forecasted using the VARX1 model. The VARX1 model tracks these variables very well in the preintroduction period. This reinforces our confidence in using the model to extrapolate the revenue components into the postintroduction period to provide the baseline for what would have happened had the stores not been introduced. Perusing the postintroduction periods in figures 5-7 (after July 26, 2000), Internet purchase frequency closely tracks the baseline. However, catalog purchase frequency does not; the actual values fall below baseline. This suggests, as expected, that the Internet was not affected by store introductions, but the catalog was.

Assessing baseline assumptions: Check for events exogenous to channel introduction

In checking for events exogenous to the store introduction that could distort our baseline, the main company-external event we examine is the potential for there to be a change in the general level of retail activity not captured by

Table 3

Descriptive Statistics for the Performance and Marketing Variables

	Mean per week before store introductions	Mean per week after store introductions
Customer base	13,492	14,993
Store purchase frequency (*$FREQ_{1ot}$*) (% who purchase)	.00%	.94%
Catalog purchase frequency (*$FREQ_{2ot}$*) (% who purchase)	1.80%	1.54%
Web purchase frequency (*$FREQ_{3ot}$*) (% who purchase)	.13%	.45%
Store return frequency (*$FREQ_{1rt}$*) (% who return)	.00%	.21%
Catalog return frequency (*$FREQ_{2rt}$*) (% who return)	.39%	.26%
Store exchange frequency (*$FREQ_{1et}$*) (% who exchange)	.00%	.12%
Catalog exchange frequency (*$FREQ_{2et}$*) (% who exchange)	.17%	.09%
Store order size (*$Size_{1ot}$*) ($ per order)	$.00	$104.98
Catalog order size (*$Size_{2ot}$*) ($ per order)	$109.99	$114.32
Web order size (*$Size_{3ot}$*) ($ per order)	$97.53	$106.93
Store return size (*$Size_{1rt}$*) ($ per return)	$.00	$88.26
Catalog return size (*$Size_{2rt}$*) ($ per return)	$85.40	$90.46
Store exchange size (*$Size_{1et}$*) ($ per exchange)	$0.00	$10.61
Catalog exchange size (*$Size_{2et}$*) ($ per exchange)	–$17.30	–$23.52
Catalogs mailed (per week)	4,292	6,147
E-mails sent (per week)	216	2,467
Store promotions distributed (per week)	19	110
Media spending	$0	$6,101
Number of weeks	*186*	*123*

the trend and seasonality variables in the VARX1 model. Changes to general retail activity reflect many exogenous factors, including recessions, the weather, shifting consumer spending patterns, supply chain disruptions, etc. To investigate this, we obtained industry-level apparel sales data and included them as exogenous variables in the VARX-models. However, this variable did not add to the model fit nor did it affect the estimated parameters of interest in any substantial way. It therefore appears that industrywide sales add little in the context of the trend, seasonal dummies, and company-specific marketing actions already in the model.

As for company-internal factors, our analysis shows that while e-mail activity in the post-store introduction period was accurately projected, catalog activity was noticeably *below* what was projected by the baseline model. Figure 8 shows that actual catalogs sent during the postintroduction period at first is on average close to baseline, but clearly dips below baseline in later periods.

Figure 8 establishes that catalog distribution decreased after store introduction. If this is due to the store introduction itself, then the baseline need not be adjusted, because the baseline accurately projects what would have happened if the stores had not been introduced. However, if the reduction in catalogs has a cause that is exogenous (unrelated) to the store introduction, then the baseline is overstated—it incorrectly assumes the

Figure 5

Weekly Customer Growth: Actual versus Baseline (VARX1)

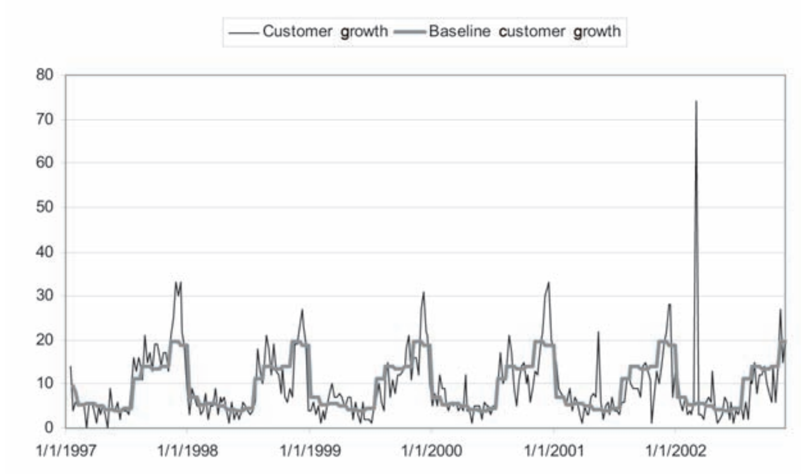


Figure 6

Catalog Order Frequency: Actual versus Baseline (VARX1)

