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Clicks and Mortar: The Effect of On-line Activities on Off-line Sales

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Abstract

Retailers did not immediately extend their business to the Internet environment, fearing that on-line activities could adversely impact their off-line sales. To facilitate assessment of the impact of on-line activities on off-line sales, we develop a method that allows retailers to use readily available market data for making informed decisions. The proposed method determines (1) the extent to which on-line sales cannibalize off-line sales, and (2) whether on-line activities build on-line equity for the firm. We illustrate the method using data from Tower Records' Internet sales division. We find that on-line sales do not significantly cannibalize retail sales and that the firm's web activities build long-term on-line equity. While the proposed method can be used by any "clicks-and-mortar" firm, our firm-specific results indicate that Towers' fears regarding cannibalization due to its own Internet activities were unfounded.

Keywords: Internet marketing, cannibalization, on-line vs. off-line

1. Introduction

In the early stages of the Internet's emergence, some retailers made only cautious attempts to extend their operations there. They feared that on-line activities would cannibalize their "off-line" business and hurt profits (Alba et al., 1997). Today, since the bursting of the Internet bubble and with Internet-only firms in trouble, retailers are ready to dominate the Internet channel as well, and their fears appear to have been misguided. Although our assessment of the threats posed by the Internet may have changed, the threats are no less real. The Internet does provide a competing channel to retailers' traditional distribution channels, and therefore any retailer transacting business on-line has to address issues regarding cannibalization of off-line operations by on-line activities, coordination of the Internet with off-line channels, and possible channel conflicts. These issues are faced by any retailer who operates multiple channels (e.g., Purohit, 1997; Iyer, 1998) and appear to be more pronounced for the Internet because of its ubiquitous nature (Balasubramanian, 1998). In other words, the Internet knows no geographical boundaries, and retailers are unable to limit customers' access to it. This deprives retailers of the benefits of traditional tools for controlling channel competition, making competition from the Internet potentially much more severe.

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Recent marketing research has started inquiry into the consequences of competition from the Internet with other channels. Specifically, Staelin et al. (2000) investigated the potential effects of direct competition from the manufacturer through the Internet. Lal and Sarvary (1999) and Zettelmeyer (2000) studied the effect of the Internet on price competition. They showed that the Internet does not necessarily intensify price competition, and can actually reduce it.

While these studies provide insight into the potential effects of competition from the Internet, managers need to complement that insight with empirical knowledge of the effects of some pertinent on-line activities (e.g., customer visits) on managerially relevant outcomes (e.g., cannibalization, brand equity formation). To this end, we propose a method that allows managers to estimate the effects of on-line activities on off-line sales and illustrate its usefulness via a real case of an established music retailer.

Our methodology can be applied using readily available market data. The Internet enables managers to track individual-level data, which can be used for understanding customers' on-line behavior (e.g., Moe and Fader, 2000a, 2000b). The availability of individual-level data for off-line behavior, however, is limited. And even when it is available, it is often impossible to match on-line and off-line behavior. Thus, to assess the off-line effects of on-line actions one usually must rely on aggregate-level data. Our model is geared toward the use of such data. We augment aggregate-level on-line data with retail sales data so that managers can assess the effects of on-line customer behavior on *both* off-line and on-line sales. Furthermore, our empirical results contribute to the sparse literature on cannibalization due to the Internet and on-line equity formation.

In section 2, we formulate a model for assessing cannibalization and on-line equity formation. We then present the data and estimation approach and describe the empirical results. Finally, we conclude by discussing the implications of the results and avenues for further research.

2. Conceptual Model

A firm is interested in assessing the impact of customers' activities on its web site on its off-line sales. The company has two sources of sales: *on-line sales* through the web site and *off-line sales* from all other channels, such as retail stores and catalogs. See Figure 1. The firm's marketing efforts (both on-line and off-line) lead consumers to visit the web site.

