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

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Abstract

A crucial decision firms face today is which channels they should make available to customers for transactions. We assess the revenue impact of adding bricks-and-mortar stores to a firm's already existing repertoire of catalog and Internet channels. We decompose the revenue impact into customer *acquisition*, *frequency* of orders, returns, and exchanges, and *size* of orders, returns, and exchanges. We use a multivariate baseline method to assess the impact of adding the physical store channel on these revenue components. As hypothesized, store introduction cannibalizes catalog sales and has much less impact on Internet sales. Also as hypothesized, returns and exchanges increase. Interestingly, transaction sizes of purchases, returns, and exchanges do not change. The "availability effect" produces a net increase in purchase frequency across channels. This more than compensates for increased returns, producing a net increase in revenues of 20% by adding the store channel. Our findings yield a deeper understanding of the revenue relation between channels, and of the dynamic cross-channel effects of marketing actions.

Keywords: Multichannel customer management; Customer relationship management (CRM); Vector autoregression models; Stores; Internet; Returns

Introduction

Spurred by advances in technology, competition, and the potential to cultivate better customer relationships, firms have been adding to the repertoire of channels through which they interact with customers (Blattberg, Kim, and Neslin 2008, p. 636; Neslin and Shankar 2009). Managers conjecture that adding retail channels is an important vehicle for revenue growth (e.g., Day 2002), and researchers have pinpointed the impact of channel additions on firm revenues as a key research question (Neslin et al. 2006). Our research is concerned with answering this question.

One path to multichannel growth is to add bricks-and-mortar "physical" stores. J. Crew, originally a cataloger, opened its first retail store in 1989. It now has more than 400 stores across the country (Hoovers 2013). Land's End created its retail footprint when it was purchased by Sears (Retailing Today 2006). GrowLife, Inc., a provider of indoor growing equipment, announced an expansion of its retail stores with the goal of becoming the "de facto leader in the online and brick and mortar specialty hydroponic industry" (Entertainment Close-Up 2013). A variety of other firms have joined the bricks-and-mortar bandwagon, including Soft Surroundings (Health & Beauty Close-Up 2011); City Sports (PR Newswire 2011), Fannie May (PR Newswire 2007a), Sundance Catalog (PR Newswire 2007b), Performance Bicycle (Janov 2007), Ballard (home décor) Design (Del Franco 2007), L.L. Bean (Catalog Age 2002), and Road Runner Sports (Tierney 2006). Dell Computer, which built its business on the direct marketing model, added major US retailers such as Best Buy and Walmart in 2007 (TWICE 2007a,b) and surpassed its US rivals in India thanks to exclusive physical outlets (Prasad 2011). It has been reported that even Amazon is building its first bricks-and-mortar store (Bensinger 2014).

The allure of adding physical stores is a larger and more satisfied customer base and hence more revenues. However,

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physical stores require huge investment and take the traditional direct marketer out of its comfortable "in-house" operation. This raises the following questions related to the revenue impact of additional physical stores:

- Does the physical store cannibalize the firm's Internet or catalog operation?
- If so, which is cannibalized more, the Internet or the catalog?
- What is the impact on the total level of product returns and exchanges?
- Do customers respond by spreading out purchases among channels, resulting in an increase in purchase frequency but a decrease in order size per purchase occasion?
- How do marketing communications influence the impact of new stores?
- What is the net impact of adding a physical store on total firm revenues?

The purpose of this paper is to (1) develop a multichannel framework for examining the impact of channel additions, (2) develop hypotheses related to the above questions that can be tested using this framework, and (3) test these hypotheses using data for a multichannel retailer. Our empirical method uses a "multivariate baseline", and thus another contribution of the paper is to demonstrate the applicability of this approach.

Previewing our results, we find that the addition of the physical store cannibalizes the catalog channel but leaves the Internet untouched, increases purchase frequency but has little impact on order size per purchase, and increases the volume of returns. We calculate the addition of the physical channel increases average weekly total revenues by 20%. This is due mainly to the increase in purchase frequency overcoming the cannibalization of the catalog and the increase in returns.

From a broad perspective, our goal is to provide insight into the "multichannel cross-elasticity" matrix articulated by Neslin and Shankar (2009), that is, the impact of introducing Channel A on revenues from Channel B. Zhang et al. (2010, p. 173) state, "Marketing researchers have attempted to address some of the 'cells' in this matrix. . ., yet much more needs to be done." Our intended contribution is to help fill this need.

Literature Review

The Impact of the Channel Additions

Researchers have investigated whether adding the Internet enhances or cannibalizes existing sales. Deleersnyder et al. (2002) analyzed the circulation of 67 newspapers that added an Internet version of their print newspaper. They found the impact was most often insignificant, but when significant, likely to be positive. Biyalogorsky and Naik (2003) examined the impact of adding an Internet channel on sales in a bricks-and-mortar store. They found the impact to be directionally negative but not statistically significant. Lee and Grewal (2004) found in a study of 106 firms that faster adoption of the Internet enhanced stock market performance if the Internet was adopted as a communications medium, while its impact on performance was neutral if it was adopted as a sales channel. Weltevreden (2007) found little short run impact of the Internet on center-city shopping, but that cannibalization could occur in the long run. More recently, Van Nierop et al. (2011) found that an informational website decreased offline purchase frequency and order size as some consumers close to the store reduced shopping trips (Pauwels et al. 2011).

The above offers important and interesting insights, but focuses entirely on the Internet. There is reason to believe the impact might be quite different when adding the physical channel. First, the Internet likely caters to a different market segment than do retail stores or catalogs (Alreck and Settle 2002; Kushwaha and Shankar 2013; McGoldrick and Collins 2007). Second, channels differ in the "value proposition" they offer the customer (Grewal, Iye, and Levy 2004; Grosso, McPherson, and Shi 2005). Verhoef, Neslin, and Vroomen (2007) suggest that the Internet excels on search convenience and information comparisons, while the store excels on service, assortment, after-sales support, and risk reduction. Third, there are differences in the consumer decision-process in shopping at various channels. For example, the Internet might be more goal-directed whereas retail stores and catalogs might be more conducive to recreational browsing.

Avery et al. (2012) took an important step forward in their analysis of the impact of adding a retail store channel on catalog and Internet sales. They theorize this impact will depend on the capabilities of the new channel viz-à-viz existing channels. They identify two key aspects of these capabilities: (1) complements versus substitutes – to the extent that the new channel's capabilities are substitutes, the impact on other channels will be negative, and (2) transparent versus experiential capabilities – to the extent that the new channel's capabilities are new and therefore not well-known to customers (experiential) as opposed to immediately transparent, the impact will be exerted more in the long term. The authors posit that the retailer's brand name and associations are an important experiential capability. Avery et al. use zip-code matching to create a control group, and find that the introduction of a new retail channel decreased catalog and Internet sales in the short run but increased them in the long run. This suggests that in their case, the capabilities of the retail channel were mostly substitutable but also highly experiential.

Avery et al.'s work is a significant contribution. We build on their work in several ways: (1) Substantively, we consider order size as well as frequency, and we also consider returns and exchanges. This enables us to calculate total revenue impact and decompose it into purchase frequency, purchase quantity, returns, and exchanges. (2) Methodologically, we use a baseline approach to infer the "control" rather than relying on matching. (3) Theoretically, we base our hypotheses on a number of factors that moderate the customer decision process, including consumer shopping goals, market segments, expertise, research shopping, and marketing.

Determinants of Customer Channel Choice

Factors that influence customer channel choice include channel attributes, customer characteristics, marketing, and shopping situation (see Blattberg, Kim, and Neslin 2008; Neslin et al. 2006 for detailed reviews).

Among channel attributes, particularly relevant for our study is convenience (e.g., Verhoef, Neslin, and Vroomen 2007). To the extent that the retailer provides more channels it can decrease customers' search costs (Bhatnagar and Ratchford 2004), thereby making shopping more convenient. Neslin et al. (2006) propose an "availability effect," that adding channels is a form of increasing distribution, which lowers search costs and increases sales. For example, Coca Cola was originally available in drug stores. As the product penetrated other channels, such as retail stores, restaurants, soda machines, entertainment events, and so forth, sales increased simply because it was so easily available.