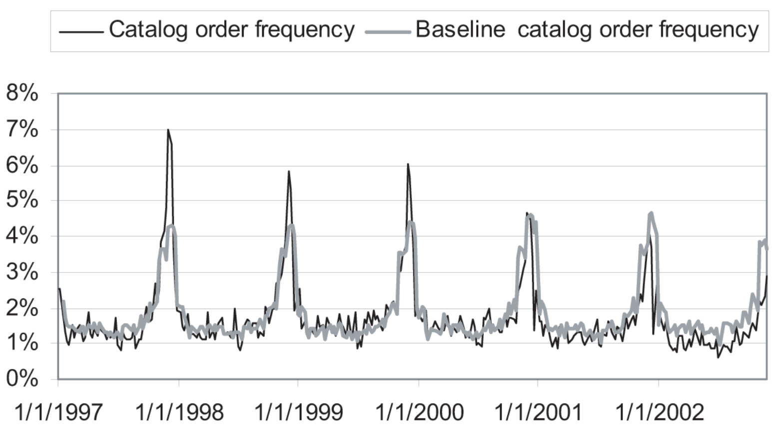
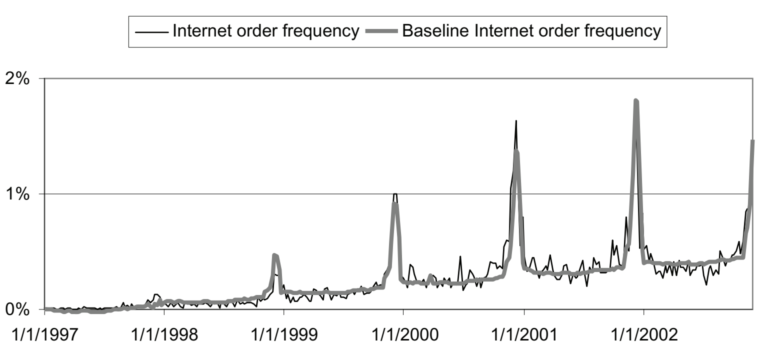


Figure 7

Internet Order Frequency: Actual versus Baseline (VARX1)



company will have sent more catalogs than they would have had the stores not been introduced. This increases the baseline for various revenue components and hence decreases the value added by the store channel.

To investigate whether the decrease in catalogs was exogenous or endogenous to the store introductions, we contacted company management. They told us clearly that the catalog reductions were not at all related to the store introductions: the reductions were part of an overall policy to reduce catalog mailings due to a suspicion the company was overloading customers with catalogs. This means that the catalog reduction is an exogenous event, and we must adjust for it in our baseline.

Table 4 provides impulse response results from the VARX1 model showing the impact of catalogs and e-mails on the various revenue components. As to be expected, the results show that catalog distribution affects catalog purchase frequency the most, while e-mails affect Internet purchasing the most. The total impact of a catalog on revenues is $1.55. Our calculations imply that there were 808 fewer catalogs in the poststore period than projected by the initial baseline. This multiplies out to $1,252.40 (808 × $1.55). This means that the decrease in catalogs relative to baseline might have subtracted $1,252 in baseline revenues. However, this is the maximum potential impact because catalogs were decreased later in the postintroduction period, and the impulse response function extends over time (see figures 9 and 10). To accurately adjust the baseline for the decrease in catalogs, we subtract actual catalogs sent from baseline projected catalogs sent in each postintroduction period and then utilize the period-by-period impact of catalogs to calculate the total impact on the baseline for each revenue component.