Our model assumes that the firm tracks a number of metrics on *customer on-line behavior* (e.g., number of customer visits or pages viewed) in order to assess the impact of its web site. It is interesting to note that without such metrics the firm is unable to estimate the effect of its on-line effort on sales because a web site is always open and consequently lacks the variability that is necessary for estimation purposes. If we consider, for example, measurement of advertising or salesforce effort, we observe that firms employ metrics such as media expenditure and number of sales call per week that are good proxies for the level of activity. But on-line efforts involve development and maintenance costs, neither of

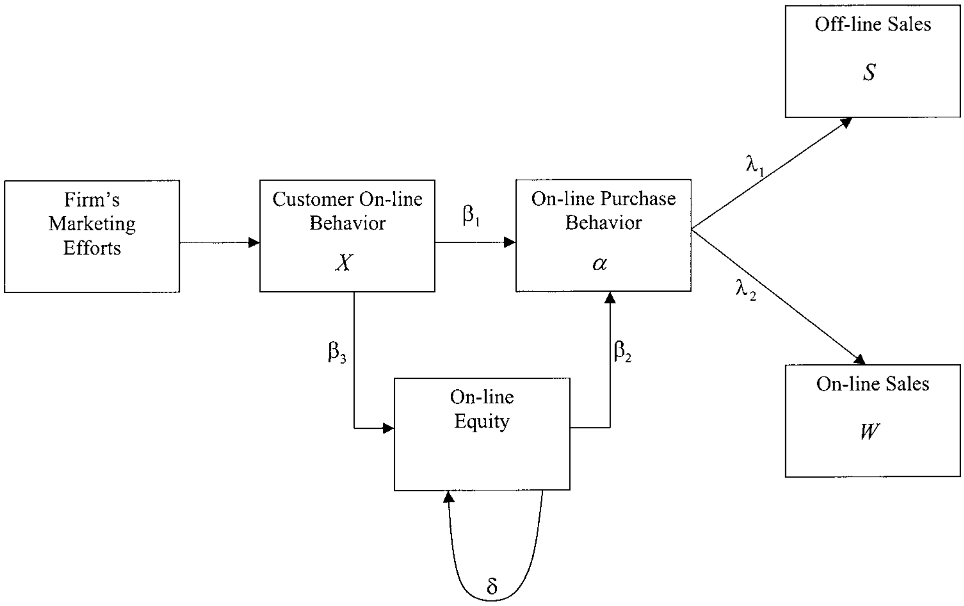

Figure 1. A Model for Measuring the Impact of Customer On-line Behavior on Off-line and On-line Sales.

which serves as good proxies because of insufficient variability over time. Hence, the firm needs to track customers' actual on-line behavior.

We hypothesize that customer on-line behavior affects *on-line purchase behavior* and denote this effect by β_1 in Figure 1. In other words, after visiting the web site and viewing web pages, some customers buy the firm's products on-line. The cumulative value of orders across customers in a given time period (for a week for example) constitutes the firm's *on-line sales*. Because orders placed on-line may reduce *off-line sales,* we represent this cannibalization effect by λ_1, where a negative value indicates cannibalization of off-line sales due to on-line orders, while a positive value indicates synergy between on-line and off-line purchases (see Figure 1). Furthermore, on-line purchase behavior depends on the firm's *on-line equity*, the long-term value of the firm's on-line efforts. This concept is similar to the notion of brand equity, which is created partly by goodwill accumulation due to past advertising (see Hanssens et al., 2001; Leeflang et al., 2000). Because brand equity affects the effectiveness of marketing programs (Keller, 1993), we expect the firm's on-line equity to increase the effectiveness of converting on-line visits into on-line purchases. This leads to the interaction, denoted by β_2 in Figure 1, between on-line equity and customer on-line behavior. Next, we expect that the formation of on-line equity takes time to build. To account for its dynamics over time, we introduce the impact of previous on-line equity on the current level of on-line equity via the parameter δ in Figure 1. This approach is consistent with extant dynamic models of advertising (see, e.g., Little, 1979; Naik et al., 1998).

Using estimated effects, managers can assess the total effect of on-line activities. Specifically, we need to know the main effects of on-line behavior on purchases and on-line equity $(\beta_1, \beta_3)'$, the interaction (β_2) between on-line equity and on-line behavior, the cannibalization rate (λ_1), the impact of on-line purchases (λ_2), and the rate of on-line equity formation (δ). Then, if on-line efforts generate customer on-line behavior, which is measured by some metric X, the long-term steady-state sales are given by $X(\frac{\beta_2\beta_3}{1-\delta}X + \beta_1)(\lambda_1 + \lambda_2)$.[1] Next, we explain how to estimate these parameters using on-line and market data.

