Koen Pauwels & Allen Weiss

Moving from Free to Fee: How Online Firms Market to Change Their Business Model Successfully

Moving from free to "free and fee" for any product or service represents a challenge to managers, especially when consumers have plenty of free alternatives. For one online content provider, this article examines (1) the sources of long-term revenue loss (through attracting fewer free subscribers) and (2) how the firm's marketing actions affect its revenue gains (through attracting paid subscribers). The authors quantify revenue loss from several sources, including the direct effects of charging for part of the online content and the reduced effectiveness of search-engine referrals and e-mails. The analysis suggests several managerial implications. Managers should focus their price promotions on stimulating new monthly subscriptions, rather than the current promotional focus on stimulating new yearly contracts. In contrast, e-mail and search-engine referrals appear to be effective at generating yearly subscriptions. Meanwhile, free-to-fee conversion e-mail blasts are a double-edged sword; they increase subscription revenue at the expense of advertising revenue. Finally, further analysis shows that the move was preceded by the buildup of momentum in new free subscriptions, which appears to be beneficial for the move's success. The decomposition and comparison of the sources of revenue loss versus gains reveals several trade-offs facing companies moving from free to free and fee.

Keywords: free to fee, online content, price, marketing communication, search-engine referrals, time-series analysis, vector-autoregressive models

A decade ago, Peterson, Balasubramanian, and Bronnenberg (1997) heralded the Internet as a promising new channel for products and services that are low outlay, are frequently purchased, and have a value proposition of an intangible or informational nature. Such content providers have indeed become popular with consumers (Saba 2005). Recent research in marketing has made significant advances in the understanding of various Internet marketing issues, including Web-browsing behavior (Bucklin and Sismeiro 2003), search-engine visits (Telang, Boatwright, and Mukhopadhyay 2004), and recommendation agents (Cooke et al. 2002; Diehl, Kornish, and Lynch 2003). However, a vexing problem for practitioners has remained virtually untouched by formal analysis—namely, how firm performance is affected by moving from free to free and fee (i.e., from offering all content for free to charging for at least some of it).[1] A prominent fear among content providers is the likely loss of customers to the many still-free competitors. Moreover, the impact of marketing actions to stimulate paid subscriptions is uncertain given the general consensus among Web surfers that "content is free" (Dyson 1995). Empirical findings on these issues are scarce because firms are uneasy sharing data with academic researchers for confidentiality and competitive reasons.

Consumers like getting products and services for free. Beyond the absence of monetary costs, a free good is free of trade-offs and reduces consumer psychological costs (Ariely and Shampan'er 2004). Thus, being free offers an incentive to try a new product. However, it may pose a problem if the company decides that customers should begin paying. The issue of moving from free to fee matters in many industries, including entertainment content providers and the publishing industry, which represented $240 billion in 2004, according to the U.S. Census Bureau (see http://www.census.gov/svsd/www/services/sas/sas_data/51/2006_NAICS51.pdf). After the Internet "bubble" burst—this period was characterized by free online content that was supported by investor funding and high advertising income—many companies tried charging for their Web content, with varying levels of success.[2] Research by economists on the pricing of information goods (e.g., Bakos and Brynjolfsson 2000; Jain and Kannan 2002; Varian 1995) identifies various pricing models that can be employed to

[1]Throughout this article, we use "the move from free to fee" as a shorter term for "the move from free to free and fee."

[2]Insight into this issue appears to be crucial for content providers, whose increasing investment in producing high-quality content has put a strain on an advertising-only business model. At the same time, this traditional advertising income faces new competition in several forms, such as search-engine advertisements and classified advertisements from successful entrants (e.g., Google Base, Craigslist, Wikipedia). Therefore, getting subscribers to pay for at least some valued content may represent a more stable and sustainable strategy in the long run.

Koen Pauwels is Associate Professor of Business Administration, Tuck School of Business, Dartmouth College (e-mail: koen.h.pauwels@dartmouth.edu). Allen Weiss is Professor of Marketing, Marshall School of Business, University of Southern California (e-mail: amweiss@marshall.usc.edu).

ISSN: 0022-2429 (print), 1547-7185 (electronic)

guide these decisions. These include usage-based pricing, micro payments, and subscription models. Regardless of the pricing model, however, managers are understandably concerned about the performance impact of the move from free to fee. Consumers have been conditioned to expect free online content, and there often are many, sometimes thousands of, competing alternatives from which they can choose. When the *New York Times* moved to a paid version of its editorial pages, one reader commented, "The only thing the [*New York Times*] will achieve is a reduced readership for its writers. No one will, nor should we, pay for online content. It's a big, free Web out there" (Haga 2005). The ultimate abandonment of the payment system (on September 19, 2007) appears to vindicate these arguments and illustrates the challenge content providers face online.

In summary, despite high managerial importance, little empirical research has addressed the following questions that companies face when they move from free to fee:

1. What are the long-term performance effects of such a move? In particular, what are the sources of revenue loss that might offset the revenue gains from user fees?
2. What is the role of marketing actions in the free- and fee-user response? In particular, which actions are especially successful in increasing free and fee subscriptions, for both short-term and long-term contracts?

This research attempts to shed light on these issues by focusing on the adoption behavior for free- and fee-based Web content and marketing actions that may affect this behavior. Indeed, the numbers of new free and paying subscribers are key performance indicators for content providers, which depend on these numbers for both advertising and subscription income. The potential drivers of these subscriber numbers are many, including consumer characteristics (e.g., price sensitivity, perceived content value), competitive characteristics (e.g., market concentration, content overlap, pricing schemes), and company characteristics (e.g., content restriction, marketing decisions). In this article, we are interested in the short- and long-term effects of marketing communications and price promotions (i.e., temporary price cuts) on new free- and fee-user subscriptions.[3] To this end, we apply several modern time-series techniques to a daily data set from a commercial Web site in the "business content" industry. Next to "personals/dating" and "entertainment/lifestyles," this industry is among the top three categories for online content, with a 2005 total spending of $312 million and a growth of 49% compared with 2001 (Online Publishers Association 2005).

Research Background

Previous research has examined several phenomena related to our research questions. Three decades ago, Scott (1976) studied the effect of a free two-week trial subscription on consumer willingness to pay for a six-month newspaper subscription. Notably, consumers who were offered the free trial were less likely than those in the control group to become paying subscribers. More recently, Gedenk and Neslin (1999) and Bawa and Shoemaker (2004) analyzed the impact of free samples on subsequent (paid) purchases. The former study found that distribution of free samples increased the probability that consumers would buy the brand in the future. The latter study explicitly distinguished and allowed for potential negative effects (cannibalization of paid purchases) and positive effects (acceleration of purchases by customers and expansion; i.e., purchases by noncustomers). Importantly, both short-term and long-term effects of free samples were positive; they yielded higher customer retention after trial, a larger potential for acceleration of purchases by new consumers, and a higher purchase probability among those who would otherwise not have tried the brand.