Despite the above adjustments, we cannot guarantee that we have accounted for everything. One possible concern is competitive activity. Note, as discussed previously, that if competitive

Figure 8

Weekly Number of Catalogs Sent: Actual versus Baseline (VARX1)

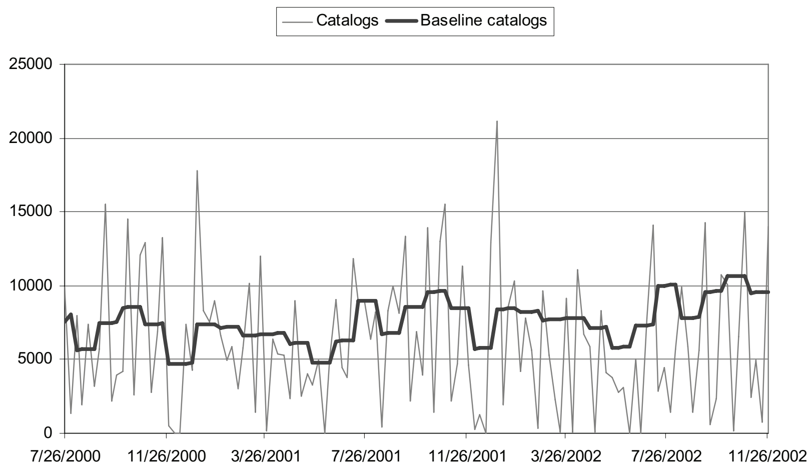


Table 4

Total Effects of Marketing on Revenue Components, Prestore Introduction (based on VARX1 model)

	Catalog	E-mail
Customer base	$.07	$.03
Catalog purchase frequency	$1.02	$.16
Internet purchase frequency	$.46	$.87
Catalog return frequency	–$.21	–$.11
Catalog exchange frequency	$.05	$.06
Catalog order size	$.16	$.00
Internet order size	$.00	$.00
Catalog return size	$.00	$.00
Catalog exchange size	$.00	$.00
Total Revenue Effect	$1.55	$ .91
Actual post–store introduction weekly level minus baseline weekly level	–808	–22

activity is endogenous to the store introductions, then we do not need to adjust the baseline. If, however, there was a change in competitive activity unrelated to store introduction, we would have need to correct for this. We are not aware of such a change and therefore assume that the trends and relationships estimated in the preintroduction period reflect the general level of changes in competitive activity; there was no major "shock" in these trends during the postintroduction period. Likewise, management confirmed that there was no major change to other marketing actions, such as pricing or product shipping charges.

Initial and adjusted estimates of the revenue impact of store introduction

Table 5 shows the initial and adjusted impact of adding the store channel on each revenue component (Equation 1). The first column is the initial baseline, i.e., without store introduction, we predict on average 1.96% of customers would purchase each week. The second column is the adjusted baseline, i.e., due to the reduction in catalogs, we only would have averaged 1.90% of customers purchasing each week. The differences between initial and adjusted are not that huge, because the reduction of 808 catalogs per week on a base of 6,147 catalogs per week (Table 3) is only about 15%.

The third column shows the actual revenue component values. The fourth column shows actual minus unadjusted baseline, and the fifth column shows actual minus adjusted baseline. Table 5 reveals several interesting findings:

- The store introductions cannibalize purchase frequency from the catalog but not the Internet. The weekly percentage of customers buying from the catalog decreases from 1.90% to 1.54%, but the weekly percentage of customers buying from the Internet is virtually unchanged (0.45% versus 0.43%).
- The store introductions have basically no impact on order sizes, either from the catalog or the Internet. The store order size is also roughly the same as for catalog and Internet. That purchase frequency is affected whereas order size is not is consistent with Ansari, Mela, and Neslin (2008), who found that marketing variables in a multichannel context affect purchase incidence more than purchase quantity.
- The store apparently shifts returns from the catalog to the store, with a net increase in

Figure 9

Impulse Response of Catalog Order Frequency to a Catalog Sent

(1 standard error bounds in dotted lines)