Marketing communications play a key role in channel choice (Kumar and Venkatesan 2005; Thomas and Sullivan 2005; Ansari, Mela, and Neslin 2008; Valentini, Montaguti, and Neslin 2011). For example, Ansari et al. find that emails unsurprisingly are associated with customer selection of the Internet as opposed to catalog. The implication is that to gauge the impact of an additional channel, in this case the physical store, we must control for the firm's marketing activities.

Customer attributes including demographics and purchase behavior relate to channel choice (Thomas and Sullivan 2005; Venkatesan, Kumar, and Ravishanker 2007; Blattberg, Kim, and Neslin 2008, pp. 641–643). A particularly interesting customer attribute is "human capital." Putrevu and Ratchford (1997) argue that customers accumulate experiences that allow them to shop more efficiently. Ward (2001) argues that customer shopping skills may "spill over" to different channels, making these channels substitutable. Direct marketing and the Internet would be substitutable because they both require the skill of selecting a product without touching it. In an empirical analysis, Ward finds that direct marketing and Internet have the highest spillover effect, but interestingly, physical store is a closer substitute to direct marketing than to Internet shopping.

Among situational factors, an important distinction is whether shopping is "goal directed" or "experiential" (e.g., Novak and Hoffman 2003). Goal-directed, or "planned" shopping, is when the shopping task has a particular objective. Experiential, or "recreational" shopping, pertains to the hedonic benefits of shopping itself. There is evidence that the Internet is especially amenable to goal-directed shopping (Wolfinbarger and Gilly 2001; To, Liao, and Lin 2007; Bridges and Florsheim 2008). The role of experiential factors in store shopping is well-documented (e.g., Dholakia 1999; Jarratt, 1996). Catalogs appear 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.[2]

Another important phenomenon is "research shopping" (Verhoef, Neslin, and Vroomen 2007). Research shopping is when the customer gathers information on one channel but purchases from another. A common form is gathering information from the Internet but then buying from the store. Verhoef et al. find little research shopping between catalog and store. Verhoef et al. explain their findings in terms of three factors – attribute differences between channels, the ability of a channel to "lock in" the customer, and synergy between channels. For example, one important reason for the predominance of Internet => Store research shopping is the inability of the Internet to lock in the customer (otherwise known as the "cart abandonment problem"). Verhoef et al.'s results are consistent with recent findings of strong cross-channel effects of search advertising on offline sales (Wiesel, Pauwels, and Arts 2011; Dinner, van Heerde, and Neslin 2014). The close relationship between Internet search and store purchase is particularly relevant in the category we will be studying, apparel.

The Customer Management Perspective on Multichannel Strategy

Neslin et al. (2006) define "multichannel customers management" as the "the design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development." (p. 96). This means that in evaluating the revenue impact of adding a channel, we need to consider customer acquisition as well as retention and development indicators such as purchase frequency, order sizes, product returns, and exchanges. In addition, Neslin et al. propose a consumer shopping process of need recognition, search, purchase, and after-sales to study multichannel environments. We will draw on the multichannel customer management perspective in creating our multichannel framework.

In summary, there is an emerging literature on the impact of adding the Internet channel, on how customers choose channels in which to shop, and on the multichannel customer management perspective. Our core contribution builds on this literature in the following ways: First, we examine the addition of the physical store channel on purchase frequency, order size, returns, exchanges, and newly acquired customers, generating a decomposition of the total revenue impact. Second, we draw on the determinants of channel choice and the multichannel customer management perspective to develop a framework that in turn enables us to develop hypotheses regarding the impact of the store introduction. Third, we control for and measure the role of marketing in producing the total impact of adding the physical channel.

Multichannel Framework

Fig. 1 draws on the above literature to develop a framework for analyzing the impact of adding the physical store channel. We use this to (1) derive a revenue model for evaluating the financial impact, and (2) derive hypotheses for how we expect that impact to play out. The framework starts with a customer base, which can change over time as customers are acquired. These

[2] Internet retailers have been trying to make the purchase experience more esthetic, hence more similar to the store. Menon and Kahn (2002) and Verhoef et al. (2007) find support for this in that "Enjoyment" drives Internet sales just as it does catalog sales.

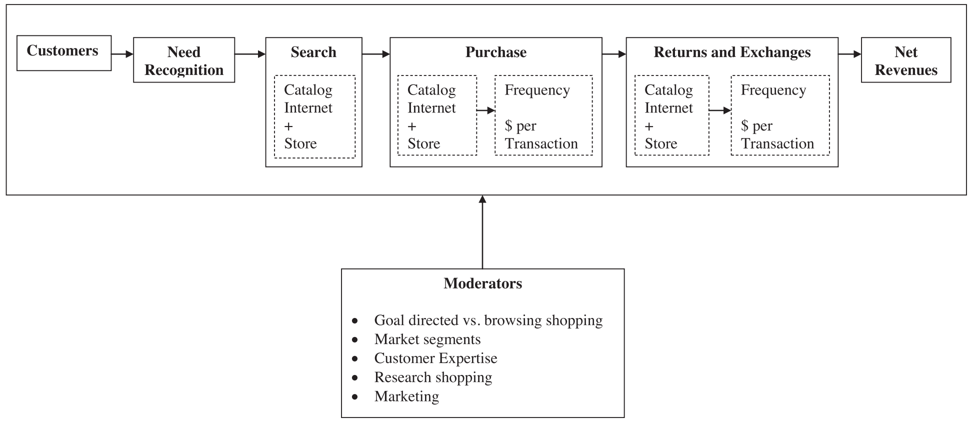

Fig. 1. A Multichannel framework for analyzing the impact of adding the physical store channel.

customers develop needs, search channels for information and purchase in a particular channel. After-sales in our context takes the form of returns and exchanges. This produces net revenues. Our literature review suggests this process is moderated by the customer's shopping goals, customer segmentation, customer expertise, research shopping and marketing.

Revenue Model

We translate the framework in Fig. 1 into an equation we can use to calculate the revenue 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. $NCUST_t$ = 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. $FREQ_{jot}$ = Percentage of customer base that purchases through channel j in period t. $FREQ_{jrt}$ = Percentage of customer base that returns through channel j in period t. $FREQ_{jet}$ = Percentage of customer base that 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 Eq. (1) is very rich and influenced by marketing activities. For example, a mailed catalog may induce a customer to order a coat through the catalog. However, upon receiving the garment, the customer finds that it does not fit. Rather than returning the garment through the mail, the customer now goes to the store and exchanges it for the right size, and purchases a scarf to match. The customer is quite satisfied, 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, described in the methodology section.

Hypotheses

Which Channel Gets Cannibalized in Terms of Purchases?

We summarize how each of the moderators in our framework bears on the question of whether the catalog or Internet will be cannibalized in terms of purchase.

First, the nature of consumer shopping goals points to the catalog being more cannibalized by store introduction. As discussed earlier, research indicates the Internet is most amenable to goal-directed shopping and catalogs and physical stores are similar in their amenability to experiential shopping.[3] This suggests the physical store and catalog are likely to be the closest substitutes among the three channels.

Second, research on market segmentation points to the catalog being more cannibalized by store introduction, because stores and catalogs appeal to more similar segments than does the Internet. Compared to catalogs and stores, the Internet appeals to customers who are younger, higher income, from larger families, and more likely to be male. Kushwaha and Shankar (2013) find the online customer is younger and has higher income compared to the offline (catalog) customer. Chintagunta, Chu, and Cebollada (2012) find that the online customer is more likely to be higher income and represent larger families. McGoldrick

[3] A different perspective is offered by Kukar-Kinney, Ridgway, and Monroe (2009). They found that Internet shoppers are indeed very different in their shopping orientation than physical store shoppers, but the difference is that Internet shoppers are more compulsive. This is different than our reasoning, but the net result is the same – that Internet shoppers are motivated differently than physical store shoppers.

and Collins (2007) find that “Internet-prone” customers skew younger and higher income compared to store and catalog users. Alreck and Settle (2002) find that while women and men have similar images of Internet, catalog, and stores, women have more positive attitudes toward catalogs and stores, which offer more esthetic experiences (Klerk and Lubbe 2008).