Although our research shares a similar focus on the performance effects of marketing actions, it differs from previous studies in at least two important ways. First, all the studies we mentioned examine the effects of marketing actions on purchase behavior in contexts in which people are used to paying, and ultimately expect to pay, for the product or service. In contrast, we examine markets in which (potential) customers have likely become accustomed to free content and thus have a zero reference price. It is not clear how this will affect the impact of marketing on subscriptions. Therefore, our exploratory analysis may provide new insights into marketing effects in such an environment. Second, the move from free to fee is virtually always partial for online content. Firms maintain a mix of free and for-fee content and, therefore, of free and for-fee subscribers. Because content providers often rely on growing free users to attract advertisers, this research is unique in examining how marketing decisions affect both paying customers (who yield subscription revenue) and nonpaying customers (who yield advertising revenue).

In our context, the revenue implications of the move from free to fee may be written in terms of changes to free subscribers (Fsub) and paying subscribers (Psub):

$$\Delta\text{Revenue} = \Delta\text{Fsub} \times \text{Advertising revenue per free subscriber} + \Delta\text{Psub} \times \text{Fee}, \tag{1}$$

where Δ is the difference between the actual value of a series and its benchmark (i.e., a model-forecasted value of the series in the absence of the move). The first part of Equation 1 represents a potential revenue loss from fewer free subscribers, and the second part represents a potential revenue gain from paying subscribers. We proceed by considering the likely drivers of this revenue loss and revenue gain.

Sources of Revenue Loss: How Does the Move from Free to Fee Hurt Free-User Growth?

In a general sense, content providers that move from free to fee are making two strategic decisions: a restriction-level decision and a pricing decision.[4] The restriction-level deci-

[3]These marketing actions are variables in our data set. In general, content providers use many tactics to encourage payment for content, including free daily passes and free trial subscriptions to protected content.

[4]Data limitations prohibit us from analyzing the effect of these strategic marketing decisions, leaving us with the tactical marketing actions, such as price promotions and e-mails.

sion is the extent to which formerly free content is restricted to paying users. Conceptually, restriction can range along a continuum, from complete restriction to highly selective restrictions (i.e., most of the content is free, except for a few selections). Often, at least part of the content remains free (e.g., the *New York Times*, ESPN, our data provider), resulting in a combination of free and fee subscribers.

When content providers decide to move from free to fee, their site may become less attractive to free users. There are at least two reasons for this. First, such change blocks free access to certain aspects of the provider's content, thus reducing free users' perceived benefits and, consequently, demand (Brynjolfsson, Hu, and Smith 2003). Second, potential users are typically accustomed to obtaining content for free on the Web and likely expect the same from any specific provider. Thus, any (short-term or long-term contract) price is likely to be rejected (Brehm 1966) by some potential users whose preferences for free content have been formed. Fitzsimons and Lehmann (2004) note that encountering unexpected paid content tends to decrease the attractiveness of free content and to reduce satisfaction with the choice options. Conversely, a move from free to fee may expand the market for fee content because of price signaling—that is, the price of fee content signals a higher quality to the (potential) subscriber (Zeithaml 1988).

In addition to its direct effect on new free subscribers, the move from free to fee may decrease the effectiveness of marketing communications on generating free subscriptions. Indeed, the short-term and long-term effects of marketing communications likely depend on the perceived value of the offer (Hanssens and Ouyang 2001). By closing off the for-fee part of content to free subscribers, providers may lower the perceived value of a free subscription. Especially harmful would be a refocus of the communication message on stimulating for-fee, rather than free, subscriptions. Such "conversion" efforts typically highlight the benefits of fee content, at the expense of free content.

In summary, the move from free to fee may influence new free subscriptions (1) directly, (2) through changes in the effectiveness of marketing communications, and (3) through conversion efforts, as represented in Equation 2:

(2) $\Delta\text{Fsub} = \Delta\text{Move} + \Delta\text{Marcom effectiveness} + \Delta\text{Conversion}.$

Sources of Revenue Gain: How Do Marketing Actions Stimulate Fee-User Growth?

Given this potential for revenue loss, it is crucial for the company's performance to generate paid subscriptions. Typically, online content providers offer the choice between short-term contracts and long-term contracts. Across all online content categories, subscriptions represent 78.4% of content purchases (Online Publishers Association 2005); monthly and annual contracts account for 92% of these subscriptions (the remainder are weekly, quarterly, and semiannual forms of subscriptions). The key distinction between short-term and long-term contracts is the length of time the user commits to paying for the content. Commitment issues are particularly important when firms move from free to fee; users accustomed to the no-commitment, no-trade-off situation of free content (Ariely and Shampan'er 2004) suddenly face the choice of whether, and for how long, to commit. We expect that price promotions and marketing communications have different effectiveness in stimulating new short-term versus long-term contract subscriptions.

Some users will be reluctant to make a long-term commitment. Short-term contracts allow such users to try a product with minimal commitment and to diagnose the extent to which the content is useful, thus facilitating their adoption decision (Rogers and Shoemaker 1971). Regret is less likely to occur with a short-term contract; if users find better or equivalent content at a lower price, they can switch sooner with a short-term contract than with a long-term contract. To the extent that price promotions offer a risk premium for trial (Gedenk and Neslin 1999; Pauwels, Hanssens, and Siddarth 2002), they may be effective for stimulating short-term contracts.

Price promotions may be less effective in stimulating long-term contracts. Users willing to commit to such contracts believe that the content will interest them over a long period (Laurent and Kapferer 1985). Moreover, when accessing the content is considered a virtue (versus a vice), users may prefer a long-term contract for precommitment reasons (Wertenbroch 1998). Finally, users may prefer long-term contracts for convenience reasons; that is, they can renew their subscriptions less often (Lambrecht and Skiera 2006). This factor appears to be especially powerful when someone else (e.g., the user's employer) is paying the bill. Given these reasons, price promotions should be less powerful in increasing new long-term contracts.

Instead, marketing communications may play a larger role in generating new long-term contracts. Among such actions, content-based Web sites spend most communication dollars to obtain a high ranking on search-engine sites, such as Google, Yahoo, and MSN, and invest in the optimization of a site so that Web users can find it during an Internet search (Telang, Boatwright, and Mukhopadhyay 2004).[5] Moreover, many sites employ targeted e-mails to free subscribers, with the intent of upselling them to paying services. In summary, we consider how moving from a free- to a restricted fee-based offering affects (1) the "advertising revenue" component of the online content provider, through free-user growth; (2) the "subscription revenue" component, through paid-user growth; and (3) the effectiveness of marketing actions to stimulate free- and paid-user growth.

Empirical Setting

Our data set covers a period of almost four years (June 14, 2001–March 27, 2005) with 1383 daily observations at an online content provider. Its site permits visitors to read articles that provide analysis and opinion on topics of interest to marketing professionals. Visitors register for free content by providing an e-mail address and choosing a password.[6]

[5]Other marketing communication tools are banners of various types on external sites, as well as the use of unsold inventory on the focal site.