3. Data and Estimation

We illustrate our methodology by applying it to the on-line activities of Tower Records. Tower Records is a leading music retailer that operates a chain of stores dedicated to music sales. After the emergence of on-line music retailers such as *CDNow*, Tower opened a web site. The web site is sales-oriented and serves as the Internet selling arm for Tower. Our data consist of weekly observations of operations from August of 1998 to July of 1999, which covers the web site's operations from a few months after its launch. That is, the web site's operation is in a growth phase, not having reached a stable point yet. At the same time, Tower is a follower in the Internet music-retailing category that was created by dot-com firms such as *CDNow* that were then considered success stories.

We observed weekly dollar sales on the web site (W_t), the numbers of orders placed (O_t), and weekly dollar sales in retail stores in North America (S_t) for $t = 1, \ldots, 52$ weeks. Although Tower operates internationally, we considered only North American sales data because virtually all of Tower's web sales are confined to North America. We used the number of unique visits each week (X_t) as the metric for customer on-line behavior. In addition, we gathered information on weekly off-line sales (LS_t) for the previous year (August 1997 to July 1998). Music sales exhibit seasonality with peaks on special occasions like Christmas. Because previous year's sales exhibit similar seasonal patterns, we used LS_t to control for the seasonal effects. LS_t also provides a baseline for determining the extent of cannibalization in the current year's off-line sales due to on-line activities. See Table 1 for notational summary, and Table 2 for summary statistics of the data.

3.1. *Formal Model*

We formalized the conceptual model in Figure 1 into the following set of simultaneous dynamic equations:

$$S_t = \lambda_1\alpha_t + \gamma LS_t + \varepsilon_{1t}, \tag{1}$$

$$W_t = \lambda_2\alpha_t + \varepsilon_{2t}, \tag{2}$$

$$O_t = \alpha_t + \varepsilon_{3t}, \tag{3}$$

$$\alpha_t = \beta_1 X_t + \beta_2\mu_{t-1}X_t + \varepsilon_{4t}, \tag{4}$$

$$\mu_t = \delta\mu_{t-1} + \beta_3 X_t + \varepsilon_{5t}, \tag{5}$$

Table 1. Notations

Symbol	Meaning
Observed Variables	
W	Weekly on-line sales (dollars)
O	Number of on-line orders each week
S	Weekly off-line sales (dollars)
LS	Weekly off-line sales a year ago (dollars)
X	Number of unique visits each week
Latent Constructs	
α	On-line purchasing behavior
μ	On-line equity
Model Parameters	
β_1	Direct effect of on-line visits on on-line purchasing behavior
β_2	Interaction effect of on-line equity and on-line visits on on-line purchasing behavior
β_3	Effect of on-line visits on build-up of on-line equity
λ_1	Effect of on-line orders on contemporaneous (same week) off-line sales
λ_2	Scale factor between on-line sales (dollars) and on-line purchasing behavior
δ	On-line equity carryover effect

Table 2. Summary Statistics

			Correlation Matrix				
	Means (000's)[a]	Std. Dev.	Off-line sales	Last year sales	On-line sales	Unique visitors	Orders
Off-line sales (S)	1213.04	304.38	1.000				
Last year sales (LS)	1304.22	293.76	0.970	1.000			
On-line sales (W)	80.53	25.84	0.127	0.117	1.000		
Unique visitors (X)	102.92	23.67	0.114	0.163	0.607	1.000	
Orders (O)	2.52	0.80	0.078	0.069	0.969	0.613	1.000

[a] Values are disguised to preserve confidentiality.

where the observed variables S_t, LS_t, W_t, and O_t denote off-line sales, last year's off-line sales, on-line sales, and the number of orders placed, respectively. The unobservable constructs α_t and μ_t denote on-line purchase behavior and on-line equity, respectively. Note, that μ, is lagged in Equation (4) because conceptually only the equity that has already been accumulated should affect current on-line purchasing behavior. Each error term $\varepsilon_{it} \sim N(0, \sigma_i^2)$ for $i = 1, \ldots, 5$.

The on-line purchasing behavior construct (α) enters Equation (1) with a subscript t. This reflects an assumption that any cannibalization due to on-line sales is contemporaneous and will impact off-line sales in the same week. This is a reasonable first approximation in the case of music sales, which are largely driven by the release dates of hit songs and consumer exposure to them through radio, etc. In other cases, market researchers may need to account for possible non-contemporaneous cannibalization. This can be accomplished by expanding Equation (1) to include lagged terms of α.

