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, cannibalization occurs for catalog sales, not for Internet sales, and for purchase frequency, not for order size. Moreover, returns and exchanges shift to the new channel. However, the "availability effect" (precipitating an overall increase in purchase frequency) more than compensates for cannibalization: the net effect of adding the store channel is to increase revenues by 20%. Our findings yield a deeper understanding of the revenue relation between channels, and of the dynamic cross-channel effects of marketing actions.

1. 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 et al. 2008, p. 636; Neslin and Shankar 2009). Managers conjecture that adding retail channels is an important vehicle for revenue growth (e.g., NY Times 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, especially popular among direct marketers, is the addition of bricks-and-mortar "physical" stores. J. Crew, originally a cataloger, opened its first retail store in 1989. It now has more than 300 retail stores across the country (J. Crew Website 2011). Land's End created its retail footprint when it was purchased by Sears (Retailing Today 2006). A variety of other firms have joined the bricks-and-mortar bandwagon, including Performance Bicycle (Bicycle Retailer & Industry News 2007), Ballard (home décor) Design (Multichannel Merchant 2007), L.L. Bean (Catalog Age 2002), and Road Runner Sports (Multichannel Merchant 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 recently surpassed its US rivals in India thanks to exclusive physical outlets (CNN Money 2011).

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

- What role do marketing communications play in creating the net impact of the 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 revenue 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 channel cannibalizes the catalog channel but leaves the Internet untouched, increases purchase frequency but has little impact on order size per purchase, and increases the dollar volume of returns. In total, we calculate that the addition of the physical channel increases average weekly revenues by 20%. This is due primarily to the increase in purchase frequency overcoming the cannibalization of the catalog and the increase in returns.

2. Literature Review

2.1 The Impact of the Internet

In the aftermath of the "dot-com boom," researchers investigated whether adding the Internet channel enhanced or cannibalized existing sales. Deleersnyder et al. (2002) analyzed the circulation of 67 newspapers that added an Internet version of their off-line 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. In a

more recent study, van Nierop et al. (2011) found however that an information website had a

negative effect on offline purchase frequency and order size. Weltevreden (2007) found little

short run impact of the Internet on center-city shopping, but emphasized that cannibalization

could occur in the long run.

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 caters to a different market segment than do retail stores or catalogs (Alreck and

Settle 2002; Kushwaha and Shankar 2007; McGoldrick and Collins 2007). Second, channels

differ in the "value proposition" they offer to the customer (Grewal et al 2004; Grosso et al.

2005). For example, Verhoef et al. (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.

2.2 Determinants of Customer Channel Choice

There is a rich body of research on the factors that determine which channels customers

choose for shopping. These factors include channel attributes, customer characteristics,

marketing, and shopping situation (see Blattberg et al. 2008, Chapter 25; Neslin et al. 2006 for

complete reviews).

Among channel attributes, particularly relevant for our study is convenience (e.g.,

Verhoef et al. 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, etc., 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 et al. 2008, Valentini et al. 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 et al. 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 the shopping situation 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, is when the task is related 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 et al. 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 et al. (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]

2.3. The Customer Management Perspective on Multichannel Strategy

An important emerging concept is that of "multichannel customer management," defined by Neslin et al. (2006) as "the design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development." This means that in evaluating the revenue impact of a 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. We will draw on the multichannel customer management perspective in creating our multichannel revenue 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 to differentiate from the Internet-dominated literature on multichannel expansion. Second, we draw on the determinants of channel choice, especially the availability effect, 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. Fourth, we utilize the multichannel customer management perspective in developing our analysis framework.

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[1] Internet retailers have been trying to make the purchase experience more aesthetic, 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.

3. Multichannel Revenue Framework

Figure 1 proposes a multichannel customer management framework for analyzing the revenue contribution of a new channel. Revenues depend on the size of the customer base, multiplied by the per-customer transaction frequency and size per transaction 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 added channel targets a new set of customers. Purchase, return, and exchange frequency can increase due to availability. Transaction sizes might also change due to convenience or customer satisfaction factors.

[Figure 1 Goes Here]

We translate the framework in Figure 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.
$FREQ_{jot}$	=	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 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 discovers 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.

4. Hypotheses

The introduction of the physical store can influence all the components in Figure 1. In this section, we state our hypotheses regarding channel cannibalization and the net impact of the store addition, summarized in Table 1.

[Table 1 Goes Here]

4.1. Where Does Cannibalization Occur?

Three factors point to the physical store cannibalizing the catalog rather than the Internet. First, compared to catalogs and stores, the Internet appeals to a different type of customer – younger, higher income and more likely to be male. In particular, McGoldrick and Collins (2007) find that "Internet-prone" customers skew younger and higher income compared to store and catalog users. Kushwaha and Shankar (2007) find the online customer is younger and has higher income compared to the offline (catalog) customer. 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 aesthetic experiences (Klerk & Lubbe,

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2008). Recent studies continue to find that "women are focused on the experience, while men are on a mission", aka "women shop, men buy" (Alavi, 2009; Passyn, Diriker and Settle, 2011). Second, Ward's (2001) work on human capital "spillover" suggests that the catalog and physical store require more similar human capital than do the Internet and the physical store. This may be due to the Internet requiring facility with computers. Third, as discussed earlier, the Internet is most amenable to goal-directed shopping, and we conjecture that catalogs and physical stores are similar in their amenability to experiential shopping.[2] These three factors point to the physical store and catalog as most likely the closest substitutes among the three channels.