[6]In principle, free users can be anybody who reads content for free. Unfortunately, we were not able to obtain the complete log files or to distinguish who in the existing log files were paid users. Moreover, we do not know the renewal rates of the paid sub-

The site was supported solely through advertising income until January 1, 2004, at which time a fee-based subscription business model was introduced in which paying subscribers received access to advanced articles and other services, such as a buyer's guide and the guarantee that they would see no third-party advertising.[7] Because advanced articles used to be free, this situation likely represented a loss of value to the free subscribers. Paying subscribers were given the option of either a monthly or a yearly fee, corresponding to our distinction between short-term and long-term contracts. Promotions on these fees were run periodically. Because the restriction of free content occurred on the same day as the charging of fees for accessing the restricted content (as is usual for content providers), we cannot separate these two effects. Instead, we refer to January 1, 2004, as the move from free to fee. Thus, our data capture a single "natural experiment," the analysis of which has a long tradition in the social sciences, including marketing (e.g., Ailawadi, Lehmann, and Neslin 2001; Neslin and Shoemaker 1983). For this proprietary data set, Table 1 displays summary statistics on the subscription and price series.

On average, 111 users each day register for free content, and this number is growing by approximately 5.5 per week (.185 a day). As for paid subscriptions, yearly contracts are more popular than monthly contracts, probably because the former presents a better deal for long-term use. Indeed, the regular monthly price is $4.95, whereas the regular yearly price is $49.95 throughout the sample, and several price promotions are run (in the model, we use these price promotions as variables because the charging of regular prices occurs at the same time as the move from free to fee). These prices are representative of the entire online content industry, for which the latest available figures indicate an average annual subscription fee of $49.69 in 2001 and $48.94 in 2002 (Online Publishers Association 2003).

As for the content provider's marketing efforts, we have data on two types: targeted communication through e-mails to current subscribers and mass-market communication yielding search-engine referrals. Targeted communication includes e-mail "blasts" sent to potential and current free subscribers, with the intention of upselling them to paid-subscription levels. Moreover, we have data on other e-mails sent to a certain number of subscribers, with a variety of news, including announcements of new services and events. In terms of mass-market communication, our data include the number of referral searches from all major search engines to the Web site.[8] This variable is not truly a marketing control variable but rather the outcome of consumer searches and a host of contributing management activities, such as search-engine optimization (which the company started about a year before the move), links from other sites, and a multitude of other promotion and advertising activities that a site engages in to increase its rankings. Given the absence of information on the timing and magnitude of each of these activities, search-engine referrals represent our best proxy measure. For these variables, Table 2 contrasts the average (daily) levels before and after the move from free to fee.

Search-engine referrals increase from 410 in the for-free period to 2921 in the for-fee period. Likewise, e-mails increase from 505 to 7085. In other words, both activities are higher in the period after the move from free to fee and during the for-fee period when virtually all blasts aiming to upgrade (potential) free subscribers to the paid service occur (the one blast in the for-free period occurred shortly before the move, and we do not include it in our analysis, because our series of paying subscriptions starts on January 1, 2004). Finally, we compare the average of daily new free subscriptions before and after the move; this number

scribers. Free users typically stay on (they are unlikely to remove themselves from the list) but often become less active over time. Therefore, the data provider communicated that new registrations of free and fee users were its primary performance criteria.

[7]This lack of advertising income from paid subscribers enables us to calculate the trade-off between free-subscriber loss and paid-subscriber gain. Other reasons to keep adding free subscribers (e.g., the creation and maintenance of critical mass for community building) are harder to quantify and are not considered in the analysis. Other content providers may make different decisions, such as continuing third-party advertising to paid subscribers. We leave the analysis of such scenarios for further research.

[8]The company does not engage in paid advertising, because it believes that natural search (i.e., through search-engine optimization) is the best way to attract people interested in the site. This appears to be typical for (smaller) online content providers, in contrast to several companies that sell physical products online.

TABLE 1
Descriptive Statistics of Daily New Subscriptions and Subscription Prices

	M	Mode	SD	Trend[a]
New free subscriptions	111	82	96.6	.185
New monthly subscriptions	2.06	1	3.24	.0125
New yearly subscriptions	5.55	3	6.85	.0181
Monthly subscription price	$4.94	$4.95	$.062	–.0001
Yearly subscription price	$48.0	$49.95	$5.30	–.0131

[a]Significant trend estimate when we control for daily seasonality, intercept, and autoregression (AR[1]).

TABLE 2
Comparison of Free- Versus Fee-Period Daily Subscriptions and Marketing Actions

	Free-Period Mean	Fee-Period Mean
Search-engine referrals	410.26	2921.32
Targeted e-mail offers	505.18	7084.83
Blasts to switch to fee	1 time	29 times
New free subscriptions	64.13	208.57

increased from 64 to 209. This growth is also evident from Figure 1, which displays the free subscription time series.

Apart from the positive trend, a key feature of the new subscription data is seasonality of two types: high frequency (day of week) and low frequency (year-end holiday). Pauwels and Dans (2001) observe similar patterns in daily data for online newspapers and offer several reasons. First, the Web site is dedicated to the marketing profession, so new users typically discover it during a workday, not the weekend or holidays. Second, Internet access is typically available at work but may not be available at home (especially in developing countries, from which our data provider attracts some subscribers). Note also that as in Table 2, Figure 1 does not show any easily recognizable harm of the move from free to fee (January 1, 2004) to new free subscriptions. It could be that no such harm occurred or that it is masked by the content provider's increased marketing efforts. Therefore, to address our research questions, we need to go beyond a before/after comparison and formulate a model that accounts for marketing actions.

Methodology

In light of our research questions and data, our choice of methodology is driven by four main considerations. First, the model should control for trend and seasonality patterns, and it must provide a forecasted, expected baseline for each performance variable so that we can capture the impact of unexpected events (e.g., the move from free to fee) as deviations from this baseline (Abraham and Lodish 1987). Second, the model should be robust to deviations from stationarity, which can lead to spurious regression problems (Granger and Newbold 1986).[9] Third, the model should provide a flexible treatment of both short-term and long-term effects of marketing actions on performance (Dekimpe and Hanssens 1999). Fourth, the model should allow for various dynamic interactions among performance variables (e.g., the likely interaction between new free and paid subscriptions), among marketing variables (e.g., a likely increase in marketing communication each time a fee price is promoted), and between marketing and performance variables (e.g., a decrease in new free subscriptions induces the content provider to send more e-mails).[10]

In summary, our model should account for the time-series properties of performance and marketing variables and for their dynamic interactions. The persistence modeling framework (Dekimpe and Hanssens 2004) addresses these four criteria in several methodological steps, which we summarize and extend (with robustness checks) in Table 3.