Equation (2) is an accounting equation relating on-line sales to number of orders through a parameter λ_2, which captures the average dollar amount per order. Equation (3) establishes the scale for on-line purchase behavior based on the observed number of orders placed. While it is possible to combine Equations (2) and (3) by relating α_t directly to on-line sales, we estimate them separately so that we can use multiple measures (W_t, O_t) to infer information about the latent construct α_t, thus yielding robust estimates.

3.2. Estimation Method

Using the above data, we sought to estimate the system of simultaneous and dynamic Equations (1)–(5). We first collected the dynamic Equations (4) and (5) in the following *vector* transition equation:

$$\begin{bmatrix} \alpha_t \\ \mu_t \end{bmatrix} = \begin{bmatrix} 0 & \beta_2 X_t \\ 0 & \delta \end{bmatrix} \begin{bmatrix} \alpha_{t-1} \\ \mu_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_1 X_t \\ \beta_3 X_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix}. \tag{6}$$

Then, we collected the remaining Equations (1)–(3) in the following *vector* observation equation:

$$Y_t = \begin{bmatrix} S_t \\ W_t \\ O_t \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ \lambda_2 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \alpha_t \\ \mu_t \end{bmatrix} + \begin{bmatrix} \gamma LS_t \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}. \tag{7}$$

Finally, we applied the Kalman filter recursions (see Naik et al., 1998, p. 233) to compute the likelihood function for the observed data $Y = (Y_1, Y_2, \ldots, Y_T)'$ for T periods:

$$L(\Theta; Y) = \prod_{t=1}^{T} f(Y_t | \Im_{t-1}), \tag{8}$$

where $f(\cdot|\cdot)$ denotes the conditional density function given information up to the last period $\Im_{t-1}$. We note that previous marketing applications of Kalman filtering involve only a single dependent variable at any time t (e.g., sales or awareness). A point of departure here is that we observed three dependent variables contemporaneously, two of which provide multiple measures for one construct. Specifically, we measured *off-line sales* by S_t and *on-line sales* by two measures, W_t and O_t. Formally, we obtained the log-likelihood function,

$$LL(\Theta) = -\frac{T}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \ln |F_t| - \frac{1}{2} \sum_{t=1}^{T} v_t' F_t^{-1} v_t, \tag{9}$$

where $|F_t|$ denotes the determinant of F_t, which is the covariance matrix of the observation vector Y_t, and v_t is the forecast error vector $Y_t - \hat{Y}_{t|t-1}$. Applying maximum-likelihood theory, we maximized Equation (9) to obtain parameter estimates and their standard errors. The resulting estimates are unbiased and have minimum variance across all estimators because the model is linear in the state variables $(\alpha_t, \mu_t)'$ and the error terms are normally distributed.

3.3. *Missing Values*

In practice, some observations are likely to be missing. For example, our time series for on-line sales, orders, and visits are each missing 10 observations at different times during the 52 weeks, so we had to interpolate the missing values. To this end, we forecasted the dynamic trend in a time series by assuming that second-order differences are small on average (Shumway, 1988, p. 185). Consider a time series variable $y_t = x_t + \omega_t$, where x_t has a smooth yet non-stationary trend and ω_t is an irregular white noise. Then, we have the second-order difference:

$$\nabla^2 x_t = (x_t - x_{t-1}) - (x_{t-1} - x_{t-2}),$$

which follows a zero-mean normal random variable, and which we write in the state-space form:

$$\begin{bmatrix} x_t \\ x_{t-1} \end{bmatrix} = \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ 0 \end{bmatrix}, \quad \text{and} \tag{10}$$

$$y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \end{bmatrix} + \omega_t, \tag{11}$$

where $\varepsilon_t \sim N(0, \sigma^2)$ and $\omega_t \sim N(0, \sigma_\omega^2)$. Applying Kalman filtering, we estimate Equations (10) and (11) and replace the missing y_t by its filtered estimate $\hat{x}_{t|t}$. This approach is a discrete version of the cubic spline smoothing technique (Shumway, 1988). Next, we report the empirical results.