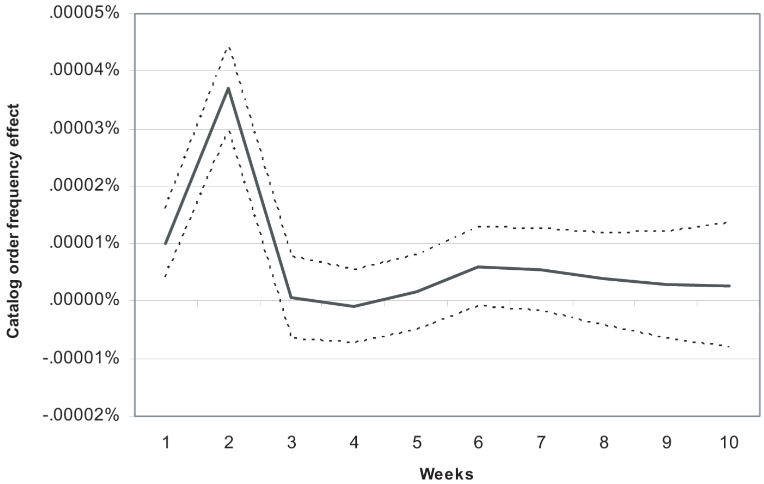
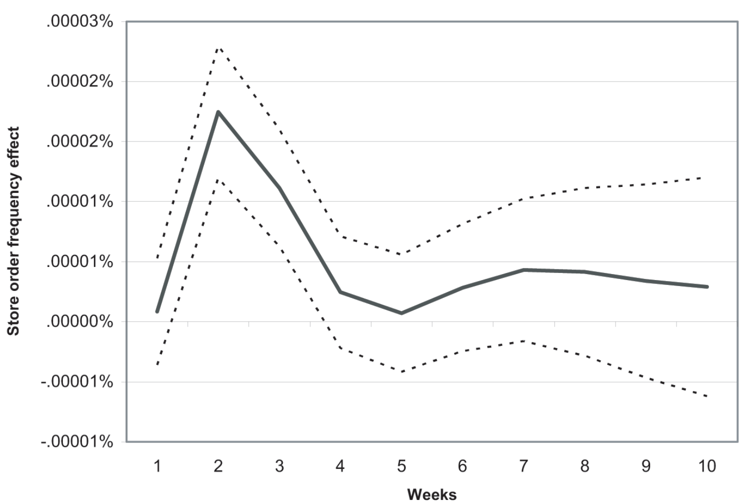


Figure 10

Impulse Response of Store Order Frequency to a Catalog Sent

(1 standard error bounds in dotted lines)



the number of returns. This is shown by the fact that .21% of customers return to the store each week, while catalog returns decrease only by .05%. Since the size of returns is roughly the same, this means that the impact of store introductions on returns is a net loss for the company.

- The store apparently shifts exchanges from the catalog to the store and encourages more exchanges in total (the weekly percentage of customers exchanging through the catalog decreased by .06%, while the percentage exchanging through the store is .12%). However, the average store exchange is *positive*, meaning the customer spends more when making a store exchange. This speaks to the appeal of the store and/or its employees: it is easier to buy something extra when one is in the store.
- The number of customers in the house list increases by 32 customers per week. This is a small increase, but one should keep in mind that we only have information about identifiable customers on the "house list" (as discussed in the data description and the limitations).

We insert the values from Table 3 into Equation 1 to calculate the net impact of the store introduction and display the results in Table 6. The net (adjusted) impact is $7,243 per week on a base of $36,619. That is, the introduction of stores increased net revenues from the customer base living within 50 miles of these stores by 19.8% per week. Table 6 shows the gain is due primarily to new purchase revenue from the stores, which offsets the decrease in catalog revenue and increase in losses due to returns. The shift from negative to positive exchange revenues also contributes to the net gain. More specifically, of the $7,243 total revenue impact of the store additions, $8,684 is due to increased orders ($14,798 – $6,315 + $201), –$2,100 is due to increased returns (–2,771 + $671), and $659 is due to increased exchange revenue ($198 + $462).

While the above discussion shows that store introductions exert an impact on many components of firm revenue, the most important impact is the increase in purchase frequency. This is shown most clearly in Table 5. The adjusted baseline says that 1.90% + .45% = 2.35% of customers would have purchased every week had the stores not been introduced. However, with the store introduction,

Table 5
Impact of Adding the Physical Store on Each Revenue Component

Component		Channel	Unadjusted Baseline	Adjusted Baseline	Actual Postintroduction	Unadjusted Impact	Adjusted Impact
Purchases	Frequency	Store			.94%	.94%	.94%
		Catalog	1.96%	1.90%	1.54%	–.42%	–.36%
		Internet	.45%	.43%	.45%	.00%	.02%
	Order size	Store			$105	$105	$105
		Catalog	$114	$114	$113	–$1	–$1
		Internet	$107	$107	$105	–$2	–$2
Returns	Frequency	Store			.21%	.21%	.21%
		Catalog	.15%	.14%	.09%	–.06%	–.05%
	Size	Store			–$88	–$88	–$88
		Catalog	–$90	–$90	–$90	$0	$0
Exchanges	Frequency	Store			.12%	.12%	–.12%
		Catalog	.16%	.15%	.09%	–.07%	–.06%
	Size	Store			$11	$11	$11
		Catalog	–$35	–$35	–$24	$11	$11
Number of Customers			14,961	14,961	14,993	32	32