Permanent Versus Temporary Change: Unit Root and Cointegration Tests

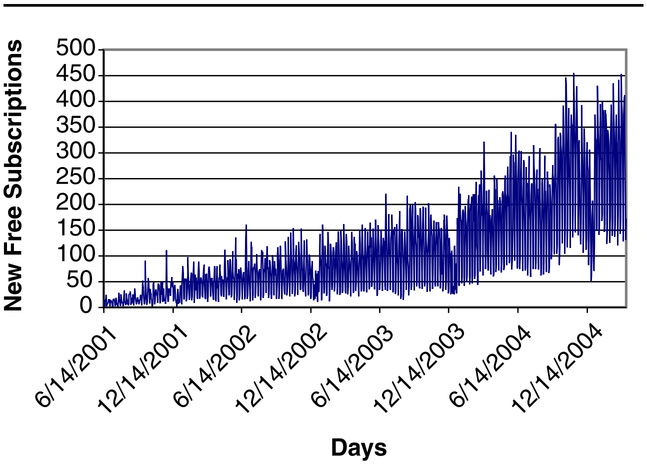
Unit root tests verify the univariate time-series properties (stationarity versus evolution) for each variable. The substantive question they address is whether our performance variables (new subscriptions) are mean reverting (stationarity) or have changed permanently in the data sample (evolution). We use both the augmented Dickey–Fuller test procedure (see Enders 2003) and the KPSS test (Kwiatkowski et al. 1992). The former maintains evolution as the null hypothesis (and is the most popular in marketing applications), and the latter maintains stationarity as the null hypothesis. Each test is estimated in two forms: with and without a deterministic time trend. Convergent conclusions of these different tests yield greater confidence in our variable classification (Maddala and Kim 1998). Next, we examine the robustness of our unit root test conclusion to structural breaks (Perron 1989, 1990) because the move from free to fee is an obvious choice for such a break point. Finally, Johansen, Mosconi, and Nielsen's (2000) cointegration test verifies whether any combination of evolving variables is in long-term equilibrium, allowing for structural breaks in these variables.

Modeling Dynamic Interactions: Vector-Autoregressive Models

Next, we specify vector-autoregressive (VARX) models that are well suited to measuring the dynamic performance response and interactions between performance and marketing variables (Dekimpe and Hanssens 1999). Both performance variables and marketing actions are endogenous; that is, they are explained by their own past and the past of the other endogenous variables. Specifically, VARX models not

[9]Stationary variables fluctuate as temporary deviations around a fixed mean or trend. Evolving variables have a unit root; that is, they fluctuate without reversion to a fixed mean or trend. For technical definitions and applications in marketing, see Dekimpe and Hanssens (1999) and Pauwels and colleagues (2004).

FIGURE 1
Daily Data for New Free Subscriptions



[10]We note that the restricted and free content varies over time as new (restricted and free) articles are added to the site. Therefore, at any given day, the perceived consumer benefits of a free subscription versus a paid subscription likely depend on the perceived value of the restricted versus free content. In other words, we expect that there is a negative correlation between free subscriptions and paid subscriptions, which logically leads to a dynamic system model, such as a VARX model or the simultaneous equation system we estimate.

TABLE 3
Overview of Methodological Steps

Methodological Step	Relevant Literature	Research Question
1. **Unit Root and Cointegration Tests**		
Augmented Dickey–Fuller test	Enders (2003)	Are variables stationary or evolving?
KPSS test	Maddala and Kim (1998)	Are the unit root results robust to null hypothesis?
Perron test	Perron (1989, 1990)	Are the unit root results robust to structural breaks?
Cointegration test	Johansen, Mosconi, and Nielsen (2000)	Are evolving variables in long-term equilibrium?
2. **Model of Dynamic Interactions**		
VARX model	Pauwels, Hanssens, and Siddarth (2002) Pauwels et al. (2004)	How do sales and marketing variables interact in the long run and the short run, when the unit root and cointegration results are taken into account?
VARX in differences	Dekimpe and Hanssens (1999)	
Vector error correction model	Dekimpe and Hanssens (2004)	
3. **Policy Simulation Analysis**		
Impulse-response function	Dekimpe and Hanssens (1999)	What is the dynamic (performance) response to a (marketing) impulse?
Generalized impulse response	Pesaran and Shin (1998)	What is the immediate effect of an impulse, without imposing a causal ordering?
Long-term marketing effect	Dekimpe and Hanssens (2004)	What is the long-term impact of a marketing impulse on performance?
4. **Robustness Checks**		
Bootstrapping model parameters	Bradley and Tibshirani (1993)	How stable are the model parameters?
Estimation of regression and simultaneous equation model	Zellner and Theil (1962)	Do the VARX models outperform simpler models with dynamic marketing effects on performance?

only measure short-term and long-term response to marketing actions but also capture the performance implications of complex feedback loops.

Vector-autoregressive models are specified in levels or differences (d) of each endogenous variable, depending on the results of its unit root tests. Model specification requires two remaining choices: determining the number of lags K, also known as the order of the model, and determining which variables to include as endogenous. We base the former on the Bayesian information criterion, which is a consistent estimator of lag length (Lütkepohl 1993), and test whether we should add lags to pass diagnostic tests on residual autocorrelation (Franses 2005). Regarding the latter, we include all variables as endogenous for which Granger-causality tests reveal that they are caused by another variable in the system (Enders 2003). The remaining variables (in our case, only the move from free to fee) are included as exogenous variables, with as many lags as indicated by residual tests.[11] Finally, as control variables (the vector C), we include an intercept, six day-of-week seasonal dummies (in which Friday is the benchmark), a dummy for the year-end holidays, and a time trend to capture external factors (to the extent possible), such as growth in Internet access, growth in people with high-speed bandwidth, and general increases in content and content providers.

Given the nature of our data and research focus, we must be careful which data periods to analyze. There were no paying subscribers before January 1, 2004, and the regular price jump from zero to the regular (monthly and yearly) prices is likely to have had a different impact than the subsequent price promotions off the regular price. Therefore, we specify two different models.

Model 1. For the full data period, Model 1 includes new free subscriptions, both marketing efforts (e-mails and blasts), and search-engine referrals. The impact of the move from free to fee on free subscriptions manifests in two ways: (1) The pulse variable "move" (taking on a value of 1 at the time of the move from free to fee) measures the direct effect on the subscription series, and (2) the step variable "fee" (0 in the for-free period and 1 in the fee-and-free period) interacts with search-engine referrals and e-mail to assess how their effectiveness differs after the move.[12] All

[11]All Granger-causality tests with lags of up to 120 indicate that new free subscribers do not cause the move from free to fee. As a robustness check, we included the move from free to fee as an endogenous variable, and indeed we found no difference in our substantive results.

[12]We do not need to interact blasts with fee, because blasts are logically related to the fee period (see the "Empirical Setting" section).

variables may have an immediate (same-day) or a lagged effect. Equation 3 presents the model:

$$
(3)\quad \begin{bmatrix} dFsub_t \\ dSearch_t \\ E\text{-}mail_t \\ Blast_t \\ Search \times Fee_t \\ E\text{-}mail \times Fee_t \end{bmatrix} = C_1 + \sum_{k=1}^{K} B_k \times \begin{bmatrix} dFsub_{t-k} \\ dSearch_{t-k} \\ E\text{-}mail_{t-k} \\ Blast_{t-k} \\ Search \times Fee_{t-k} \\ E\text{-}mail \times Fee_{t-k} \end{bmatrix} + \sum_{j=0}^{J} \Gamma_j \times \begin{bmatrix} Move_{t-j} \\ Move_{t-j} \\ Move_{t-j} \\ Move_{t-j} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} u_{Fsub,t} \\ u_{Search,t} \\ u_{E\text{-}mail,t} \\ u_{Blast,t} \\ u_{S \times F,t} \\ u_{E \times F,t} \end{bmatrix},
$$

where Fsub is the number of new free subscriptions, Search is the number of search-engine referrals, E-mail is the number of general e-mails sent, Blast is the presence of free-to-fee conversion e-mails, C is the (6×1) vector of control variables, K is the order of the model, B_k and Γ_j are the (6×6) and (6×1) vectors of dynamic coefficients, J is the maximum of lags selected for the effect of move on each endogenous variable, and $(u_{Fsub,t}, \ldots, u_{E \times F,t})' \sim N(0, \Sigma_u)$. We estimate this model in units (instead of logarithms) to obtain a managerially relevant decomposition of the effects of interest (Van Heerde, Gupta, and Wittink 2003).