4. Empirical Results

We estimated different versions of the basic model in Figure 1 (e.g., a model without the on-line equity term). Computing Akaike Information Criterion (AIC) and its bias-corrected version (AIC_C) developed by Hurvich and Tsai (1989), we retained the model that yields the lowest value on these criteria.[2] By replacing parameters in Equations (1)–(5) with their corresponding estimates for the music retailer data, we present the retained model in Equations (1a)–(5a). (The standard errors are reported in the parentheses.)[3]

$$\hat{S}_t = \underset{(1.157)}{-0.888}\,\hat{\alpha}_t + \underset{(0.023)}{0.950}\,LS_t, \tag{1a}$$

$$\hat{W}_t = \underset{(0.346)}{32.061}\,\hat{\alpha}_t, \tag{2a}$$

$$\hat{O}_t = \hat{\alpha}_t, \tag{3a}$$

$$\hat{\alpha}_t = \underset{(0.860)}{1.527}\,X_t + \underset{(0.828)}{1.210}\,\hat{\mu}_{t-1} X_t, \tag{4a}$$

$$\hat{\mu}_t = \underset{(0.170)}{0.705}\,\hat{\mu}_{t-1} + \underset{(0.00018)}{0.00024}\,X_t. \tag{5a}$$

We note that all estimates are in the expected direction. For example, the estimated coefficient for LS_t (i.e., last year's weekly sales) is 0.95, which is also statistically significant (t-value $= 41.3$). We expect this coefficient to be close to unity because sales of music CDs during that period were flat.[4] Furthermore, from Equation (2a) we observe that *each on-line order generates on average $32.06 in on-line sales.* Indeed, this estimate is close to the sample average of about $30 per order in our data set. Thus the retained model seems reasonable. In the next section we turn to the interpretation of the implications of these results.

5. Implications

In our model, the negative value of λ_1 indicates cannibalization of off-line sales S_t due to on-line purchase behavior in the same period, α_t (see Equation (1)). For this retailer, $\hat{\lambda}_1 = -0.888$, which is not significant (p-value > 0.2). Furthermore, because the units of α are determined by O_t (see Equation (3)), the cannibalization effect is about $0.89 per order. When we compare it with the estimated order value of $32.06, we find that the cannibalization rate is 0.89/32.06 or 2.8% of on-line sales. Thus, *the contemporaneous cannibalization of off-line sales due to on-line sales is negligible.*

Overall, these results suggest that Tower need not worry about cannibalization due to its on-line activities. We note that, at the time, at least some people within the organization felt that the cannibalization was likely to be high, and that concern caused Tower Records to make a late entry into on-line retailing. Our analysis, however, indicates that such fears were not warranted. Hence, by applying the proposed method to market data, marketers can make better inferences and improve decision-making.

On-line equity. We find a significant effect for the interaction between on-line equity and visits (p-value < 0.10). Because we measure X_t in hundreds of visits per week, we interpret Equation (4a) as follows: The retailer can expect 1.527 orders for every 100 customer visits to the web site. Furthermore, the existence of non-zero on-line equity amplifies this direct effect by $1.210\mu_{t-1}$. To learn the impact of this interaction effect, we plot in Figure 2 the proportion of on-line purchases due to on-line equity. Figure 2 shows that *on-line equity accounts for about 38% of on-line purchases on average; in some weeks, it influences more than 50% of on-line purchases.* These numbers underscore the importance to the firm of building on-line equity.

An interesting question naturally arises: what factors drive the formation of on-line equity? The two terms on the right-hand side of Equation (5a) provide some initial answers. The first term, with $\hat{\delta} = 0.705$, which is statistically significant (p-value < 0.001), indicates the carryover in the dynamics of on-line equity. To better understand this effect, we compute the duration required for on-line equity to depreciate by 90% (see Naik, 1999 for details). The estimated duration is about seven to eight weeks, which means that *if the*