4.2 How Does Cannibalization Occur?

An important question when adding a channel is whether the convenience of multiple channels encourages customers to purchase more often but just by spreading out their purchases, i.e. increase *purchase frequency* but decrease their *order size* (Neslin et al. 2006). There is not much theory to shed light on this issue, but empirical evidence suggests that customers are more malleable in purchase frequency when faced with multiple channels. For example, Ansari et al. (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.

4.3. What gets Cannibalized?

While virtually all previous multi-channel studies focus on (initial) purchase effects, retailers also care about product *returns and exchanges*, which reportedly cost them upwards of $100 billion per year in retail value and logistics (TrafficWorld 2003). Consumers typically find

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[2] A different perspective on this 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.

it more convenient to return merchandise to a (reasonably closeby) 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') 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.

In sum, we conjecture that cannibalization occurs (1) in the catalog channel, not the Internet, (2) on purchase frequency, not on order size, and (3) for returns and exchanges as well as for purchases. We therefore formulate the following hypotheses:

Hypothesis 1: The introduction of physical stores (a) reduces purchase frequency in the catalog channel but (b) does not affect purchase frequency in the Internet channel, nor order sizes in (c) the catalog channel or (d) the Internet channel.

Hypothesis 2: The introduction of physical stores reduces return frequency in the catalog channel.

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

4.4. Net Impact: Does the Availability Effect Dominate the Cannibalization Effect?

As to the net revenue impact of adding physical stores, the question is whether the availability effect dominates the cannibalization effect. In other words, will customers simply switch their purchases, returns and exchanges to the new channel or will they buy more overall from the company? We expect the latter, due to the availability effect mentioned earlier: adding channels is a form of increasing distribution, which lowers search costs and thus increases purchases (Bhatnagar and Ratchford 2004, Kumar and Venkatesan 2005). 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. Likewise, adding a channel with high perceived convenience of

returns and exchanges lowers the perceived costs of engaging in returns and exchanges.

Therefore, we expect:

Hypothesis 4: The introduction of physical stores increases overall purchase frequency across the three channels.

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

Hypothesis 6: The introduction of physical stores increases overall exchange frequency across the three channels.

In light of the above, what do we expect on the total revenue impact of introducing physical stores? On the purchase side, revenues should increase, given our expectations of higher overall purchase frequency and similar order size after introduction of the store channel. This increase is unlikely to be completely offset by the expected increase in returns. Returning to the store may actually enable the company to sell other items, because customers enjoy the service, assortment and after-sales support offered in the store (Verhoef et al. 2007). While returning an item, customers observe other merchandize in the store and may be responsive to store personnel actively making suggestions for an exchange.

Hypothesis 7: Total revenue increases with the introduction of the physical store channel.

5. Methodology

5.1. Multivariate Baseline Analysis

Our goal is to measure how the elements of equation (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 equation (1) from a "pre-period" (before store introduction) into a "post-period" (after store introduction). The difference between each variable's *actual* post-period value and its post-period *baseline* value is assumed due to the impact of the store – an assumption we investigate in more detail later.

Baseline analysis has been used successfully and commercialized in the sales promotion field (Abraham and Lodish 1993). 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 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. Subtract actual minus baseline for each revenue component.

6. Compute total 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 2 variables have a unit root, we test for cointegration using Johansen et al. (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 equation (1)). Proposed as a feasible way to estimate large unrestricted models by Nobel Prize winner Chris 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 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 (Ansari et al. 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 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[3] baseline model thus 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 Emails Sent ($EMAILS_t$).   None of these is store-related. This is because the baseline model is estimated on the pre-store introduction period. We represent lags by B^k, a (11×11) matrix of coefficients, and 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. Equation 2 displays the VARX1 model in its general form (variables are included in levels or first

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

differences, depending on whether the unit root tests classify the variable as stationary or

evolving):

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

Equation (2) provides the means to project the 11 endogenous variables from the pre- to post-

introduction 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).

Step 3: Project Baseline to Post-Store Introduction Period

        Once VARX1 has been estimated, it is relatively simple to project each of the

endogenous variables into the post-store 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).

Step 4: Adjust for Exogenous Events not Included in the Baseline.

        Events unrelated to the store introduction may occur in the post-store introduction period

that were not included in the VARX1 model. These events can be external to the company or

internal. An external event would be an unexpected change in retail market growth. This would result in our baseline being too pessimistic and overstating 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 pre-store introduction period. For example, a decision to depart from 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, 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, they should be incorporated in the baseline. Second, the VARX1 model also provides a baseline of the company's existing marketing actions, i.e. 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 post-introduction marketing activity.

It is important to emphasize that 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 post-introduction 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: Subtract Actual Minus Baseline for Each Revenue Component.

Once we have our final baseline, we subtract the actual value of each revenue component, which includes the impact of the store introduction, minus the baseline projection of each component, which does not include the impact of the store introduction. The difference is the incremental impact of the store introduction on each revenue component.

Step 6: Compute the Total Impact of Store Introduction.

Once we have the impact of store introduction on each revenue component, we use equation (1) to compute the total impact of the store introduction on firm revenues.