Third, Ward’s (2001) work on human capital “spillover” suggests stores will cannibalize the catalog because catalog and physical stores require more similar human capital (“expertise”) than the Internet demands. This may be due to the Internet requiring facility with computers. This is a very interesting finding since one might have suspected Internet and catalog would be most similar because they are both direct channels. However, catalog ordering is done through a call center and involves human interaction, whereas Internet ordering is done by manipulating a computer, a fundamentally different way of interacting with a direct channel.

Fourth, the research shopping phenomenon points to the store affecting the Internet more than the catalog. This is because, as noted earlier, the Internet has poor channel lock-in and hence Verhoef, Neslin, and Vroomen (2007) find more research shopping of the form Internet => store than catalog => store. Internet cannibalization implies that, in the absence of the company’s store channel, the customer would have bought from the Internet channel. Alternatively, poor Internet channel lock-in can lead to the prospective customer buying from competitors or not buying at all.

The impact of our fifth factor, marketing, on which channel gets cannibalized depends on the relative power of emails versus catalogs. Catalogs and emails are the two key marketing activities in our application. As Ansari, Mela, and Neslin (2008) show, catalogs feed purchases in the catalog channel, thus insulating catalogs from the impact of the store. However, Ansari et al. also show that emails feed the Internet channel, thus insulating the Internet from the impact of the store. We cannot say for sure how these forces will balance out – it is an empirical question.

In summary, three of the five moderators point to the physical store cannibalizing the catalog rather than the Internet, while only ‘research shopping’ implies otherwise. This suggests the store will cannibalize the catalog more than the Internet, since more factors point in that direction.

How Does Cannibalization Occur – Purchase Frequency or Transaction Size?

An important question when adding a channel is whether the availability effect of multiple channels encourages customers to purchase more often but just by spreading out their purchases, that is, increases their *purchase frequency* but decreases their *order size* (Neslin et al. 2006). Empirical evidence suggests that customers are more malleable in purchase frequency when faced with multiple channels. For example, Ansari, Mela, and Neslin (2008) studied channel choice for an apparel retailer and found that marketing communications such as catalogs and emails had significant effects on purchase incidence and channel choice but little effect on order size. However, Konuş, Neslin, and Verhoef (2014) hypothesized based on economic order quantity theory that when the catalog channel is eliminated, purchase frequency should decrease but order size increase. This indeed is what they found. For that reason, we are more confident hypothesizing cannibalization in terms of purchase frequency than of order size.

Cannibalization Hypothesis

In sum, we see arguments for and against cannibalization of order sizes so do not propose a hypothesis on order sizes. However, our review of five moderators suggests the catalog will be cannibalized more than the Internet in terms of purchase frequency:

Hypothesis 1. The introduction of the physical stores will reduce purchase frequency in the catalog channel more than it reduces purchase frequency in the Internet channel.

Impact of Store Introduction on Returns and Exchanges

Returns and exchanges are major issue for retailers, reportedly costing them upwards of $100 billion per year in retail value and logistics (Enright 2003). The Internet channel cannot be used for returns and exchanges since our application is for a physical, not a virtual, product.[4] So before store introduction, catalog is the only return/exchange channel. First, a case can be made that returns and exchanges will be diverted from the catalog to the store. Consumers typically find it more convenient to return merchandize to a (reasonably close by) store than via mail (Eng 2005). A Jupiter Media Matrix (2001) study around the time we observe the introduction of physical stores (see ‘Data Description’ section) found that 83% of online buyers would like to be able to return online purchases at offline stores. Thus, we expect that adding the physical store channels will divert returns and exchanges to this channel. Second, it makes sense that the total number of returns/exchanges should increase, because the store adds another option for the consumer. These arguments yield the following hypotheses:

Hypothesis 2. The introduction of physical stores increases the total frequency of returns and exchanges.

Hypothesis 3. The introduction of physical stores reduces return frequency in the catalog channel.

Hypothesis 4. The introduction of physical stores reduces exchange frequency in the catalog channel.

H2–H4 refer to the frequency of returns and exchanges. As with the case of purchase order size, we find arguments on both sides regarding the transaction size of returns and exchanges. Hence we do not propose specific hypotheses. For example, the average transaction size of store returns could be smaller than that of the catalog because now that another option is

[4] We define a return or an exchange as it applies to a physical purchase that the customer made. For example, we do not count a canceled order as either a return or exchange, because no physical product is delivered to the customer in this case.

available, it makes sense that the consumer will return lower-value merchandize that heretofore was not worth the effort. The counter-argument is that shipping costs are higher for high-value items (which are typically larger in size), and these will be shifted to the store to avoid postage. Regarding exchanges, the average transaction size may increase if the customer exchanges merchandize in the store and while there is tempted to buy other products. On the other hand, an exchange may signify customer dissatisfaction and hence the customer will exchange for a lower priced items and not buy anything else while in the store

Net Impact on Revenues

With regard to purchase frequency, the question is whether customers will simply switch their purchases to the new channel or will they purchase more overall from the company? We expect the latter. Most companies do not have close to 100% share-of-wallet among their customers. Therefore, there is room to grow revenues by offering the customer more, and at least for some, more convenient ways of transacting with the company. We earlier referred to this as the availability effect: adding channels is a form of increasing distribution, which lowers search costs and thus increases purchases (Bhatnagar and Ratchford 2004, Kumar and Venkatesan 2005). Therefore, we expect:

Hypothesis 5. The introduction of physical stores increases overall purchase frequency across the three channels.

We do not offer a hypothesis regarding the net impact on revenues. In favor of a positive impact is H5, that purchase frequency should increase. However, we cannot hypothesize the impact on purchase transaction sizes, which could very well decrease as customers spread their purchases among more channels. In addition, we hypothesize more returns and exchanges (H2–H4), but cannot hypothesize the transaction sizes for these as well. We therefore will “let the data speak” on this matter and gain insight from our framework-motivated decomposition (Eq. (1)).

Methodology

Multivariate Baseline Analysis

Our goal is to measure how the elements of Eq. (1) – size of customer base, frequency and 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 series of dynamic interactions among the store, catalog, and Internet that are difficult to disentangle analytically. We therefore adopt a “baseline analysis”. Baseline analysis projects the several interacting revenue variables in Eq. (1) from a “preperiod” (before store introduction) into a “postperiod” (after store introduction). The difference between each variable’s *actual* postperiod value and its postperiod *baseline* value is assumed due to the impact of the store – an assumption we investigate in more detail later.

The advantages of baseline analysis are simplicity and flexibility. Another approach would be to try to directly model the introduction of the store. However, this would require an explicit model of the dynamics set in motion by the store introduction. This would in turn require assumptions that would be difficult to justify. As the Lucas critique implies, a policy change such as a channel introduction changes the optimal decisions rules of the economic agents and thus sets in motion a series of expectation adjustments and dynamic interactions among consumer and management choices (Van Heerde, Dekimpe, and Putsis 2005). It is difficult to disentangle each of these issues analytically after the fact and even harder to accurately predict reactions before the policy change. For instance, a physical store introduction can lead some forward-looking consumers to buy more items as they anticipate an easier return/exchange later. Baseline approaches are agnostic with respect to these issues. They extrapolate into the store introduction period what would have happened had the store not been introduced. The residual of actual sales versus this baseline incorporates the myriad changes that the store sets in motion.

Baseline analysis has been used successfully to evaluate sales promotions (Abraham and Lodish 1993). Applications have involved brand sales. Our problem is more challenging because we have several target variables that feed back on each other over time. We will therefore use a vector auto-regression (VARX) to develop our baseline, entailing the following steps:

1. Conduct preliminary data tests for model specification.
2. Estimate baseline model.
3. Project baseline to store introduction period.
4. Adjust for exogenous events not included in the baseline.
5. Calculate the average weekly impact of store introduction on each revenue component.
6. Compute the total average weekly impact of store introduction.