Model 2. For the for-fee period starting January 1, 2004, Model 2 includes new free subscriptions and all three marketing efforts (e-mails, search, and blasts) and adds new subscriptions for the monthly (Msub) and yearly (Ysub) contracts. Moreover, instead of the regular prices (which are constant throughout the for-fee period), we include price promotions (dollars off) for monthly (Mprom) and yearly (Yprom) contracts:

$$
(4)\quad \begin{bmatrix} dFsub_t \\ dMsub_t \\ dYsub_t \\ dSearch_t \\ E\text{-}mail_t \\ Blast_t \\ Mprom_t \\ Yprom_t \end{bmatrix} = C_2 + \sum_{k=1}^{K} B_k \times \begin{bmatrix} dFsub_{t-k} \\ dMsub_{t-k} \\ dYsub_{t-k} \\ dSearch_{t-k} \\ E\text{-}mail_{t-k} \\ Blast_{t-k} \\ Mprom_{t-k} \\ Yprom_{t-k} \end{bmatrix} + \begin{bmatrix} u_{Fsub,t} \\ u_{Msub,t} \\ u_{Ysub,t} \\ u_{Search,t} \\ u_{E\text{-}mail,t} \\ u_{Blast,t} \\ u_{Mprom,t} \\ u_{Yprom,t} \end{bmatrix},
$$

where Fsub is the number of new free subscriptions, Msub is the number of new monthly contract subscriptions, Ysub is the number of new yearly contract subscriptions, Search is the number of search-engine referrals, E-mail is the number of general e-mails sent, Blast is the presence of free-to-fee conversion e-mails, Mprom is the dollar amount of a price promotion on the monthly subscription price, Yprom is the dollar amount of a price promotion on the yearly subscription price, C is the (8×1) vector of control variables, K is the order of the model, B_k is the (8×8) vector of dynamic coefficients, and $(u_{Fsub,t}, \ldots, u_{Yprom,t})' \sim N(0, \Sigma_u)$. We estimate Equation 4 both in units and in logarithms. The former yields a managerially relevant assessment of marketing effectiveness, and the latter directly yields unit-free elasticities (Pauwels, Hanssens, and Siddarth 2002), which allow for the comparison of percentage gains of marketing communication and price promotions for monthly versus annual contracts.

Long-Term Impact of Marketing Actions: Impulse-Response Functions

A VARX model estimates the baseline of each endogenous variable and forecasts its future values on the basis of the dynamic interactions of all jointly endogenous variables. Based on the VARX coefficients, impulse-response functions track the over-time impact of unexpected changes (shocks) to the marketing variables on forecast deviations from baseline for the other endogenous variables.

To derive the impulse-response functions of a marketing action, we compute two forecasts, one based on the information set without the marketing action and the other based on the extended information set that accounts for the marketing action. The difference between these forecasts measures the incremental effect of the marketing action. These dynamic effects are not a priori restricted in time, sign, or magnitude. As for the immediate (same-day) effects, we adopt the generalized, simultaneous-shocking approach (Pesaran and Shin 1998), which uses information in the residual variance–covariance matrix of the VARX model rather than requiring the researcher to impose a causal ordering among the endogenous variables (Dekimpe and Hanssens 1999). Finally, we follow established practice in marketing research and assess the statistical significance of each impulse-response value by applying a one-standard-error band, as Pesaran, Pierse, and Lee (1993) and Sims and Zha (1999) recommend. Our interpretation of the estimated effects focuses on the immediate (same-day) effect and the permanent effect (i.e., the value at which the impulse-response function stabilizes). These numbers operationalize, respectively, the short-term and the long-term effects of variables on the subscription series. Finally, we compare the long-term effects on the basis of the significance tests for the difference in impulse-response functions, as Pauwels (2004) outlines. In particular, two impulse-response functions are considered significantly different if their long-term effect is significantly different (using the standard error of the accumulated response function, based on the joint distribution of the individual period's standard errors, as detailed in Lütkepohl [1993, Chap. 3.7]).

Results

Unit Root Tests and VARX Model Fit Assessment

The unit root tests (Table 4) reveal evolution in all three subscription variables and in search-engine referrals (even after we allow for a structural break at the time of the move) but reveal stationarity for e-mails, blasts, monthly contract, and yearly contract price promotions. Because no combination of evolving variables shows evidence of cointegration, we proceed by estimating our models with the three sub-

TABLE 4
Summary of the Unit Root Test Results

	Augmented Dickey–Fuller Test Without Trend	KPSS Test Without Trend	Augmented Dickey–Fuller Test with Trend	KPSS Test with Trend
Free subscriptions	*–.23*	*4.02*	*–2.87*	*.67*
Monthly contract subscriptions	*–1.20*	*2.73*	*–3.18*	*.19*
Yearly contract subscriptions	*–3.10*	*1.33*	–4.10	*.19*
Search-engine referrals	*–.38*	*3.88*	*–2.58*	*.87*
E-mails	–6.24	.42	–33.93	.06
Blasts	–22.47	.32	–22.56	.05
Monthly contract price promotion	–5.04	.33	–5.27	.08
Yearly contract price promotion	–4.88	.37	–6.68	.12

Notes: Number in italics indicate that the series is classified as evolving.

scription variables and search-engine referrals in differences. Significant marketing effects on performance difference (or "growth") imply that the action has permanently changed the performance level (Dekimpe and Hanssens 1999; Pauwels et al. 2004).

Both estimated VARX models have significant F-statistics for overall model fit (95.5 and 14.65, respectively). Moreover, they adequately explain the performance series. The adjusted R-squares for new free-subscription growth are .832 for Model 1 and .865 for Model 2; for new monthly and yearly subscription growth, the adjusted R-squares are, respectively, .597 and .683 (Model 2). Likewise, growth in search-engine referrals follows predictable patterns. The explanatory power for the marketing action variables is logically lower (between .12 and .28), indicating that they are mostly unexpected "shocks" to the system and, thus, plausibly unexpected to customers as well. Finally, both models pass the diagnostic tests (Franses 2005) for residual correlation (the Durbin–Watson test and Lagrange-multiplier tests), residual normality (the Jarque–Bera test), and heteroskedasticity (the White test).