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 for example 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 pre-period could become important in the post-period. It is for this reason that we included Step 4, baseline adjustment, in our method.

5.2. 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, physical store channel) played in producing the total impact of the store introduction. 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 store advertising (Adv_t), the extent to which we consider endogenous to the store openings. The data include three store openings, so we quantify these as 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:

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

with A_t a 19×14 matrix of control variables (see equation 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 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.

6. 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. As this customer management is the lifeblood of the company, we require customer identification for a customer to be counted as 'new' (added to the house list). However, the introduction of bricks-and-mortar stores means the firm may no longer be able to identify each of its customers, because it is

inherently difficult to "match back" store purchases to its house 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 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 kilometers) of at least one of the three

stores to ensure these customers are within the service area of at least one store. For the selected

customers, we observe their orders, returns, exchanges, catalogs received, and emails received.[4]

We aggregate this transaction-level information into a weekly dataset, from 1/1/1997 until

11/27/2002, a total of 309 weeks[5]. The three stores open respectively on 7/26/2000, 5/2/2001 and

8/14/2002. 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 number of customers making returns

and exchanges via the store and the catalog. Note that stores quickly become as important as the

catalog as a medium for returning items, and even more so for exchanging items.

<center>[Figures 2-4 Go Here]</center>

 Table 2 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 3 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.

<center>[Table 2 Goes Here]</center>

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[4] Store promotions mailed to customers and media store advertising spending are separate weekly variables,
available at the aggregate level.
[5] 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.

7. Results

7.1 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, and accounting for structural breaks at store openings does not change this classification. Cointegration tests found no significant evidence for cointegration, so we estimate our 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 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.

7.2. Initial Baseline Projections vs. 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. VARX1 tracks these variables very well in the pre-introduction period. This reinforces our confidence to use the model to extrapolate the revenue components into the post-introduction period to project what would have happened had the stores not been introduced. Perusing the post-introduction periods in Figures 5-7 (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.

[Insert Figures 5-7 Here]

7.3 Checking for Channel Introduction-Exogenous Events

Following Step 4, we check for events exogenous to the store introduction that could distort our baseline. The main company-external event we examine is potential change in the general level of retail activity. Changes to 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 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 post-store introduction period was accurately projected, actual catalog activity in the post-store introduction period was noticeably *below* what was projected by the baseline model. Figure 8 shows that actual catalogs sent during the post-introduction 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 Appendix, and adjust the baseline accordingly.

[Figure 8 Goes Here]

7.4. Initial and Adjusted Estimates of Revenue Impact of Store Introduction

Table 3 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 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 2) 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 3 Goes Here]

Table 3 reveals several interesting findings:

- In support of *Hypothesis 1*, the store introductions cannibalize purchase frequency of the catalog (H1a) but not the Internet (H1b). 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 (0.43% to 0.45%). In contrast, the store introductions have no significant impact on order sizes, either from the catalog (H1c) or the Internet (H1d).

- In support of *Hypothesis 2,* return frequency decreases in the catalog channel, from 0.14% to 0.09%. Return size remains unchanged.

- In support of *Hypothesis 3,* exchange frequency decreases in the catalog channel, from 0.15% to 0.09%. Again, exchange size does not significantly change.

- In support of *Hypothesis 4,* 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 support of *Hypothesis 5*, total return frequency increases: 0.21% of customers return to the store each week, while catalog returns by 0.05%. The size of returns is roughly the same between the store and the catalog.

- In support of *Hypothesis 6*, total exchange frequency increases: exchange frequency in the store channel is 0.12%, double the loss of exchange frequency in the catalog channel.

- The number of customers in the house list increases by 32 customers per week. This increase is significant, but rather small. It represents a conversative estimate because we only have information about identifiable customers on the 'house list' (as discussed in the data description).

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 4. 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. This supports *Hypothesis 7*. Table 4 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).

[Table 4 Goes Here]

While these results show that store introductions exert an impact on many components of firm revenue, Tables 3 and 4 suggest the most important impact is the increase in purchase frequency. From a customer management perspective, this suggests customer *retention* is 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 non-contractual setting where

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

7.5. 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, as illustrated in Figure 9 and summarized in Table 5.

[Table 5, Figure 9 Go Here]

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 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.

8. Summary and Conclusions

In summary, we have 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 magnitude per purchase, return, or exchange. We showed

that a multivariate baseline method could be used to measure the impact of the 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.

We expected an increase in revenues and indeed found it, but we learned more by examining the mechanisms by which this increase occurred. First is that the store cannibalized catalog sales to a significant degree, but had virtually no impact on the Internet. We anticipated that there would be more transactions on the store, fewer via the catalog, and no impact on 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 "user friendly," 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 also mean 'less efficient' for the time-sensitive goal-directed shoppers that are attracted to the Internet in the first place. These issues need more investigation.

We expected and found a minimal impact on purchase order sizes. However, our hypothesis was based on the supposition that there was room to grow purchase frequency without adversely affecting order sizes. This finding may be highly context-specific, and needs to be examined in other industries.

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. One might have expected the average value of a return to decrease in the store, since more minor items would be returned, but this did not occur. As a result, the increase in returns indeed did detract from the overall impact of the store introductions.