Step 1: Preliminary Data Tests

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). To the extent these tests converge, we are more confident in whether to classify a variable as stationary or evolving (Maddala and Kim 1998). If at least two variables have a unit root, we test for cointegration using Johansen, Mosconi, and Nielsen (2000), who account for structural breaks.

Step 2: Estimation of Baseline Model

We use a VARX model to produce our baseline because VARX models are particularly effective in capturing the dynamic interplay among several variables (in our case, the revenue components in Eq. (1)). Proposed to estimate large unrestricted models by Sims (1980) in economics, such models have also become popular in marketing (e.g., Dekimpe and Hanssens 1999, 2000; Franses 2004; Pauwels et al. 2004), especially for forecasting applications involving several endogenous variables.

We model the revenue components of Eq. (1) as endogenous, that is, 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 (Ansari, Mela, and Neslin 2008). Moreover, 'catalogs sent' and 'emails sent' are expected to be endogenous as the company uses "RFM" measures to target catalogs, and gathers email addresses when purchases are made. As a result increases in the revenue components of Eq. (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[5] baseline model thus includes eleven 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 Emails Sent ($EMAILS_t$). 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. U_t is an (11×1) vector or 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. Eq. (2) displays the VARX1 model in its general form (variables are included in levels or first differences, depending on whether the unit root tests classify the variable as stationary or evolving):

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

Eq. (2) provides the means to project the eleven endogenous variables from the preintroduction to postintroduction periods, producing our baseline. We decide on the number of lags (K) based on the Bayesian Information Criterion (BIC), which is a consistent estimator of lag length (Lutkepohl 1993), and examine whether we should add lags based on the diagnostic tests on residual autocorrelation described in Franses (2005).

[5] We estimate another VARX model later so we differentiate between VARX1 and VARX2.

Step 3: Project Baseline to Poststore Introduction Period

Once VARX1 has been estimated, we project each endogenous variable into the poststore introduction period. This projection represents our best estimate of how each of the endogenous variables would have behaved had the stores not been introduced. This is because the stores did not exist during the period when VARX1 is estimated, so projections into future periods forecast what would have happened in the absence of store introductions (i.e., the baseline). Note the baseline projection is dynamic – it includes the impact of endogenous variables in period t on variables in period $t+1$ – but we only use endogenous data from the estimation period to make the projection. That is, we recursively predict for period t and then use that number to predict for period $t+1$, and so forth

Step 4: Adjust for Exogenous Events Not Included in the Baseline

Events unrelated to the store introduction but not included in the VARX1 model may occur in the poststore introduction period. These events can be external to the company or internal. An external event would be an unexpected increase in market growth. This would render our baseline too pessimistic and overstate the revenue impact of the store channel introduction. An internal event might be a change in marketing expenditures not predictable by the trend in marketing expenditures in the prestore introduction period. For example, a decision to depart from historical patterns and decrease catalogs sent would produce 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, 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, they should be incorporated in the baseline. Second, the VARX1 model provides a baseline of the company's existing marketing actions, that is, catalogs and emails 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.

Note the baseline only needs be adjusted if something occurs that is not included in the VARX1 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 postintroduction sales. The baseline need not be adjusted because it will still 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.

Step 5: Calculate Average Weekly Impact of Store Introduction on Each Revenue Component

Once we have our final baseline, we calculate the average weekly baseline and the average weekly actual for each component, during the store introduction period. We subtract these numbers to compute the average weekly impact of store introduction on each component.

Step 6: Compute the Total Average Weekly Impact of Store Introduction

We insert the average weekly baseline and actual for each component into Eq. (1) to compute the total average weekly revenue impact of the store introduction on firm revenues. We use the average weekly number of customers for baseline and actual as the base for these calculations.

In summary, the strengths of this approach are the ability of the VARX1 model to track a vector of variables and the flexibility of the VARX1 model in capturing what could be a complex dynamic interplay among these variables. We considered a structural break approach, using the introduction of each store as a structural break. However, each store introduction might not have an immediate effect on the variables of interest, and the effect, once it did start, might occur gradually over time in a highly nonlinear, complex manner. We would have had to make many assumptions in formulating such a model. The baseline approach does not rely on direct modeling assumptions – it simply projects what would have happened without the introduction, and subtracts that from what actually did happen. One weakness of our approach is the possibility that exogenous factors not present in the preperiod could become important in the postperiod. It is for this reason that we included Step 4, baseline adjustment, in our method.

Additional Analysis: The Impact of Marketing Actions After Physical Store Introduction

An additional goal of our analysis is to assess the role that marketing actions (especially those related to the new store channel) play in producing the total impact of store introduction. To this end, we employ a second VARX model (VARX2), estimated over the poststore 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 Store Advertising (Adv_t), which we consider endogenous to the store openings. The data include three store openings. The first one marks the start of the VARX2 dataset, so we quantify the other two openings as dummy variables (Open_{st}, $s = 2, 3$ indexing each store). The control variables are the same as those in Eq. (2) (intercept, trend, and seasonal dummies). Eq. (3) displays the VARX2 model:

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

with A_t a 19 × 14 matrix of control variables (see Eq. (2)), K the number of lags selected for the endogenous variables, B^k the 19 × 19 matrix of dynamic coefficients, L the number of lags selected for the three exogenous store opening variables, λ the effect estimates of the exogenous store opening variables, and $U_t = [u_{Cust,t}, \ldots, u_{Adv,t}]' \sim N(0, \Sigma_u)$. We use VARX2 to measure the impact of store-related marketing actions on store-related endogenous variables. From the VARX2 model estimates, we derived the generalized impulse response functions (GIRFs), which capture the over-time cumulative effects of a change to marketing. To tease out contemporaneous effects, we employed simultaneous-shocking (Pesaran and Shin 1998), which uses the information in the residual variance–covariance matrix of Eq. (1) to derive a vector of *expected* instantaneous shock values. The advantage of this approach is that it does not require selecting a causal ordering among the variables (Dekimpe and Hanssens 1999). Following standard practice in the literature (e.g., Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002; Srinivasan et al. 2004), we defined the short-term, immediate impact as the effect derived from estimates of the VARX model for the first time period; and the long-term, cumulative effect as the accumulated impact of the IRF until it becomes non-significant (Sims and Zha 1995).

Data Description

The data provider sells durables and apparel in mature categories predominantly through catalogs and 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. Managing the house list is the lifeblood of the company. However, the introduction of bricks-and-mortar stores means the firm may not be able to identify each of its customers, because it is inherently difficult to "match back" store purchases to its house list. This is a classic problem in multichannel marketing (Neslin et al. 2006). The match-back rate in our data, that is, the percentage of store purchases that for whom 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 30 miles (48 km) of at least one of the three stores to ensure these customers are within the service area of at least one store. We observe these customers' orders, returns, exchanges, catalogs received, and emails received.[6] We aggregate this transaction-level information into a weekly dataset, from 1/1/1997 until 11/27/2002, a total of 309 weeks[7]. The three stores open on 7/26/2000, 5/2/2001 and 8/14/2002.

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

[7] Starting 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 they felt these events had a major impact on performance, and are clearly separate from the opening of physical stores.

Table 1
Descriptive statistics of 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)	0.00%	0.94%
Catalog purchase frequency ($FREQ_{2ot}$) (% who purchase)	1.80%	1.54%
Web purchase frequency ($FREQ_{3ot}$) (% who purchase)	0.13%	0.45%
Store return frequency ($FREQ_{1rt}$) (% who return)	0.00%	0.21%
Catalog return frequency ($FREQ_{2rt}$) (% who return)	0.39%	0.26%
Store exchange frequency ($FREQ_{1et}$) (% who exchange)	0.00%	0.12%
Catalog exchange frequency ($FREQ_{2et}$) (% who exchange)	0.17%	0.09%
Store order size ($Size_{1ot}$) ($ per order)	$0.00	$104.98
Catalog order size ($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)	$0.00	$88.26
Catalog return size ($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
Emails sent (per week)	216	2,467
Store promotions distributed (per week)	19	110
Media spending	$0	$6,101
Number of weeks	*186*	*123*

Table 1 presents the means of the revenue components before and after the introduction of the first store. Store purchases take off, while catalog order frequency decreased, Internet order frequency increased, catalog return frequency decreased, and emails increased. However, Table 1 cannot tell us which of the changes represent a true impact of store channel addition, nor can it prioritize the reasons why the key variables change. To this end, we proceed with our analysis.