Table 6
Net Impact of the Addition of Stores on Total Revenue

Component		Unadjusted Baseline	Adjusted Baseline	Actual Postintroduction	Unadjusted Impact	Adjusted Impact
Purchases	Store	$0	$0	$14,798	$14,798	$14,798
	Catalog	$33,429	$32,406	$26,091	–$7,338	–$6,315
	Internet	$7,204	$6,884	$7,084	–$120	$201
Returns	Store	$0	0	–$2,771	–$2,771	–$2,771
	Catalog	–$2,020	–$1,885	–$1,214	$805	$671
Exchanges	Store	$0		$198	$198	$198
	Catalog	–$838	–$785	–$324	$514	$462
Total		$37,775	$36,619	$43,862	$6,087	$7,243

Note: These numbers are derived from Table 3, guided by Equation 1. The general approach is to multiply number of customers times frequency times size. For example, the adjusted weekly baseline for catalog purchase revenue is 1.90% purchase frequency × $114 average purchase size × 14,991 average number of customers = $32,406.

purchase frequency is .94% + 1.54% + .45% = 2.93%. From a customer management perspective, this suggests customer *retention* is clearly the main beneficiary of store introductions, as opposed to customer development (which would have been manifested in order sizes), or customer acquisition (which would have been manifested in more customers added to the firm's customer file). The interpretation of increased purchase frequency as increased retention is due to the fact that retailing is a noncontractual setting in which

Table 7

Total Effects of Marketing on Revenue Components, Post–Store Introduction (Based on VARX2 Model)

	Store Promotion	Media Spending
Customer base	$.24	$.00
Store purchase frequency	$1.87	$.00
Catalog purchase frequency	$.70	$.05
Internet purchase frequency	$.69	$.01
Store return frequency	$.00	$.00
Catalog return frequency	$.00	$.00
Store exchange frequency	–$.06	$.00
Catalog exchange frequency	$.18	$.00
Store order size	$.00	$.00
Catalog order size	$.00	$.00
Internet order size	$.00	$.01
Store return size	–$.01	$.01
Catalog return size	$.10	$.00
Store exchange size	$.00	$.00
Catalog exchange size	–$.01	$.00
Total revenue effect	$3.71	$.07
Actual postintroduction level (per week)	110.07	5,100.87
Average Weekly Impact	$407.85	$455.16

the customer migration framework of lifetime value is appropriate (Berger and Nassr 1998; Blattberg, Kim, and Neslin 2008; Pfeifer and Cararaway 2000). Therefore, retention is manifested in getting customers to buy more often (see Borle et al. 2005 for a similar perspective).

The contribution of store marketing actions

To further understand the impact of the store introduction, we estimate the impulse response of revenue components to store marketing activities—media advertising and direct mail store promotions. Table 7 shows the results.

Store promotions most directly affect store purchasing, but also spill over to both the catalog and the Internet. Interestingly, media advertising for the store helped catalog purchasing more than store purchasing. This is somewhat surprising since the media advertising was publicizing the store. However, it is plausible that the advertising generally worked on awareness, in this case company awareness, while the direct mail store promotions actually did the work of getting customers into the store. The total average weekly impact of the promotions was $408, while that of advertising was $455. The $863 total accounts for about 11.9% of the weekly $7,243 increase in revenues attributed to the store introduction.

Conclusions

The net impact of the store was to increase annual revenues by 19.8% among customers contained in the firm's customer database. While a nontrivial portion of this impact was due to poorer performance on returns and improved performance on exchanges, the majority was due to higher purchase revenues. In turn, the higher purchase revenues were due to higher purchase frequency, an increase from 2.33% to 2.93% per week. Order sizes remained roughly the same. From a customer management perspective, the benefit in adding the new channel was felt in customer retention—more frequent customer–firm contacts.

We did indeed observe the increase in revenues that we conjectured in Table 2, but we learned more by examining the mechanisms by which this increase occurred. First, we discovered that the store cannibalized catalog sales to a significant degree, but had virtually no impact on the Internet. As we had anticipated that there would be more transactions at the store, fewer via the catalog, and no impact on the Internet, this finding supported our hypothesis. Our conjecture was based on differences in customers who use the store, catalog, and Web, differences in human resources in using these channels, and on similarity in the aesthetic drivers of store and catalog use, as opposed to the more transaction-oriented Internet.