Results regarding exchanges turned out largely as anticipated. We expected 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 as well as the ease in picking up additional items while at the store. The result was that the total number of exchanges increased, and the value of these exchanges became more favorable, so the net impact on exchanges was positive and contributed to increased revenues.

A result warranting further discussion is that we found relatively little impact of the store on customer acquisition. This may be related to our conservative definition of a customer – an identified purchaser who can be recorded on the company house list. However, only about 55% of store purchases could be matched to the house list. We 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% un-identified purchases probably disproportionately represent customers that 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, at least indirectly, are fertile grounds for future research.

Our work has the following implications for researchers: First, the finding that adding a store channel increases retail revenues primarily through more frequent transactions without hurting order sizes is a key result that needs to be replicated. Second, bricks-and-mortar stores apparently substitute more readily for catalogs than the Internet. Therefore, our study helps to "fill in" the top two right boxes in the multichannel cross-elasticity matrix shown in Table 6.

However, this result also needs generalization and the full cross-elasticity matrix needs to be developed. Third, multivariate baseline analysis using vector auto-regressive 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.

[Table 6 Goes Here]

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 exchanges made in stores are 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 multiple interactions across channels, they contribute to all channels. As a result, 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 that suggest further research. First, we analyze data from one company, and other studies are needed to generalize our results. An encouraging indication is that Avery, Steenburgh, Deighton and Caravella (2009) report a similar revenue increase for another company, in another geographical location. Still, this study also investigates a company which started with catalogs, then added the Internet channel and finally moved to physical stores. Perhaps the *order* of channel introduction matters, implying a dynamic component to Table 6. Moreover, 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 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, 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. Fourth, we have conducted an aggregate, weekly level analysis rather than a customer-level analysis. The advantage of our aggregate approach is that 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. 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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Table 1

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
# Transactions	+	-	0	+	+	-	na	+	+	-	na	+
Order Size / Transaction	0	0	0	?	-	?	na	-	+	?	na	+

Note: The number of purchase, return, and exchange transactions for the store must increase since this is the new channel. In the case of Size per Transaction, for the store, a 0 means "equal to the catalog and Internet (if applicable)", a + means "higher than the catalog and Internet (if applicable)", a - means "less than the catalog and Internet (if applicable)"; for the catalog and Internet, a + means "increase", 0 means "no change", and - means "decrease". "na" means not applicable.

Table 2: 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 3: Impact of Adding the Physical Store on Each Revenue Component*

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

* standard errors in parentheses, significant differences at the 5% level in bold italics

Table 4: Net Impact of the Addition of Stores on Total Revenue

Component		Unadjusted Baseline	Adjusted Baseline	Actual Post-Introduction	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 # 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.

Table 5: Total Effects of Marketing on Revenue Components, Post-Store 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 post-introduction level (per week)	**110.07**	**5,100.87**
Average weekly impact	**$407.85**	**$455.16**

Table 6

The Multichannel Cross-Elasticity Matrix – The Role of This Paper and the Potential for Future Research

		Impact on:		
		Store	Catalog	Internet
Channel Introduced	Store		This Paper	This Paper
	Catalog	?		?
	Internet	Biyalogorsky and Naik (2003) Deleersnyder et al. (2002) van Nierop et al. (2011)	?	