Results

Preliminary Tests and Estimating the VARX Models

The unit root analysis classified Internet order frequency and size as stationary in all tests. This provides initial support for our hypothesis that the Internet channel would not be affected by the introduction of physical stores. Other variables were classified as evolving in at least one test in both full and subsamples, and accounting for structural breaks at store openings does not change this classification. Cointegration tests found no

Table 2
Impact of adding the physical store on each revenue component.

Component		Channel	Unadjusted baseline	Adjusted baseline	Actual postintroduction	Unadjusted impact	Adjusted impact
Purchase	Frequency	Store			0.94%	0.94%	0.94%
		Catalog	1.96%	1.90%	1.54%	***−0.42%***	***−0.36%***
			(0.08%)	(0.09%)		***(0.08%)***[a]	***(0.09%)***[a]
		Internet	0.45%	0.43%	0.45%	0.00%	0.02%
			(0.05%)	(0.06%)		(0.05%)	(0.06%)
	Order size	Store			$105	$105	$105
		Catalog	$114	$114	$113	−$1	−$1
			($6.81)	($7.45)		($6.81)	($7.45)
		Internet	$107	$107	$105	−$2	−$2
			($8.23)	($8.35)		($8.23)	($8.35)
Returns	Frequency	Store			0.21%	0.21%	0.21%
		Catalog	0.15%	0.14%	0.09%	***−0.06%***[a]	***−0.05%***[b]
			(0.02%)	(0.02%)		(0.02%)	(0.02%)
	Size	Store			−$88	−$88	−$88
		Catalog	−$90	−$90	−$90	$0	$0
			($16.70)	($17.13)		($16.70)	($17.13)
Exchange	Frequency	Store			0.12%	0.12%	−0.12%
		Catalog	0.16%	0.15%	0.09%	***−0.07%***[a]	***−0.06%***[a]
			(0.02%)	(0.02%)		(0.02%)	(0.02%)
	Size	Store			$11	$11	$11
		Catalog	−$35	−$35	−$24	$11	$11
			($26.44)	($27.12)		($26.44)	($27.12)
Number of customers		14,961(3)	14,961	14,993	32	32	
			(4)		(3)	(4)	

Note: standard errors in parentheses. Not all the impacts we measure are accompanied by hypotheses, so to be consistent, we use two-sided tests for all results. Bold-italic values represent significant difference.
[a] Signifies statistically significant at $p < 0.01$.
[b] Signifies statistically significant at $p < 0.05$.

Table 3
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 Eq. (1). The general approach is to multiply # 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 × 14,961 average number of customers = $32,406.

significant evidence for cointegration, so we estimate the VARX models with the evolving variables in first differences.

The Granger Causality tests confirm that all revenue components, catalogs and emails, are caused by other variables, supporting our specification of these variables as endogenous. The lag order for both the endogenous and exogenous variables (K in Eq. (2); K and L in Eq. (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. The observation-to-parameter ratio for VARX1 is 7.44 (186 weeks for 11 endogenous variable and 14 exogenous variable coefficients) and for the additional analysis in VARX2 is 3.73 (123 weeks for 17 endogenous variable and 16 exogenous variable coefficients)[8]. Leeflang et al. (2000, p. 304) suggest a minimum of 5.00 as a desirable observations-to-parameters ratio. Therefore VARX1, the basis for our major conclusions

[8] These unrestricted VAR-models are estimated equation-by-equation: because all right hand side variables are identical across equations, Seemingly Unrelated Regression (SUR) does not improve efficiency.

Table 4
Total effects of marketing on revenue components, poststore introduction (based on VARX2 model).

	Store promotion	Media spending
Customer base	$0.24	$0.00
Store purchase frequency	$1.87	$0.00
Catalog purchase frequency	$0.70	$0.05
Internet purchase frequency	$0.69	$0.01
Store return frequency	$0.00	$0.00
Catalog return frequency	$0.00	$0.00
Store exchange frequency	−$0.06	$0.00
Catalog exchange frequency	$0.18	$0.00
Store order size	$0.00	$0.00
Catalog order size	$0.00	$0.00
Internet order size	$0.00	$0.01
Store return size	−$0.01	$0.01
Catalog return size	$0.10	$0.00
Store exchange size	$0.00	$0.00
Catalog exchange size	−$0.01	$0.00
Total revenue effect	$3.71	$0.07
Actual postintroduction level (per week)	110.07	5,100.87
Average weekly impact	$407.85	$455.16

(Tables 2 and 3), is quite acceptable. VARX2 has a lower observations-to-parameter ratio than this rule of thumb, so the reader should keep this caveat in mind when interpreting the results based on VARX2 (Table 4).

Initial Baseline Projections Versus Actual Sales

Figs. 2–4 compare actual weekly customer growth, catalog and Internet purchase frequency with their baselines as forecasted by the VARX1 model. Because our seasonal dummy variables are monthly, the models capture high-season months, but not the exact week of highest sales. However, they do track the revenue components well on average in the preintroduction period. This reinforces our confidence to use the model to extrapolate the revenue components into the postintroduction period, projecting what would have happened had the stores not been introduced. Perusing the postintroduction periods in Figs. 2–4 (after 7/26/2000), Internet purchase frequency closely tracks the baseline. However, actual catalog purchase frequency falls below baseline. This again suggests, as expected, that the Internet was not affected by store introductions, but the catalog was.

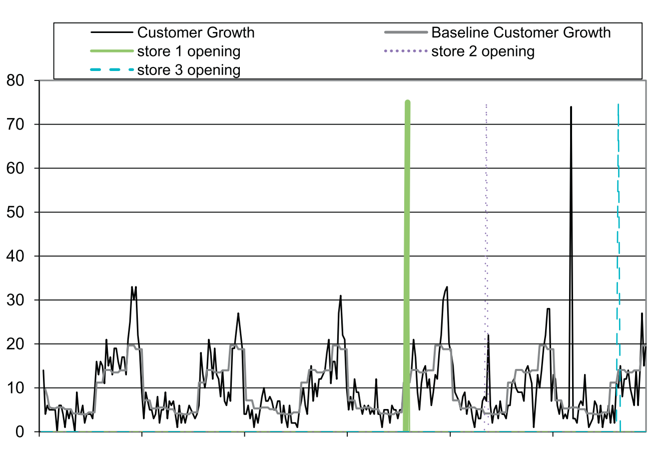

Fig. 2. Weekly customer growth: actual versus baseline (VARX1).

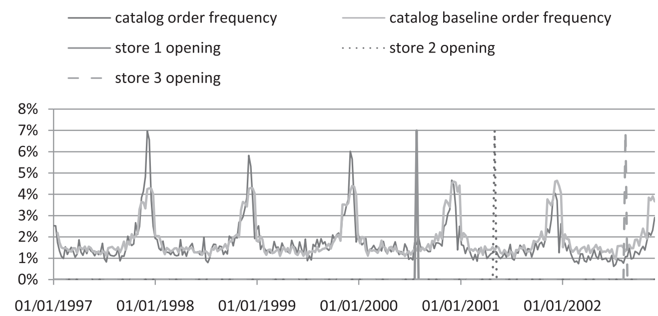

Fig. 3. Catalog purchase frequency: actual versus baseline (VARX1).

Checking for Channel Introduction-Exogenous Events

Following Step 4, we check for exogenous events that could distort our baseline. The main company-external event we examine is potential change in the level of retail activity. Changes to retail activity reflect many exogenous factors, including recessions, the weather, shifting consumer spending patterns, and so forth. 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 industry-wide sales add little in the context of the variables already in the model.