A valuable path for future research would be to distill which of these factors contributed most to the results. For example, there is currently movement toward making the Internet more pleasant and enjoyable to use. Is this a wise decision? Perhaps companies gain sales by making their channels different from each other, rather than more similar. "More enjoyable" may also mean "less efficient" for the time-sensitive shoppers that are attracted to the Internet in the first place. These issues need more investigation.

While we had solid conjectures regarding the impact of the store on purchase frequency, which were confirmed, we were uncertain about the impact on order sizes. It turned out that the store introduction had virtually no impact on order size. This is consistent with Ansari, Mela, and Neslin (2008), who in a similar multichannel environment found purchase incidence to be more fungible than purchase quantity. Future research might delve into the details of why this is the case.

A second set of findings involved the impact on returns. As anticipated, the store diverted returns from the catalog to the stores, and increased the total number of returns. This undoubtedly was due to the ease in returning an item to a store. We had thought that perhaps the average value of a return would decrease in the store, since more minor items would be returned, but this turned out not to be the case. As a result, the increase in returns did indeed detract from the overall positive impact of the store introductions.

A third set of findings involves exchanges. Here results turned out largely as conjectured. We anticipated a diversion of exchanges from catalog to store and an increase in the total number of exchanges, and we found it. We also anticipated that the average exchange value would increase, due to store personnel actively making suggestions and because of the ease of picking up additional items while at the store. As anticipated, the total number of exchanges increased and the value of those exchanges became more favorable, so the net impact on exchanges was positive and contributed to increased revenues.

A result warranting further discussion is the relatively small impact of the store on customer acquisition. This almost certainly follows from our definition of a customer—an identified purchaser whose historical interaction with the company is recorded on the company house list. We found that only about 55% of store purchases could be matched to the house list, or the identity of a new customer recorded. We would conjecture that the 45% of sales that could not be matched to a large extent represent new customers. However, they are not *acquired* customers in the sense that the company does not know who they are. Therefore, the 45% unidentified purchases probably disproportionately represent customers who cannot (or do not like to) be managed, a crucial issue for a customer management–oriented company, and typical of the single-view-of-the-customer problems that have been noted in a multichannel environment (Neslin et al. 2006). However, the nature of this 45%, and how to manage them, at least indirectly, is fertile ground for future research.

Our work has a number of implications for researchers. First, the finding that adding a store channel increases retail revenues primarily through increased customer retention, in the form of more frequent transactions, is a key finding that needs to be replicated. It appears to support the theory that more channels, by decreasing the effort required for the customer to interact with the firm, stimulate more transactions. Second, bricks-and-mortar stores apparently substitute more readily for catalogs than the Internet. We have taken a first step toward filling in the top two right boxes in the multichannel cross-elasticity matrix shown in Table 1. However, this result needs generalization, and the full cross-elasticity matrix needs to be developed. Third, multivariate baseline analysis using vector autoregressive models appears to be a promising method for analyzing the impact of an intervention such as a new sales channel on a multiple set of endogenous variables.

There are also a number of implications for managers. First, adding channels is definitely a way to grow a company. However, cannibalization of existing channels should be expected, and cannibalization will not be apportioned equally across channels. Second, adding a store channel will probably increase losses on returns, because it is so much easier to make returns, but it also makes exchanges easier, and exchanges made in stores are more valuable than exchanges made via catalog due to cross-selling by store personnel or simply to the availability of other items when one is in the store. Third, marketing activities such as direct mail promotions and media advertising contribute significantly to the impact of adding a new channel. They contribute not only to the sales through the new channel, but to sales through all the channels in the firm's repertoire, thanks to the multiple interactions across channels. Therefore, companies should reconsider their marketing allocation rules, for instance giving catalogs credit for the total revenue they generate instead of just the purchases through the catalog channel.