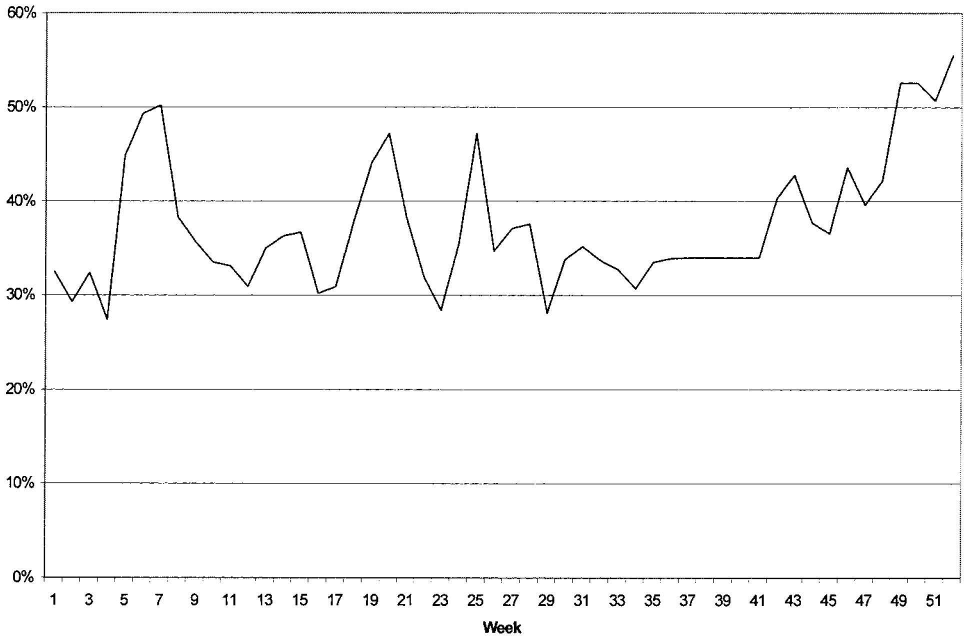

Figure 2. Share of purchases due to on-line equity.

retailer discontinues its efforts to build on-line equity, the equity it already has will erode and nearly vanish within a few months.

The second term in Equation (5a) indicates that the total number of visits to a web site has a positive and significant effect on on-line equity (p-value < 0.10). We expect that the higher the number of visits, the greater the opportunity for building on-line equity. However, in Tower's case, the size of this effect is small, and the variance explained is just 2.7%. The long-term steady-state effect of the number of web site visits on Tower's on-line equity, $\beta_3/(1-\delta) = 0.00024/0.295 = 8.1 \times 10^4$, is also small. Thus, *although customer visits are necessary for on-line equity formation, its effect is quite small for this retailer.* This may indicate that some other unmeasured on-line behavior drives on-line equity formation.

6. Summary and Future Research

This paper shows how retailers can use readily available market data to understand the impact their on-line activities have on both off-line and on-line sales. We formulate a dynamic model with simultaneous Equations (1)–(5), which incorporate the impact of on-line activities via the latent constructs of on-line purchase behavior and on-line equity formation. We show how to estimate this dynamic model using Kalman filtering methodology and apply the approach to the real situation facing Tower Records, an established music retailer that extended its operations to on-line retailing. The approach yields valuable information for improving decision-making. For example, using the parameter estimates, we find that 100 customer visits would generate about $48 in sales in the long run.[5] Thus, by incorporating information on product margin and cost of generating customer visits, the retailer can determine the profitability of pursuing on-line activities.

This study raises several issues for future research. First, does on-line sales cannibalization change over time? In our empirical example, the cannibalization rate was small at the time of extension to the Internet. But the rate can increase in the future, and so the model can be applied to new data to monitor changes periodically.

Second, while we estimate the *contemporaneous* cannibalization effect, it is possible that non-contemporaneous cannibalization effects exist as well. This empirical issue needs further investigation. One approach is to expand Equation (1) by first introducing lagged variables into it and then determining the appropriate order of the lagged terms via Akaike's information criterion.

A third issue pertains to the importance and nature of on-line equity formation. The empirical results indicate that on-line equity accounts for 38% of on-line sales, highlighting the importance of on-line equity. Some open issues include a better characterization of the nature of on-line equity, such as what kinds of activities build it and what other metrics can track it. Should firms concentrate on the number of unique visits measured or on some other measure, like the number of new visits to the site or the time spent on the site, etc. Furthermore, we estimated the carryover of on-line equity to be 0.705, which is significantly lower than the carryover effect of advertising (e.g., Leone, 1995). Does this mean that equity formation based on on-line effort is more transient than that built by classical advertising? Further research is necessary to shed light on these issues and enhance our understanding of on-line equity formation. One possible avenue for future research is to address these issues using panel data (see Moe and Fader, 2000b). Such research can provide convergent evidence to our results based on aggregate data.

Finally, the model presented in this paper can be extended in several interesting directions. The model starts with measures of consumer on-line behavior. Such behavior, obviously, is the result of marketing actions taken by the firm both on-line and off-line. Given appropriate measures of the firm's marketing efforts, the model can be extended backwards to assess how the marketing efforts led to on-line behavior, providing a fuller characterization of how marketing activities impact on-line and off-line sales. Another extension is to consider time-varying parameters. Given the changing nature of the Internet, it is possible that effect sizes may not remain constant, that rather they may change over time in predictable ways. For example, the amount of cannibalization may increase as the Internet matures. With longer time series that provide more degrees of freedom, one might address this issue by specifying an econometric model for how λ_1 might change over time (see, e.g., Reddy et al., 1994) or by testing for structural breaks (Hansen, 2001).