Short-Term and Long-Term Marketing Effects on New Subscriptions

Estimation of the impulse-response functions reveals that all dynamic effects stabilize within a week, as Figures 2–4 illustrate for the main driver affecting each of the three new subscription series.[13] The impact of search-engine referrals on new free subscriptions is significant in the first day, peaks in the second, and then settles into a significant long-term effect (Figure 2). In contrast, monthly contract price promotions have their greatest impact right away on new monthly contract subscriptions and then show a postpromotion dip before stabilizing at a significant, positive long-term level (Figure 3). In comparison, the effect of yearly contract price promotions on new yearly contract subscriptions is much smaller in magnitude. However, a small post-promotion dip is offset by positive dynamic effects, causing the long-term effect to exceed the short-term effect. Plausibly, yearly contract subscribers are not as price sensitive as

[13]Because all subscriber series enter the model in differences, we calculate and display the accumulated impulse-response functions to obtain the marketing effects on the levels of each subscriber series.

FIGURE 2
Impulse-Response Function of New Free Subscriptions to Search-Engine Referrals

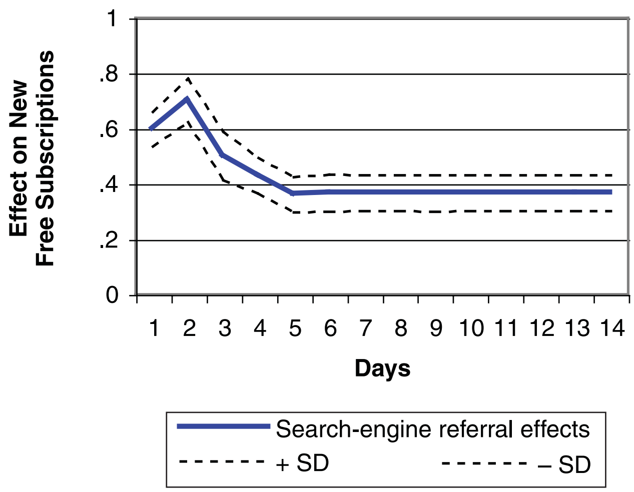


FIGURE 3
Impulse-Response Function of Monthly Contract New Subscriptions to Monthly Contract Price Promotions

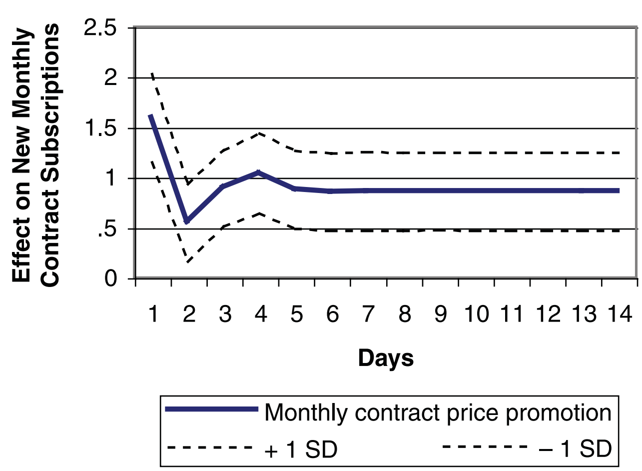
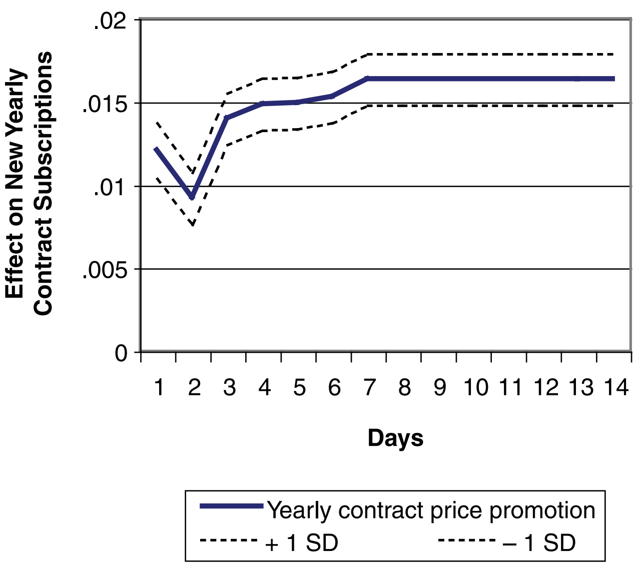


FIGURE 4
Impulse-Response Function of Yearly Contract New Subscriptions to Yearly Contract Price Promotions



monthly contract subscribers, and the promotion mostly acts as a salient attention grabber, which leads several people to sign up a few days afterward. Tables 5–6 present the full results on short- and long-term marketing effects.

Table 5 displays the unit effects of potential drivers on new free subscriptions. Both search-engine referrals and e-mails have a positive effect on new free subscriptions. However, the move from free to fee reduces the growth in free subscriptions compared with the baseline forecast. This reduction is relatively substantial; the daily number of new free subscriptions is 208 fewer in the for-fee period than it would have been had the company not started charging for content.

Moreover, the move from free to fee reduces marketing communication effectiveness. Both search-engine referrals and e-mails have lower long-term effects on new free subscriptions: 6% (–.029/.453) and 21% (–.525/2.466) fewer than before the move. We can multiply this loss in marketing communication effectiveness by the average marketing communication levels in Table 2 to conclude that the company lost 79 daily free subscriptions through the search-engine referral effect and 4 daily free subscriptions through the e-mail effect.

Finally, there is a notable twist in the effect of blasts on new free subscriptions. The short-term effect is positive, indicating a possible complementarity effect; namely, the general e-mail blasts may further raise awareness for the free site and induce free customers to recommend the site to friends and colleagues. In the long run, however, the substitution effect dominates; the blast reduces free-subscriber growth, probably because it convinces potential free subscribers to become paid subscribers instead. Indeed, Table 6 shows that blasts increase both monthly contract and yearly contract subscriptions (we provide a closer examination of this trade-off subsequently).

The marketing communication and promotion effects in Table 6 show the expected signs, including some cannibalization of monthly subscriptions through promotions on the

TABLE 5
Short-Term and Long-Term Effects of Marketing Actions on New Free Subscriptions

	VARX Model 1		VARX Model 2	
	Short-Term	Long-Term	Short-Term	Long-Term
Search engine	.866	.453	.597	.366
Search engine × fee	–.016	–.029		
E-mails (× 1000)	5.244	2.466	4.853	1.489
E-mails (× 1000) × fee	–.272	–.525		
Blast	60.742	–25.917	77.151	–38.831
Move from free to fee	–48.901	–208.059		
Monthly price promotion			–4.358	–7.684
Yearly price promotion			.000	–.999

TABLE 6
Short-Term and Long-Term Effects of Marketing Actions on New Paid Subscriptions

	Monthly Contract Subscriptions		Yearly Contract Subscriptions	
	Short-Term	Long-Term	Short-Term	Long-Term
Search engine	0	.001	0	.004
E-mails (× 1000)	0	.055	.252	.119
Blast	.194	.173	1.092	1.745
Monthly price promotion	1.589	.858	0	0
Yearly price promotion	0	–.003	.012	.016

Notes: All nonzero effects are significant; nonsignificant effects are displayed as 0.

yearly contract's price. Notably, monthly price promotions have a stronger long-term unit effect on monthly subscriptions than yearly price promotions have on yearly subscriptions. As for communication efforts, all three variables have a greater long-term unit impact on new yearly subscriptions than on new monthly subscriptions. E-mails are twice as effective in stimulating yearly versus monthly subscriptions, and search-engine referrals are three times as effective in generating new yearly versus monthly subscriptions. Finally, general e-mail blasts (designed to induce free subscribers to upgrade) are ten times more effective for stimulating yearly contracts than for stimulating monthly contracts. These long-term effect differences are significant at the 1% level.