Figure 1

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

| Number of Customers | X | **Transaction Frequency**
• Purchases
   o Store
   o Catalog
   o Internet
• Returns
   o Store
   o Catalog
• Exchanges
   o Store
   o Catalog | X | **$ Size per Transaction**
• Purchases
   o Store
   o Catalog
   o Internet
• Returns
   o Store
   o Catalog
• Exchanges
   o Store
   o Catalog | = | **Revenues** |
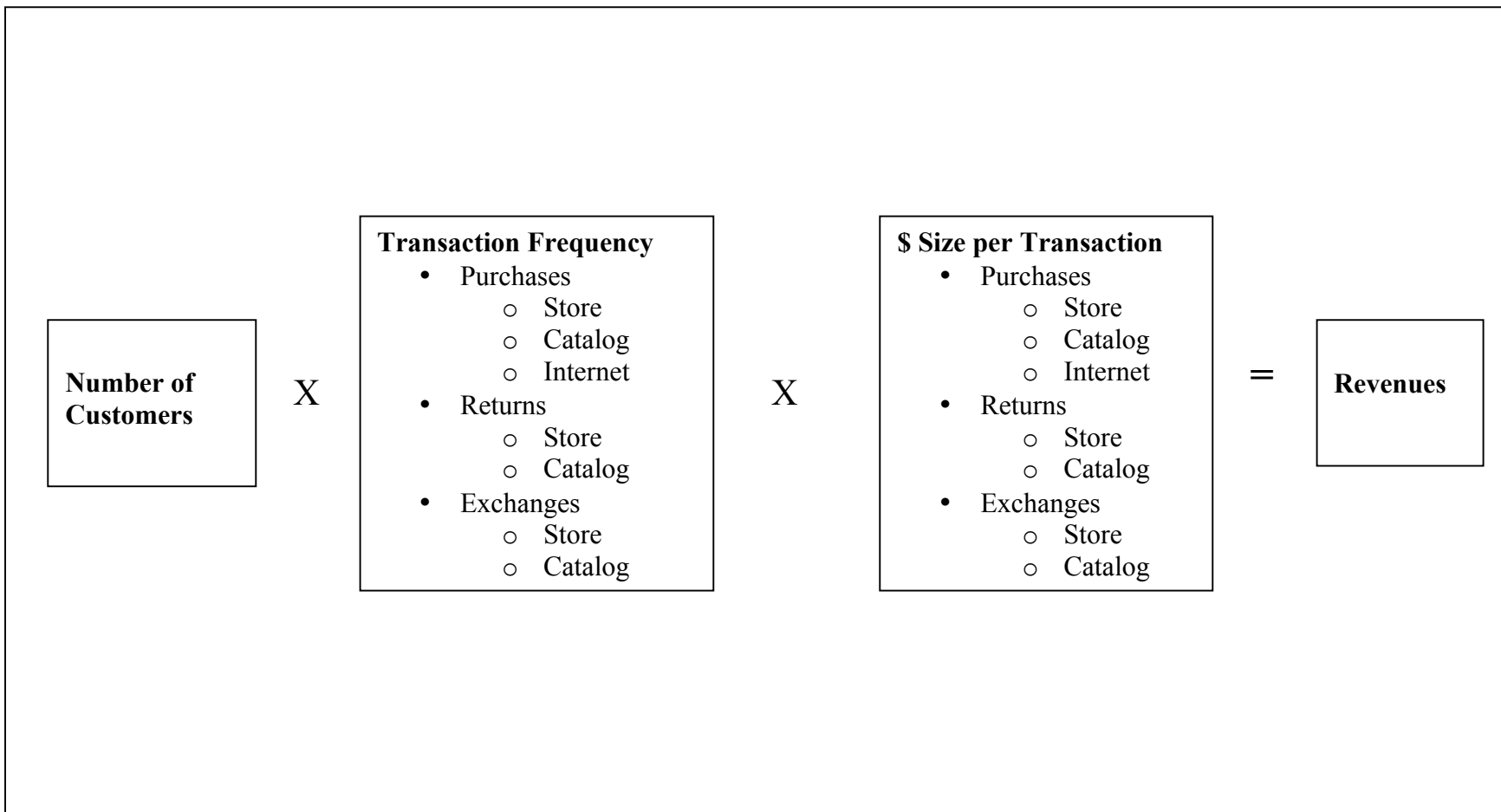
Figure 2: Weekly Shoppers at the Store, Catalog and Internet Channels
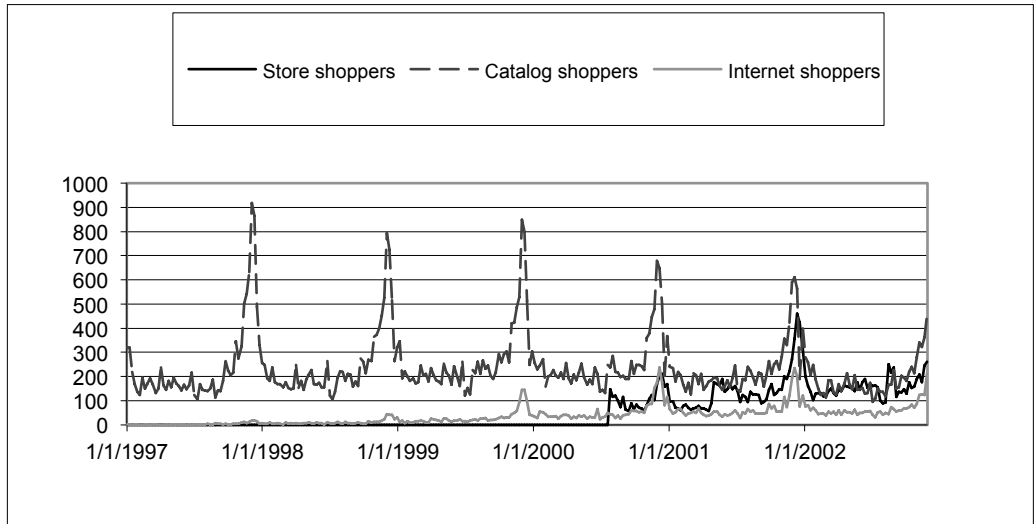
Figure 3: Weekly Shoppers Returning to the Store and to the Catalog Channels
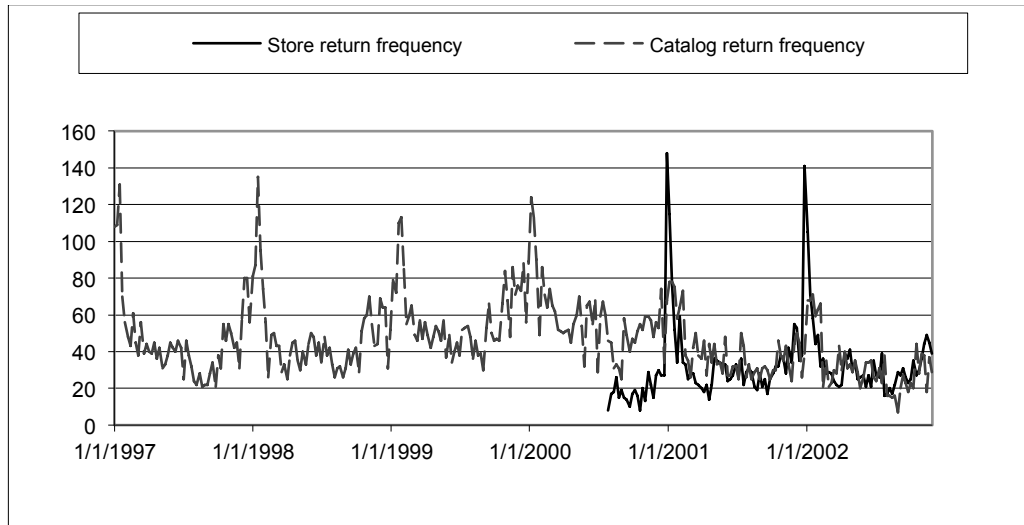
Figure 4: Weekly Shoppers Exchanging in the Store and Catalog Channels
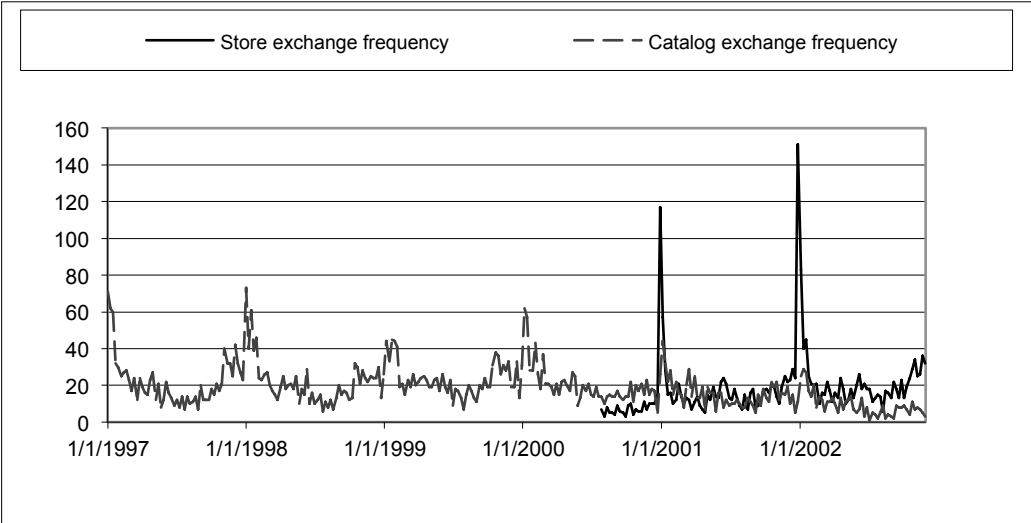
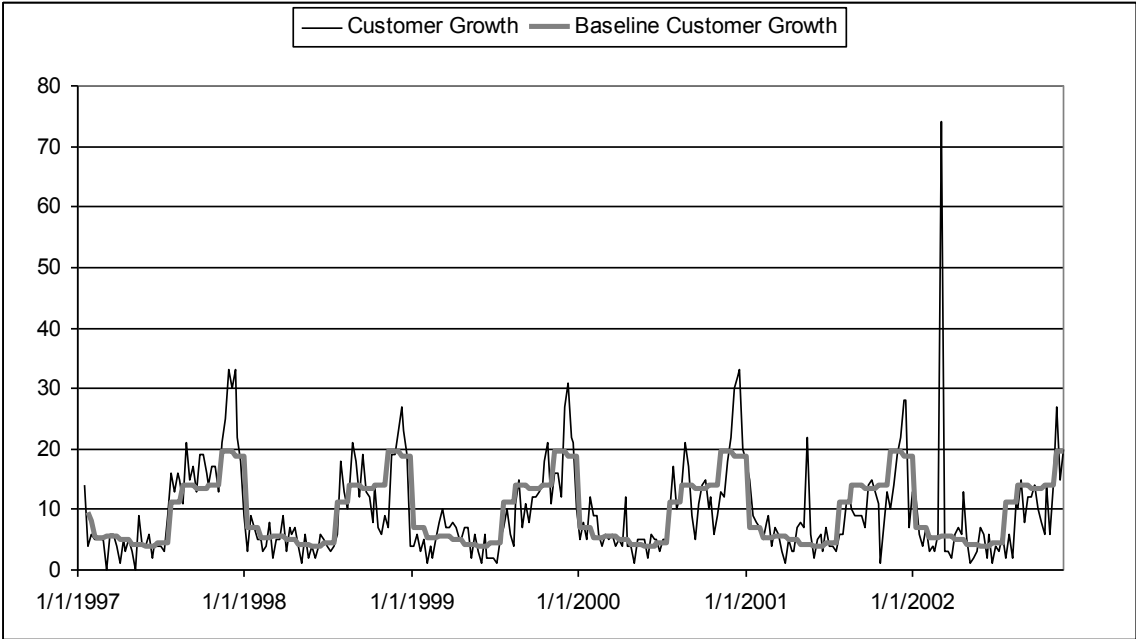**Figure 5: Weekly Customer Growth: Actual Versus Baseline (VARX1)**