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Notes

1. To get this expression we set $\mu = \mu_{t-1} = \mu^*$ in Equation (5), and substitute backwards the resulting quantities in Equations (4)−(1).
2. Alternative models that were tested are not described for the sake of brevity.
3. X_t is scaled to be in the hundreds of visits.
4. We also estimated models by including macroeconomic variables to account for any change in the economic environment. The inclusion of these variables did not alter the substantive results.
5. As mentioned, the steady-state sales estimate is given by $X(\frac{\beta_2\beta_3}{1-\delta}X + \beta_1)(\lambda_1 + \lambda_2)$, which equals \$47.63 for this retailer.

References

Alba, Joseph, John Lynch, Barton Weitz, and Chris Janiszewski. (1997). "Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces," *Journal of Marketing*, 61(3), July, 38–53.

Balasubramanian, Sridhar. (1998). "Mail Versus Mall: A Strategic Analysis of Competition Between Direct Marketers and Conventional Retailers," *Marketing Science*, 17(3), 181–195.

Hansen, Bruce E. (2001). "The New Econometrics of Structural Change: Dating Breaks in U.S. Labor Productivity," *Journal of Economic Perspectives*, 15(4), 117–128.

Hanssens, Dominique M., Leonard J. Parsons, and Randall L. Schultz. (2001). *Market Response Models: Econometric and Time Series Analysis*, 2nd Edition. Kluwer Academic Publishers: Boston, MA.

Hurvich, Clifford M., and Chih-Ling Tsai. (1989). "Regression and Time Series Model Selection in Small Samples," *Biometrika*, 76(2), 297–307.

Iyer, Ganesh. (1998). "Coordinating Channels Under Price and Nonprice Competition," *Marketing Science*, 17(4), 338–355.

Keller, Kevin L. (1993). "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *Journal of Marketing*, 57(1), 1–22.

Lal, Rajiv, and Miklos Sarvary. (1999). "When and How is the Internet Likely to Decrease Price Competition?" *Marketing Science*, 18(4), 485–503.

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

Leone, Robert P. (1995). "Generalizing What is Known About Temporal Aggregation and Advertising Carryover," *Marketing Science*, 14(3), Part 2, G141–G150.

Little, John D. C. (1979). "Aggregate Advertising Models: The State of the Art," *Operations Research*, 27(July–August), 629–667.

Moe, Wendy W., and Peter S. Fader. (2000a). "Which Visits Lead to Purchases? Dynamic Conversion Behavior at E-Commerce Sites," Wharton working paper #00-023.

Moe, Wendy W., and Peter S. Fader. (2000b). "Capturing Evolving Visit Behavior in Clickstream Data," Wharton working paper #00-003.

Naik, Prasad A., Murali K. Mantrala, and Alan G. Sawyer. (1998). "Planning Media Schedules in the Presence of Dynamic Advertising Quality," *Marketing Science*, 17(3), 214–235.

Naik, Prasad A. (1999). "Estimating the Half-Life of Advertisements," *Marketing Letters*, 10(3), 351–362.

Purohit, Devavrat. (1997). "Dual Distribution Channels: The Competition Between Rental Agencies and Dealers," *Marketing Science*, 16(3), 228–245.

Reddy, Srinivas K., Susan L. Holak, and Subodh Bhat. (1994). "To Extend or Not to Extend: Success Determinants of Line Extensions," *Journal of Marketing Research*, 31(2), 243–262.

Shumway, Robert H. (1988). *Applied Statistical Time Series Analysis*. London, UK: Prentice-Hall International, Inc.

Staelin, Richard, John Lynch, and William Boulding. (2000). "Implications of the Internet for Disintermediation: Channel Structure, Prices, and Profits," in *The World According to E: E-commerce and E-customers*, Eds. Kathy Haberkern, Katrina Hubbard, and Wendy Moe, MSI report 00-102.

Zettelmeyer, Florian. (2000). "Expanding to the Internet: Pricing and Communications Strategies When Firms Compete on Multiple Channels," *Journal of Marketing Research*, 37(3), 292–308.