Table 7 shows the estimated marketing elasticities based on the log-log version of Equation 4. Although we have no such comparison benchmark for the other marketing actions, the promotional elasticity for monthly contracts is in the range reported for sales of fast-moving consumer goods (e.g., Pauwels 2004, 2007), and the promotional elasticity for the yearly contracts is in the range reported for newspaper subscriptions (Lewis 1995) and access to telecommunications services (Danaher 2002). We observe the same relative pattern as that in Table 6; namely, price promotions have a greater long-term elasticity for monthly contracts, and marketing communication efforts have a greater long-term elasticity for yearly contracts (elasticity differences are significant at the 5% level). However, the magnitude of the difference is less outspoken because yearly contracts have a higher baseline than monthly contracts. Despite the inelastic demand for the yearly contract, it receives most of the promotional activity. This may indicate that management overestimates the price elasticity of such subscriptions, as many scholars report for the printed newspaper industry (Lewis 1995).

Robustness Checks

We assess the robustness of our substantive results in two ways. First, we investigate the parameter stability of the VARX models by bootstrapping. We draw a sample with replacement 250 times and estimate the model on each sample. A comparison of the original estimates and the distribution of the bootstrap estimates reveals that all substantive results hold. For each significant effect in the original analysis, we observe that the 90% range of the bootstrapped estimates excludes 0 (detailed results are available on request). Thus, there is no cause for concern regarding the stability of the parameters of interest, because the results are consistent with the information in the original coefficient estimates and their standard errors.

Second, we estimate a regression model explaining dFsub that corresponds to the VARX model in Equation 3 and a simultaneous equation system that corresponds to the VARX model in Equation 4, which we display in Equation 5:

$$
\begin{aligned}
(5)\quad \mathrm{dFsub}_t = {} & C_{\mathrm{Fsub},t} + \sum_{k=1}^{K} \delta_F^k \times \mathrm{dFsub}_{t-k} \\
& + \sum_{l=0}^{L} \gamma_1^l \times \mathrm{dMsub}_{t-l} + \sum_{m=0}^{M} \gamma_2^m \times \mathrm{dYsub}_{t-l} \\
& + \sum_{n=0}^{N} \beta_1^n \times \mathrm{dSearch}_{t-n} + \sum_{p=0}^{P} \beta_2^p \times \text{E-mail}_{t-p} \\
& + \sum_{q=0}^{Q} \beta_3^q \times \mathrm{Blast}_{t-q} + \sum_{r=0}^{R} \beta_4^r \times \mathrm{Mprom}_{t-r} \\
& + \sum_{v=0}^{V} \beta_5^v \times \mathrm{Yprom}_{t-v} + u_{\mathrm{Fsub},t}
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{dMsub}_t = {} & C_{\mathrm{Msub},t} + \sum_{k=1}^{K} \delta_M^k \times \mathrm{dMsub}_{t-k} \\
& + \sum_{l=0}^{L} \gamma_3^l \times \mathrm{dFsub}_{t-l} + \sum_{m=0}^{M} \gamma_4^m \times \mathrm{dYsub}_{t-l} \\
& + \sum_{n=0}^{N} \beta_6^n \times \mathrm{dSearch}_{t-n} + \sum_{p=0}^{P} \beta_7^p \times \text{E-mail}_{t-p} \\
& + \sum_{q=0}^{Q} \beta_8^q \times \mathrm{Blast}_{t-q} + \sum_{r=0}^{R} \beta_9^r \times \mathrm{Mprom}_{t-r} \\
& + \sum_{v=0}^{V} \beta_{10}^v \times \mathrm{Yprom}_{t-v} \\
& + u_{\mathrm{Msub},t}
\end{aligned}
$$

TABLE 7
Marketing Elasticity of New Paid Subscriptions (Log-Log Model)

	Monthly Contract Subscriptions		Yearly Contract Subscriptions	
	Short-Term	**Long-Term**	**Short-Term**	**Long-Term**
Search engine	0	1.42	0	2.11
E-mails	0	.19	.32	.32
Blast	.01	.01	.01	.02
Monthly price promotion	3.86	2.09	0	0
Yearly price promotion	0	–.01	.11	.14

Notes: All nonzero effects are significant; nonsignificant effects are displayed as 0.

$$
\begin{aligned}
dYsub_t = {} & C_{Ysub,t} + \sum_{k=1}^{K} \delta_Y^k \times dYsub_{t-k} \\
& + \sum_{l=0}^{L} \gamma_5^l \times dFsub_{t-l} + \sum_{m=0}^{M} \gamma_6^m \times dMsub_{t-l} \\
& + \sum_{n=0}^{N} \beta_{11}^n \times dSearch_{t-n} + \sum_{p=0}^{P} \beta_{12}^p \times E\text{-}mail_{t-p} \\
& + \sum_{q=0}^{Q} \beta_{13}^q \times Blast_{t-q} + \sum_{r=0}^{R} \beta_{14}^r \times Mprom_{t-r} \\
& + \sum_{v=0}^{V} \beta_{15}^v \times Yprom_{t-v} + u_{Ysub,t},
\end{aligned}
$$

where C stands for the deterministic terms (intercept, trend, and seasonality), all variables have the same interpretation as before, and the number of lagged terms (determined by a specification search) may differ for each variable and in each equation. We estimate this model with three-stage least squares, which accounts for the correlation of the right-hand-side variables with the error terms and for contemporaneous correlation and heteroskedasticity in the residuals (Zellner and Theil 1962), using lagged terms as instrumental variables.

Note that the model in Equation 5 controls for trend and seasonality patterns and for deviations from stationarity (variables are included in differences or levels, depending on the unit root test results). Moreover, it incorporates both immediate (short-term) and dynamic (long-term) effects of marketing actions on the subscription series and the possible relationship between free and paid subscriptions. However, it does not incorporate dynamic interactions among the marketing variables or dynamic effects of the subscription variables on the marketing actions ("performance feedback" in Dekimpe and Hanssens [1999]). Therefore, a comparison of model fit for Equations 3 and 4 indicates the extent to which such dynamic interactions help explain the data patterns. We compare both in-sample fit and forecasting accuracy (using the 2005 data as a holdout sample). Finally, a comparison of the model estimates for the common variables provides a robustness check of our substantive results.

Our estimation of the regression and simultaneous equation models yields significant F-statistics for overall fit for each model. We compare these models with the proposed VARX models using (1) in-sample explanatory power and (2) one-step-ahead forecast errors in the holdout sample. Table 8 shows that the VARX models have higher R-squares and adjusted R-squares and lower one-step-ahead root mean square errors than their corresponding equation, for each of the three subscription series in the simultaneous equation model.