As for company-internal factors, our analysis shows that, while email activity in the poststore introduction period was accurately projected, actual catalog activity in the poststore introduction period was noticeably *below* what was projected by the baseline model. Fig. 5 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. We thoroughly investigate this issue, as detailed in the Appendix, and adjust the baseline accordingly.

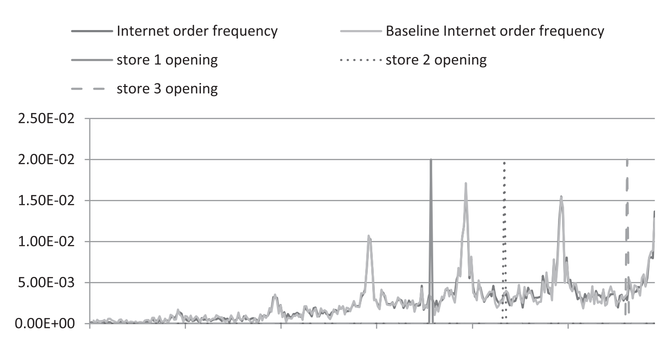

Fig. 4. Internet purchase frequency: actual versus baseline (VARX1).

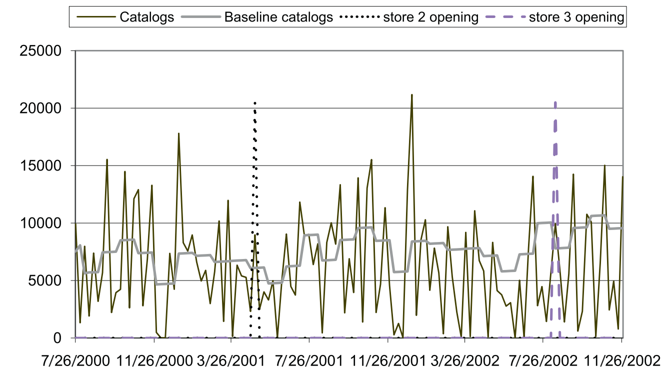

Fig. 5. Weekly number of catalogs sent: actual versus baseline (VARX1).

Initial and Adjusted Estimates of Revenue Impact of Store Introduction

Table 2 shows the initial and adjusted impact of adding the store channel on each revenue component (Eq. (1)). The first column is the initial baseline, that is, without store introduction, we predict 1.96% of customers would purchase on average each week. The second column is the adjusted baseline, that is, accounting for the reduction in catalogs, we would have averaged 1.90% of customers purchasing each week. The differences between initial and adjusted are not that huge, because the reduction in catalogs is not that huge. 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 4 reveals several interesting findings:

- In support of Hypothesis 1, store introductions reduce purchase frequency in the catalog channel more than it does in the Internet channel. The weekly percentage of customers buying from the catalog decreases from 1.90% to 1.54%, but in fact the weekly percentage of customers buying from the Internet is virtually unchanged (0.43% to 0.45%).
- We did not advance a hypothesis with regard to order size. It turns out the store introductions have no significant impact on order sizes, either from the catalog or the Internet. This is consistent with Ansari, Mela, and Neslin's (2008) findings.
- In support of Hypothesis 2, the total frequency of returns and exchanges increases, from 0.29% (0.14 + 0.15) to 0.51% (0.21 + 0.09 + 0.12 + 0.09).
- In support of Hypothesis 3, return frequency in the catalog channel decreases, from 0.14% to 0.09%. Return size remains unchanged.
- In support of Hypothesis 4, exchange frequency in the catalog channel decreases, from 0.15% to 0.09%. Exchange size does not significantly change.
- While we did not advance a hypothesis regarding the size of return transactions, we note it is not smaller in the physical store than in the catalog channel (−$88 vs. −$90).
- While we did not advance a hypothesis regarding the size of exchange transactions, we note that the exchange size is $11 for the store versus −$24 for the catalog, but the difference is not statistically significant as the standard error of catalog exchanges is $26.
- In support of Hypothesis 5, the store introductions increase total purchase frequency, from 2.33% per week (1.90 + 0.43) to 2.93% (0.94 + 1.54 + 0.45). In other words, purchases in the new store channel more than compensate for the loss in catalog purchase frequency.

In summary, store introductions decreased purchase frequency via the catalog but increased purchase frequency overall. On the minus side, store introduction increased returns and exchange frequency. On the neutral side, the transaction size of purchases, returns, and exchanges was not significantly affected, although directionally increased exchange value.

To determine the net impact on revenues, we insert the values from Table 2 into Eq. (1) and display the results in Table 3. 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 30 miles of these stores by 19.8% per week. Table 3 shows the gain primarily is due to new purchase revenue from the stores off-setting the decrease in catalog revenue and increase in losses due to returns. However, a shift from negative to positive exchange revenues also contributes to the net gain. 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 these results show that store introductions exert an impact on many components of firm revenue, Tables 2 and 3 suggest the most important impact is the increase in purchase frequency. We interpret this to mean that customer *retention* is the main beneficiary of store introduction (existing customers buy more often), 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 assertion that increased purchase frequency is a manifestation of increased retention is admittedly a matter of interpretation, but is grounded in the fact that retailing is a non-contractual setting where the customer migration framework of lifetime value is appropriate (Pfeifer and Carraway 2000; Berger and Nasr 1998; Blattberg, Kim, and Neslin 2008). 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 use the VARX2 model to estimate the impulse response of revenue components to store marketing activities – media advertising and direct mail store promotions, illustrated in Fig. 6 and summarized in Table 4.

Store promotions most directly affect store purchasing, but also spill over to both the catalog and the Internet. Media advertising for the store interestingly helped catalog purchasing more than store purchasing. This is somewhat surprising since the media advertising was publicizing the store. However, the result

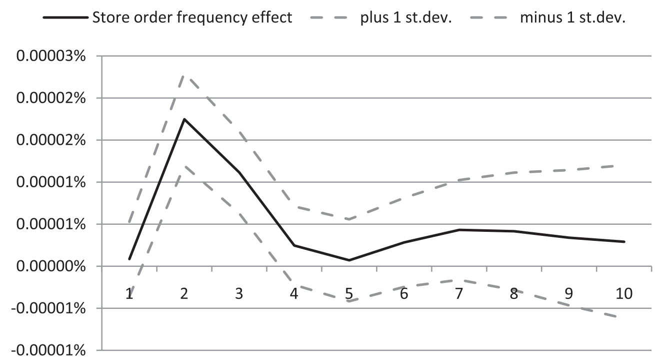

Fig. 6. Impulse response of store order frequency to a catalog sent.

makes sense if advertising generally worked on awareness, in this case company awareness, while 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.

Summary and Conclusions

We have proposed and applied a multichannel customer management framework to determine the revenue impact of introducing the bricks-and-mortar store channel by a retailer already marketing through catalogs and the Internet. We decomposed revenues into the number of customers, the frequency with which they interact with the company through purchases, returns, or exchanges, and the dollar magnitudes of these transactions. We used a multivariate baseline method to measure the impact of store introduction on this vector of variables.

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. 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.

While the "bottom line" is that store introduction increased total revenues, we learned more by examining the mechanisms by which this increase occurred. These mechanisms were hypothesized using our multichannel framework (Fig. 1). First, the store cannibalized catalog sales significantly, but had virtually no impact on the Internet. We anticipated the store would cannibalize the catalog more than the Internet, and this is what we found. Our conjecture was partially based on the notion that the Internet supports goal-directed shopping, whereas the store and catalog support experiential shopping. A valuable path for future research would be to what degree this determined the results. There is currently movement toward making the Internet more "enjoyable". Is this a wise decision? Perhaps companies gain sales by making their channels different from each other, rather than more similar. Indeed, "more enjoyable" may mean "less efficient" for the time-sensitive goal-directed shoppers who are attracted to the Internet in the first place. These issues need more investigation.

We found a minimal impact on purchase order sizes. This is consistent with earlier work that has found purchase incidence less malleable than order sizes (Ansari, Mela, and Neslin 2008). However, the result is very important, as it implies customers did not merely diversify the retailer's existing share-of-wallet among three rather than two channels.