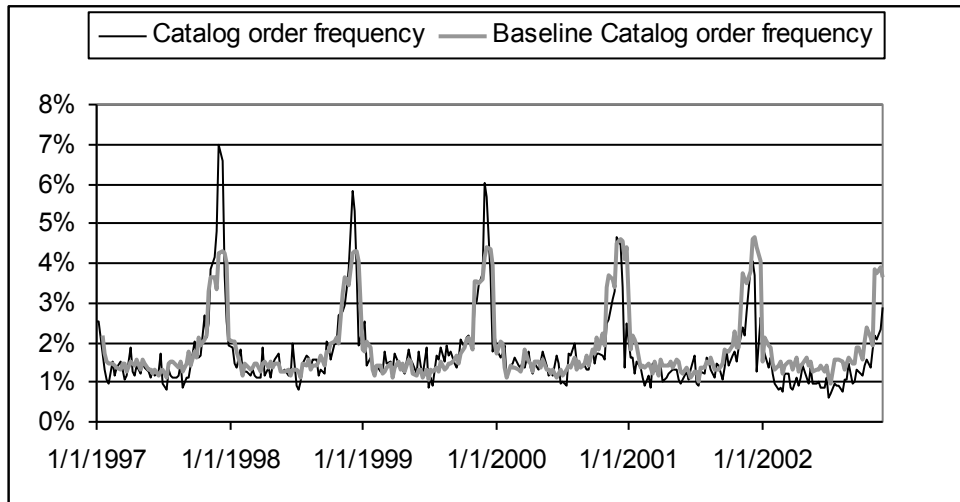**Figure 6: Catalog Order Frequency: Actual versus Baseline (VARX1)**