We close by noting a few limitations to our work that also suggest further research. First, we analyzed data from one company, which started with catalogs, then added the Internet channel, and finally moved to physical stores. Other studies are needed to generalize our results. Perhaps the order of channel introduction matters. Second, while we have measured the impact of adding store channels on revenues, we did not have the data to calculate the impact on profits. There are obvious fixed costs in operating a store, and whether these outweigh the revenue benefits is a crucial area for future research. There are also more subtle costs in having to manage more and more channels, including inventory forecasting and data collection costs (i.e., maintaining a single view of the customer), that need to be factored in. A third limitation is that we have not examined the impact of store location on revenues. Should the company locate stores in areas where it is strong in other channels, or weak? Or even within a given area, should it locate close to its customer base or further from it? These are additional questions that are beyond the scope of the current research, but fertile areas for the future.

Notes

1. We note that Internet retailers have been trying to make the purchase experience in that channel more aesthetic, hence more similar to the store. Menon and Kahn (2002) and Verhoef, Neslin, and Vroomen (2007) find that enjoyment drives Internet sales just as it does catalog sales. These recent developments might make the Internet more similar to the store and therefore more substitutable.

2. Store promotions mailed to customers and media store advertising spending are separate weekly variables, available at the aggregate level.

3. Starting in December 2002, the company started offering free shipping, followed by a substantial, across-the-board price decrease the next year. Our conversations with management revealed that they felt these events had a major impact on performance that is clearly separate from the opening of physical stores.

4. The cointegration tests also failed to show cointegration after accounting for structural breaks at store openings.

References

Abraham, Magid M., and Leonard M. Lodish (1993), "An Implemented System for Improving Promotion Productivity Using Store Scanner Data." *Marketing Science* 12 (3), 248-69.

Alreck, Pamela L., and Robert B. Settle (2002), "Gender Effects on Internet, Catalogue, and Store Shopping." *Journal of Database Marketing* 9 (2), 150-62.

Ansari, Asim, Carl Mela, and Scott Neslin (2008), "Customer Channel Migration." *Journal of Marketing Research* 45 (1), 60-77.

Bai, Jushan, and Pierre Perron (1998), "Estimating and Testing Linear Models with Multiple Structural Changes." *Econometrica* 66 (1), 47-78.

Berger, Paul D., and Nada I. Nasr (1998), "Customer Lifetime Value: Marketing Models and Applications." *Journal of Interactive Marketing*, 12 (1), 17-30.

Biyalogorsky, Eyal, and Prasad Naik (2003), "Clicks and Mortar: The Effect of Online Activities on Offline Sales." *Marketing Letters* 14 (1), 21-32.

Blattberg, Robert, Kim, and Scott Neslin (2008),

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

Dekimpe, Marnik G., and Dominique M. Hanssens (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability." *Journal of Marketing Research* 36 (4), 397-412.

Deleersnyder, Barbara, Inge Geyskens, Katrijn Gielens, and Marnik G. Dekimpe (2002), "How Cannibalistic Is the Internet Channel?" *International Journal of Research in Marketing* 19 (4), 337-48.

Dholakia, Ruby Roy (1999), "Going Shopping: Key Determinants of Shopping Behaviors and Motivations." *International Journal of Retail and Distribution Management* 27 (4), 154-65.

Enders, Walter (2003), *Applied Econometric Time Series*, 2nd ed. New York, N.Y.: John Wiley & Sons.

Forsythe, Sandra, Chuanlan Liu, David Shannon, and Liu Chun Gardner (2006), "Development of a Scale to Measure the Perceived Benefits and Risks of Online Shopping." *Journal of Interactive Marketing* 20 (2), 55-75.

Franses, Philip-Hans (2004), *Forecasting for Marketing.* Rotterdam, Netherlands: Erasmus University Rotterdam, Econometric Institute Report EI 2004-40.

Franses, Philip-Hans (2005), "On the Use of Econometric Models for Policy Simulation in Marketing." *Journal of Marketing Research* 42 (1), 1–14.

Granger, Clive W. J. (1969), "Investigating Causal Relations by Econometric Models and Cross Spectral Methods." *Econometrica* 37 (3), 424-38.

———, and Paul Newbold (1986), *Forecasting Economics Time Series,* 2nd ed. Orlando, Fla.: Academic Press.

Grewal, Dhruv, Gopalkrishnan R. Iyer, and Michael Levy (2004), "Internet Retailing: Enablers, Limiters and Market Consequences." *Journal of Business Research* 57 (7), 703-13.

Grosso, Christopher, John McPherson, and Christiana Shi (2005), "Retailing: What's Working Online?" *McKinsey Quarterly* (3), 18-20.

Jarratt, Denise G. (1996), "A Shopper Taxonomy for Retail Strategy Development." *International Review of Retail, Distribution and Consumer Research* 6 (2), 196-215.