As anticipated, the store diverted returns from the catalog to the stores, and increased the total number of returns. The likely explanation is the ease in returning an item to a store. The average value of a return remained the same, and a result, the increase in returns detracted from the overall impact of the store introductions.

We expected a diversion of exchanges from catalog to store, and an increase in the total number of exchanges, and we found it. While not statistically significant, the value of these exchanges was directionally more favorable, and the net impact on exchanges was positive and contributed to increased revenues.

We found little impact on customer acquisition. This may be due to our conservative definition of a customer – an identified purchaser who can be recorded on the company house list. We conjecture that the 45% of sales that could not be identified largely represent new customers. However, they are not *acquired* customers in the sense that the company does not know who they are. Therefore, they disproportionately represent customers who cannot (or do not like to) be *managed*, a crucial issue for a customer management-oriented company. The nature of these 45%, and how to manage them, are fertile grounds for future research.

Our work has several implications for researchers: First, the finding that adding stores increases retail revenues primarily through more frequent transactions without hurting order sizes is a key result that needs to be replicated. Second, stores apparently substitute more readily for catalogs than the Internet. Therefore, our study helps to "fill in" the multichannel cross-elasticity matrix. Further research is needed to fill in other cells in this matrix. Third, multivariate baseline analysis using vector autoregressive models appear 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.

We now have two studies that examine the impact of retail store additions on catalog and Internet sales. However, Avery et al. (2012) find that retail store addition helps both catalog and Internet sales in the long run, while we find retailer store addition hurts the catalog and has no impact on the Internet. The question is why the results differ? One possibility of course could be methodological. Both matching and baseline approaches have their advantages but both are trying to create a counterfactual that cannot be directly validated. We can't see why matching would systematically under-estimate the baseline, or why our approach would systematically over – estimate it. A more plausible explanation is the nature of the retailer involved. An important part of Avery et al.'s explanation concerns long-term learning of brand name and brand associations that emerged from the retail store introduction. While we can't identify the name of our focal company, we note it has a strong brand name. Therefore maybe that there wasn't much to learn long-term about the retailer. This left the substitutable-capability aspect more dominant, and we don't see the growth in the other channels that Avery et al. did. This of course is conjecture but points to the need for future research to reconcile our studies and perhaps develop and more complete theory (accounting for capabilities as in Avery et al., as well as market segmentation and channel-specific decision processes as advanced in our research).

Managerially, we have the following implications: First, adding channels is definitely a way to grow revenues. 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, but also increase exchanges, and although not statistically significant, we found exchanges made in stores to be more valuable than exchanges made via catalog. Third, marketing activities such as catalogs, direct mail promotions and media advertising contribute significantly to revenues not only to the sales through the new channel, but because of interactions across channels, contribute to all channels. As a result, companies should reconsider their attribution 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 that suggest further research. First, we analyze data from one company, and other studies are needed to generalize our results. The evolving nature of the Internet channel and its customer profile may eventually change the substitution patterns observed in our data. Second, while we have measured the impact of adding store channels on revenue components, 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, ranging from inventory forecasting to data collection costs that need to be factored in. A third limitation is that we had no data on competitive activity. While this limitation is typical for papers in the customer channel management literature, overcoming it may greatly enrich our understanding of the full impact of adding channels. Other omitted variables include word-of-mouth, news coverage, and a particularly appealing product (likely candidates to explain the customer growth bump in early 2002).

Fourth, we analyze the impact of a company's policy regarding channel introduction on the catalog and Internet channels. That policy was characterized by a certain set of stores with particular locations located at particular times. Further research is needed to explore how results might differ depending on opening stores in a different order or at different times. Another area to investigate is the impact of a single store introduction on other existing stores in the service area as well as catalog and Internet. Another interesting question is what happens when the first store introduction is not successful, and whether data on such cases are available to researchers (survivor bias). Fifth, our hypotheses and analysis focuses on aggregate revenue components, not on the effect of store introduction on individual consumers. The advantage of our level of analysis is we can measure the dynamic interactions among frequency and size of purchases, returns, and exchanges with a minimum number of assumptions. Examining these factors at the customer level is an interesting avenue for future research. Sixth, we may lose some coverage due to the match-back process linking store purchases to the customer file. This could possibly result in an under-estimation of incremental sales in the store channel, but should not influence our estimates of catalog or Internet sales – those can be matched perfectly since the company then has the customer's name. Finally, we have not examined the impact of store location on revenues. Should the company locate stores in areas where it is strong on 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 of multichannel retail management.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jretai.2015.02.001.

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

Ansari, Asim, Carl F. Mela and Scott A. Neslin (2008), "Customer Channel Migration," *Journal of Marketing Research,* 45 (1), 60–76.

Avery, Jill, Thomas J. Steenburgh, John Deighton and Mary Caravella (2012), "Adding Bricks to Clicks: Predicting the Patterns of Cross-Channel Elasticities Over Time," *Journal of Marketing,* 76 (3), 96–111.

Bensinger, Greg and Keiko Morris (2014), "Amazon to Open First Brick and Mortar Site," *Wall Street Journal,*, (accessed October 13, 2014), [available at http://online.wsj.com/articles/amazon-to-open-first-store-1412879124]

Bhatnagar, Amit and Brian T. Ratchford (2004), "A Model of Retail Format Competition for Non-Durable Goods," *International Journal of Research in Marketing,* 21 (1), 39–59.

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, 21–32.

Blattberg, Robert C., Byung-Do Kim and Scott A. Neslin (2008), *Database Marketing: Analyzing and Managing Customers,* New York: Springer+Business Media LLC (Chapter 28).

Borle, Sharad, Peter Boatwright, Joseph B. Kadane, Joseph C. Nunes and Galit Shmueli (2005), "The Effect of Product Assortment Charges on Customer Retention," *Marketing Science,* 24, 616–22.

Bridges, Eileen and Renée Florsheim (2008), "Hedonic and Utilitarian Shopping Goals: The Online Experience," *Journal of Business Research,* 61 (4), 309–14.

Chintagunta, Pradeep K., Junhong Chu and Javier Cebollada (2012), "Quantifying Transaction Costs in Online/Off-line Grocery Channel Choice," *Marketing Science,* 31 (1), 96–114.

Day, Sherry (2002, August 27), "L.L. Bean Tries to Escape the Mail-Order Wilderness," *New York Times,*, C.1.

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.

———————— and ———————— (2000), "Time Series Models in Marketing: Past, Present and Future," *International Journal of Research in Marketing,* 17, 183–93.

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.

Del Franco, Mark (2007), "Ballard Designs Opens Store," *Multichannel Merchant,* 3 (9), 7.

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

Dinner, Isaac M., Harald van Heerde and Scott A. Neslin (2014), "Driving Online and Offline Sales: The Cross-channel Effects of Traditional, Online Display, and Paid Search Advertising," *Journal of Marketing Research,* 51 (5), 527–45.

Dowling, Melissa (2002), "Retail Activity Is on a Roll," *Catalog Age,* 19 (9), 1+.

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

Eng, Paul (2005, January 13), "Online Retailers get Smart on Returns," *ABC News,*, (accessed December 8, 2011), [available at http://abcnews.go.com/Technology/story?id=406030&page=1]

Enright, Tony (2003, January 6), "Post-Holiday Logistics," *Traffic World,* 267 (1), 20.

Entertainment Close-Up (2013), *GrowLife Reports Hydroponic Retail Store Expansion,* (accessed July 26, 2013), [available at http://search.proquest.com/docview/1412400223?accountid=10422]

Franses, Philip Hans (2004), *Forecasting for Marketing, Econometric Institute Reports, EI 2004-40,* The Netherlands.

———————— (2005), "On the Use of Econometric Models for Policy Simulation in Marketing," *Journal of Marketing Research,* 42 (1), 4–14.

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

Granger, Clive W.J. (1969), "Investigating Causal Relations by Econometric Models and Cross Spectral Methods," *Econometrica,* 37, 424–8.