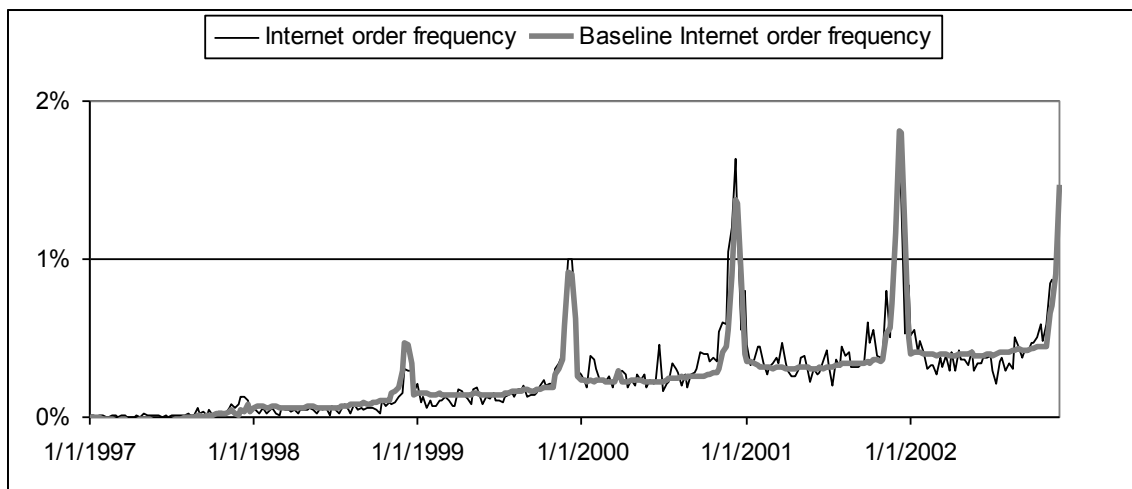**Figure 7: Internet Order Frequency: Actual versus Baseline (VARX1)**