Johansen, Søren, Rocco Mosconi, and Bent Nielsen (2000), "Cointegration Analysis in the Presence of Structural Breaks in the Deterministic Trend." *Econometrics Journal* 3 (2), 216-49.

Kumar, V., and Rajkumar Venkatesan (2005), "Who Are the Multichannel Shoppers and How Do They Perform? Correlates of Multichannel Shopping Behavior." *Journal of Interactive Marketing* 19 (2), 44-62.

Kushawaha, Tarun, and Venky Shankar (2005), "Multichannel Shopping Behavior: Drivers and Consequences." Presentation at the Informs Marketing Science Conference, Atlanta.

Kwiatkowski, Denis, Peter C. B. Phillips, Peter Schmidt, and Y. Shin (1992), "Testing for the Null Hypothesis of Stationarity against the Alternative of a Unit Root." *Journal of Econometrics* 54, 159-78.

Lütkepohl, Helmut (1993), *Introduction to Multiple Time Series Analysis.* New York, N.Y.: Springer-Verlag.

Maddala, G. S., and In-Moo Kim (1998), *Unit Roots, Cointegration and Structural Change*. Cambridge, U.K.: Cambridge University Press.

Mathwick, Charla, Naresh Malhotra, and Edward Rigdon (2001), "Experiential Value: Conceptualization, Measurement and Application in the Catalog and Internet Shopping Environment." *Journal of Retailing* 77 (1), 39-56.

Menon, Satya, and Barbara Kahn (2002), "Cross-category Effects of Induced Arousal and Pleasure on the Internet Shopping Experience." *Journal of Retailing* 78 (1), 31-40.

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

Pauwels, Koen, Jorge Silva-Risso, Shuba Srinivasan, and Dominique M. Hanssens (2004), "New Products, Sales Promotions and Firm Value: The Case of the Automobile Industry." *Journal of Marketing* 68 (4), 142-56.

Pesaran, H. Hashem, Richard Pierse, and Kevin C. Lee (1993), "Persistence, Cointegration and Aggregation: A Disaggregated Analysis of Output Fluctuations in the U.S. Economy." *Journal of Econometrics* 56 (1-2), 57-88.

———, and Yongcheol Shin (1998), "Generalized Impulse Response Analysis in Linear Multivariate Models." *Economics Letters* 58 (1), 17-29.

Pfeifer, Phillip E., and Robert L. Carraway (2000), "Modeling Customer Relationships as Markov Chains." *Journal of Interactive Marketing* 14 (2), 43-55.

Rangaswamy, Arvind, and Gerrit van Bruggen (2005), "Opportunities and Challenges in Multichannel Marketing: An Introduction to the Special Issue." *Journal of Interactive Marketing* 19 (2), 5-11.

Rogers, Dale S., and Ronald S. Tibben-Lembke (1998), *Going Backward: Reverse Logistics Trends and Practices.* Reno, Nev.: Reverse Logistics Executive Council.

Shulman, Jeffrey D., Anne T. Coughlan, and R. Kanan Savaskan (2005), "Optimal Product Return Policies and Information Obfuscation: When Reducing Returns Reduces Profit." Evanston, Ill.: Kellogg Graduate School of Management, Northwestern University, Working Paper.

Sims, Christopher A., and Tao Zha (1999), "Error Bands for Impulse Responses." *Econometrica* 67 (5), 1113-56.

Slotegraaf, Rebecca, and Koen Pauwels (in press), "The Impact of Brand Equity and Innovation on Long-term Promotional Response?" *Journal of Marketing Research*.

Swanson, Norman R., and Halbert White (1997), "Forecasting Economic Time Series Using Flexible versus Fixed Specification and Linear versus Nonlinear Econometric Models." *International Journal of Forecasting* 13 (4), 439-61.

Verhoef, Peter C., Scott A. Neslin, and Bjorn Vroomen (2007), "Multi-channel Customer Management: Understanding the Research Shopper Phenomenon." *International Journal of Research in Marketing* 24 (2), 129-48.

Ward, Michael R. (2001), "Will Online Shopping Compete More with Traditional Retailing or Catalog Shopping?" *Netnomics: Economic Research and Electronic Networking* 3 (2), 103-17.

Report No. 08-101
"Building with Bricks and Mortar: The Revenue Impact of Opening Physical Stores in a Multichannel Environment"