Grewal, Dhruv, Gopalkrishnan R. Iye 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.

Health & Beauty Close-Up (2011), *Soft Surroundings Selects JDS Solutions for Retail Store Expansion,*. August 6, 2011.

Hoovers (2013), *J. Crew Group, Inc.: Company Information,* (accessed December 18, 2013), [available at http://www.hoovers.com/company-information/cs/company-profile.J_Crew_Group_Inc.0ae3ddf44f05ad5e.html]

Janov, Jill (2007), "Performance Expands in New Markets; to Open 20 Stores in 2007," *Bicycle Retailer & Industry News,* 16 (11), 24.

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, 216–49.

Jupiter Media Matrix (2001), *Poor Online Service Drives Away Brick-and-Mortar Customers,* (accessed December 8, 2011), [available at http://www.out-law.com/page-1492]

Klerk, Helena and Stephna Lubbe (2008), "Female Consumers' Evaluation of Apparel Quality: Exploring the Importance of Aesthetics," *Journal of Fashion Marketing and Management,* 12 (1).

Konuş, Umut, Scott A. Neslin and Peter C. Verhoef (2014), "The Effect of Search Channel Elimination on Purchase Incidence, Order Size and Channel Choice," *International Journal of Research in Marketing,* 31 (1), 49–64.

Kukar-Kinney, Monika, Nancy Ridgway and Kent B. Monroe (2009), "The Relationship Between Consumers' Tendencies to Buy Compulsively and Their Motivations to Shop and Buy on the Internet," *Journal of Retailing,* 85 (3), 298–307.

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.

Kushwaha, Tarun and Venkatesh Shankar (2013), "Are Multichannel Customers Really More Valuable? The Moderating Role of Product Category Characteristics," *Journal of Marketing,* 77 (4), 67–85.

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

Lee, Ruby P. and Rajdeep Grewal (2004), "Strategic Responses to New Technologies and Their Impact on Firm Performance," *Journal of Marketing,* 68 (4), 157–71.

Leeflang, Peter H., Dick R. Wittink, Michel Wedel and Philippe A. Naert (2000), *Building Models for Marketing Decisions,* Boston, MA: Kluwer.

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

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.

Maddala, Gangadharrao Soundalyarao and In-Moo Kim (1998), *Unit Roots Cointegration and Structural Change,* Cambridge: Cambridge University Press.

McGoldrick, Peter J. and Natalie Collins (2007), "Multichannel Retailing: Profiling the Multichannel Shopper," *International Review of Retail, Distribution, and Consumer Research,* 17 (2), 139–58.

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, Jacquelyn S. Thomas and Peter C. Verhoef (2006), "Opportunities and Challenges in Multichannel Customer Management," *Journal of Services Research,* 9 (2), 95–112.

Neslin, Scott A. and Venkatesh Shankar (2009), "Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions," *Journal of Interactive Marketing,* 25 (1), 70–81.

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedict EM Steenkamps and Dominique M. Hanssens (2001), "The Category-Demand Effects of Price Promotions," *Marketing Science,* 20 (1), 1–22.

Nolan, Kelly (2006), "Sears Gives Lands' End New Beginning," *Retailing Today,* 45 (18), 1 69.

Novak, Thomas P. and Donna L. Hoffman (2003), "The Influence of Goal-Directed and Experiential Activities on Online Flow Experiences," *Journal of Consumer Psychology,* 13 (1 & 2), 3–16.

Pauwels, Koen, Dominique M. Hanssens and Sivaramakrishnan Siddarth (2002), "The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity," *Journal of Marketing Research,* 39 (4), 421–39.

Pauwels, Koen, Peter S.H. Leeflang, Marije L. Teerling and K.R. Eelko Huizingh (2011), "Does Online Information Drive Offline Revenues? Only for Specific Products and Consumer Segments!," *Journal of Retailing,* 87 (1), 1–17.

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, 142–56.

Pesaran, H. Hashem 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.

Prasad, Anurag (2011, February 10), "How Dell Conquered India," *CNN Money,*, (accessed December 8, 2011), [available at http://tech.fortune.cnn.com/2011/02/10/how-dell-conquered-india/]

PR Newswire (2007, November 15), *A Sweet November in Store as Fannie May Continues Expansion of Retail Locations: Beloved Chocolatier Set to Open Six Stores, Two Dozen Kiosks, Before Thanksgiving,.*

——————— (2007, June 20), *Sundance Catalog Flagship Retail Store Opens for Business in Denver; National Expansion Planned Over Next 5 Years,.*

——————— (2011, November 4), *City Sports Continues Store Expansion, Selects Wayne, Pa. for 20th Retail Location: Wayne Store Poised to Deliver Signature Shopping Experience from Boston Athletic Specialty Retailer,.*

Putrevu, Sanjay and Brian T. Ratchford (1997), "A Model of Search Behavior With an Application to Grocery Shopping," *Journal of Retailing,* 73 (4), 463–86.

Sims, Christopher A. (1980), "Macroeconomics and Reality," *Econometrica,* 48 (1), 1–48.

Sims, Christopher A. and Tao Zha (1995), "Error Bands for Impulse Responses," in *Federal Reserve Bank of Atlanta Working Paper 95-6.*

Srinivasan, Shuba, Koen Pauwels, Dominique M. Hanssens and Marnik G. Dekimpe (2004), "Do Promotions Benefit Manufacturers, Retailers, or Both?," *Management Science,* 50 (5), 617–29.

Thomas, Jacquelyn S. and Ursula Y. Sullivan (2005), "Managing Marketing Communications with Multichannel Customers," *Journal of Marketing,* 69 (4), 239–51.

Tierney, Jim (2006), "Road Runner Sports Races Toward Retail," *Multichannel Merchant,* 2 (10), 7.

To, Pui-Lai, Checken Liao and Tzu-Hua Lin (2007), "Shopping Motivations on Internet: A Study Based on Utilitarian and Hedonic Value," *Technovation,* 27 (12), 774–87.

Valentini, Sara, Elisa Montaguti and Scott A. Neslin (2011), "Decision Process Evolution in Customer Channel Choice," *Journal of Marketing,* 75 (6), 72–86.

Van Heerde, Harald J., Marnik G. Dekimpe and William P. Putsis (2005), "Marketing Models and the Lucas Critique," *Journal of Marketing Research,*, 15–21.

Van Nierop, J. Erjen M., Peter S.H. Leeflang, Marije L. Teerling and K.R. Eelko Huizingh (2011), "The Impact of the Introduction and Use of an Informational Website on Offline Customer Buying Behavior," *International Journal of Research in Marketing,* 28 (2), 155–65.

Venkatesan, Rajkumar, V. Kumar and Nalini Ravishanker (2007), "Multichannel Shopping: Causes and Consequences," *Journal of Marketing,* 71 (2), 114–32.

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

Wolf, Alan and Doug Olenick (2007a), "Best Buy Will Begin Carrying Dell PCs," *TWICE (This Week in Consumer Electronics),* 22 (26), 6 130.

Wolf, Alan (2007b), "Wal-Mart to Carry Dell PCs," *TWICE (This Week in Consumer Electronics),* 22 (12), 4 12.

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.

Weltevreden, Jesse W.J. (2007), "Substitution or Complementarity? How the Internet Changes City Centre Shopping," *Journal of Retailing and consumer Services,* 14 (3), 192–207.

Wiesel, Thorsten, Koen Pauwels and Joep Arts (2011), "Marketing's Profit Impact: Quantifying Online and Offline Funnel Progression," *Marketing Science,* 30 (4), 604–11.

Wolfinbarger, Mary and Mary C. Gilly (2001), "Shopping Online for Freedom, Control, and Fun," *California Management Review,* 43 (2), 34–55.

Zhang, Jie, Paul W. Farris, John W. Irvin, Tarun Kushwaha, Thomas J. Steenburgh and Barton A. Weitz (2010), "Crafting Integrated Multichannel Retailing Strategies," *Journal of Interactive Marketing,* 24 (2), 168–80.