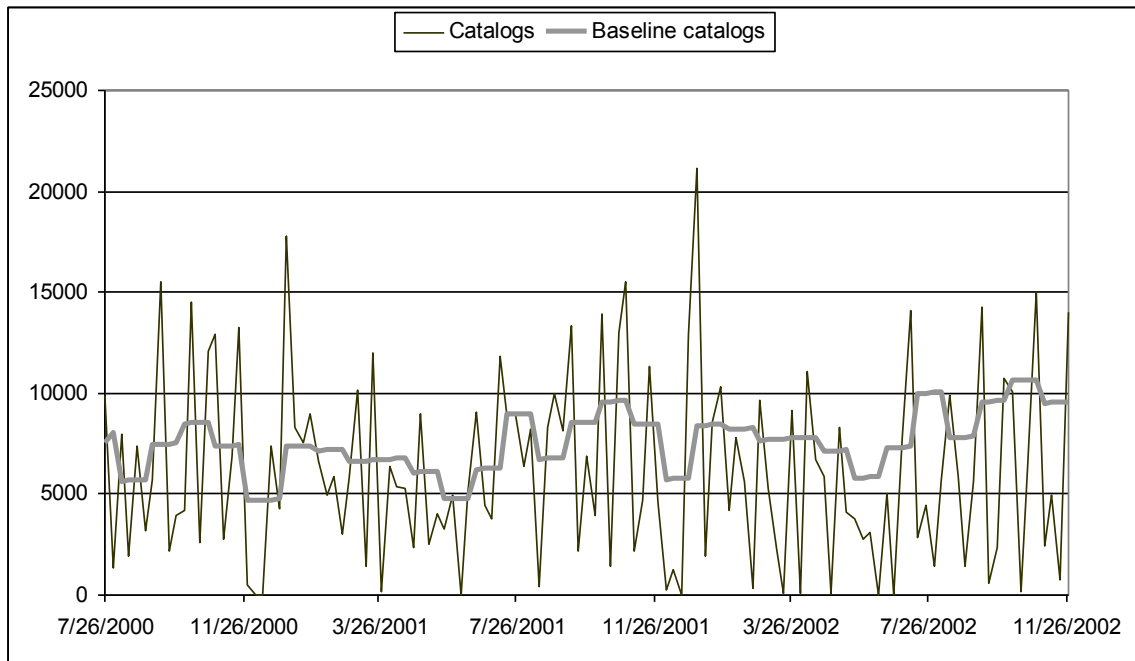**Figure 8: Weekly number of catalogs sent: actual versus baseline (VARX1)**
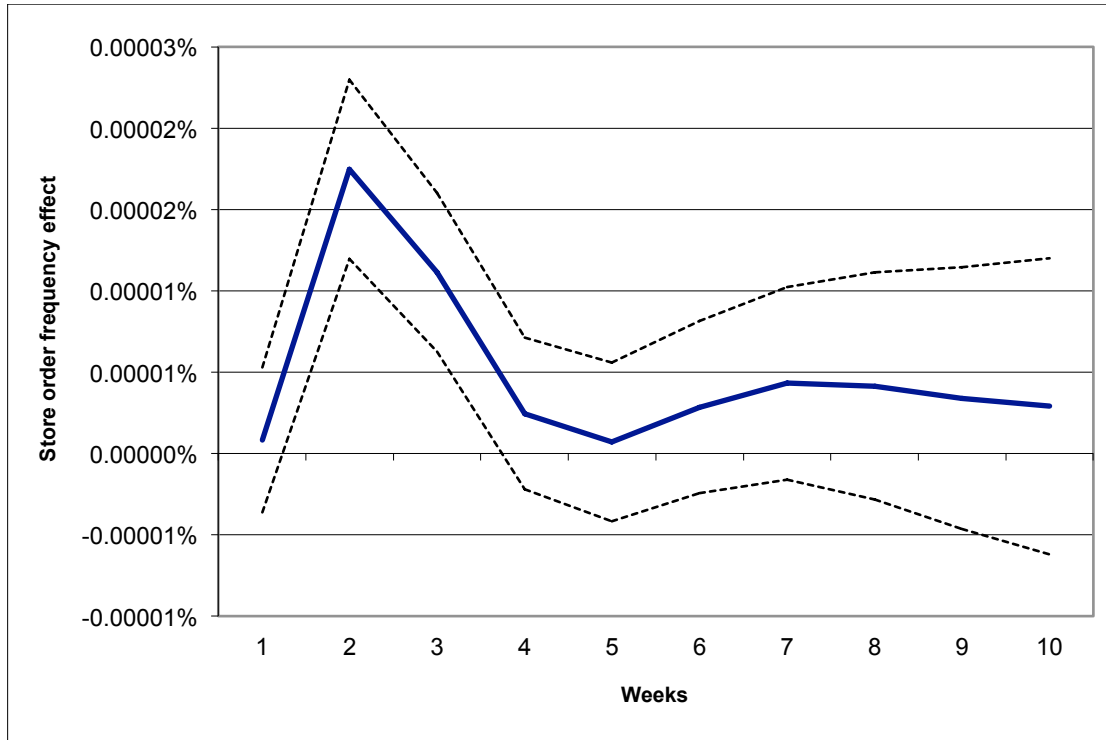
Figure 9: Impulse Response of Store Order Frequency to a Catalog Sent

Appendix: Multivariate Baseline Adjustment for Introduction-Exogenous events

Figure 8 shows that catalog distribution decreased after store introduction. To investigate whether this was exogenous or endogenous to the store introductions, we contacted company management. They told us 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 over-loading customers with catalogs. This means that the catalog reduction is an exogenous event, and we must adjust for it in our baseline.

Table A1 provides impulse response results from the VARX1 model showing the impact of catalogs and emails on the various revenue components. The results sensibly show that catalog distribution affects catalog purchase frequency the most, while emails 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 post-store 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 much of the catalog reduction occurred late in the post-introduction period, and the impulse response function extends over time. To accurately adjust the baseline for the decrease in catalogs, we subtract actual minus baseline catalogs in each post-introduction period, and then utilize the period-by-period impact of catalogs to calculate the total impact on the baseline for each revenue component.

[Table A1 Goes Here]

Finally, neither we nor company management are aware of any change in competitive activity unrelated to store introduction. As discussed, if competitive activity is endogenous to the store introductions, then we do not need to adjust the baseline. Likewise, we checked with management that no major change occurred to other marketing actions such as the company's price level or product shipping charges.

**Table A1: Total effects of marketing on revenue components,
Pre-Store Introduction (based on VARX1 model)**

	Catalog	Email
Customer base	$0.07	$0.03
Catalog Purchase Frequency	$1.02	$0.16
Internet Purchase Frequency	$0.46	$0.87
Catalog Return Frequency	-$0.21	-$0.11
Catalog Exchange Frequency	$0.05	$0.06
Catalog Order Size	$0.16	$0.00
Internet Order Size	$0.00	$0.00
Catalog Return Size	$0.00	$0.00
Catalog Exchange Size	$0.00	$0.00
Total revenue effect	**$1.55**	**$ 0.91**
Actual post-store introduction weekly level minus baseline weekly level	-808	-22