Comparing the many model estimates with the corresponding VARX model (results are available on request), we observe a strong consistency in the substantive results (sign and significance) for both models, with an almost identical estimate for the immediate (short-term) effect. The major difference lies in the long-term effects; after the first lag, the effect estimates are virtually all nonsignificant in the alternative models. Plausibly, the VARX model captures performance feedback and other complex dynamic interactions, which have made it the model of choice in many recent studies that focus on long-term effects (for a review, see Dekimpe and Hanssens 2004).

In summary, the robustness checks reveal no reason to doubt the validity of our substantive results, though replication is needed to examine whether they apply to other content providers. We offer several suggestions to this end in the section "Conclusions and Avenues for Further Research."

Decomposing the Sources of Revenue Loss and Comparing Them with Revenue Gains

We assess managerial implications by decomposing the loss of free subscriptions into its sources (Equation 2) and by comparing the resultant loss of potential advertising revenue with paid-subscriber revenue (Equation 1). To this end, we compare the actual number of new free subscriptions with the expected number based on our VARX forecasts.

TABLE 8
Comparison of Fit Statistics for the Simultaneous and VARX Models: In-Sample Explanatory Power and Root Mean Square Forecast Error (RMSE) for Holdout Sample

	Regression Model		VARX Model 1	
	Adjusted R^2	RMSE	Adjusted R^2	RMSE
D(free subscriptions)	.774 (.771)	.628	.840 (.832)	.293
	Simultaneous Equation Model		**VARX Model 2**	
	Adjusted R^2	RMSE	Adjusted R^2	RMSE
D(free subscriptions)	.757 (.753)	.306	.886 (.865)	.272
D(monthly subscriptions)	.531 (.521)	5.924	.661 (.597)	3.653
D(yearly subscriptions)	.502 (.491)	6.631	.737 (.683)	4.557

We obtain the model-forecasted levels of new free subscriptions in the absence of the move from free to fee. This average daily number is 1147 higher than in the for-free period because of the large increase in search-engine referrals and e-mails (Table 2). Because the actual daily number is only 144 higher, we attempt to explain the loss of 1003 free subscriptions a day. Our VARX model estimates reveal the following three drivers:

1. The move from free to fee itself (i.e., the combination of restricting free content and charging for content) accounts for 208 lost subscriptions a day.
2. The decrease in marketing communication effectiveness (search-engine referrals and e-mails) accounts for 71 fewer free subscriptions a day.
3. The blasts in the for-fee period decrease new free subscriptions by 752.

The total estimated loss from our model is 1031, which differs from the raw data loss of 1003 by only 28 (i.e., approximately 3%).

The relative magnitude of the first two revenue loss sources seems intuitive; that is, the reduction in marketing effectiveness matters but not nearly as much as the move from free to fee itself (i.e., the restriction of valuable content that used to be free). The impact of blasts is more surprising, but it makes sense when considered in combination with the gain in new paying subscription numbers. Indeed, although all 29 blasts together decrease new free subscriptions by 752, they increase new monthly contract and yearly contract subscriptions by 5 and 51, respectively. The relevant question then becomes which of the blasts' effects yields the highest monetary impact. In general, we need information on the advertising income generated by free users to compare their revenue contribution with that of the for-fee subscribers.

The content provider gave us its best estimates of how much advertising revenue increases for every 1000 new free subscriptions. This revenue is based almost exclusively on the advertising e-mails sent to the free subscribers; other forms of advertising derive much lower revenues. This additional revenue for an extra free subscriber is $1.63 a year, or $.0045 a day.[14] From Table 1, we know that the comparable revenue numbers are $48 for yearly contract subscribers and $4.94 for monthly subscribers (a conservative estimate, assuming that they do not renew, in which case they are worth up to 12 times more, or $59.28 a year). These paying subscribers are not exposed to e-mail advertising and thus yield only their fee in revenues. We use this number to calculate the net revenue impact of blasts and of the move from free to fee.

The blasts generate $2,454 in paying-subscriber revenue, which is double the total loss of $1,224 in free-subscriber advertising revenue. Overall, the move from free to fee yields a daily revenue loss of $4.64 (1031 × $.0045), which is more than offset by the daily average revenue of $277 (2.06 × $4.94 + 5.55 × $48) from paying subscribers. In other words, the move from free to fee is profitable for this firm; the resultant subscriber revenue is higher than the loss in advertising revenue.

Timing of the Move from Free to Fee

Although we focus on analyzing the consequences of the move from free to fee, its antecedents may also be of interest to managers contemplating such a move. In particular, it seems intuitive to wait until the free site becomes more popular, a sign that consumers have come to realize its value. We test for this intuition in several ways. First, Granger-causality tests determine whether the move can be attributed to daily changes in (new free) subscriptions. Second, the move's timing could also be influenced by trends in subscriptions.[15] Indeed, recent research offers conceptual and empirical support for the importance of such "performance regimes" (Pauwels and Hanssens 2007), operationalized as rolling-window estimates of either the deterministic trend (ibid.) or the stochastic trend in performance (Bronnenberg, Mahajan, and Vanhonacker 2000; Pauwels 2001).

A deterministic trend implies that the series steadily moves in a certain direction. A significant, positive trend represents growth, and a significant, negative trend represents decline. We test for the trend's significance in a rolling-window test that decomposes the performance series into constant, trend, and seasonal fluctuations, as depicted in Equation 6:

$$y_t = c + \delta t + \sum_{j=2}^{7} \lambda_j DoW_j + \gamma Holiday + \rho y_{t-1} + \varepsilon_t, \tag{6}$$

where t represents the deterministic time trend, DoW are the six day-of-week dummies (Friday is the benchmark) (this captures high-frequency noise), Holiday is the dummy variable for end-of-year holidays (this captures low-frequency noise), and y_{t-1} is the lagged dependent variable to capture autoregressive behavior (as indicated by the Durbin–Watson statistic). We estimate Equation 6 in rolling windows of 365 daily observations.[16] This rolling-window analysis (Leeflang et al. 2000; Swanson and White 1997) uses a data sample of fixed size, which allows for direct comparisons between the estimates in different windows. On the basis of these rolling-window tests, Pauwels and Hanssens (2007) classify performance regimes along two dimensions: the performance trend sign (up, nonsignificant, or down) and the change in this trend (accelerating or decelerating). Ranked according to managerial desirability, these

[14]To assess the generalizability of this yearly advertising revenue estimate for a free user, we obtained price quotes from several community Web sites. The average monthly number of pages viewed on a community site by unique visitors is approximately 130. Our observation across these Web sites reveals that the average page carries about two to three advertisements. As a result, the range of yearly advertising revenue from the average (free) user is ($1.25, $1.87), which contains our company's estimate of $1.63.

[15]We thank an anonymous reviewer for this suggestion.

[16]We chose 365 observations for several reasons: (1) This number covers a full year, which enables us to account consistently for seasonality in each window (Pauwels and Hanssens 2007); (2) it represents a sufficiently large sample for each individual window estimation; and (3) it is not so large as to prevent us from picking up transition points around the move from free to fee. Sensitivity analysis reveals that our empirical results hold for windows, varying from 182 to 548 observations (i.e., 6–18 months).

regimes are called "accelerating growth" (upward trend with accelerating trend change), "saturating growth" (upward trend with decelerating trend change), "improving stability," "lessening stability," "decline turnaround," and "deteriorating decline."

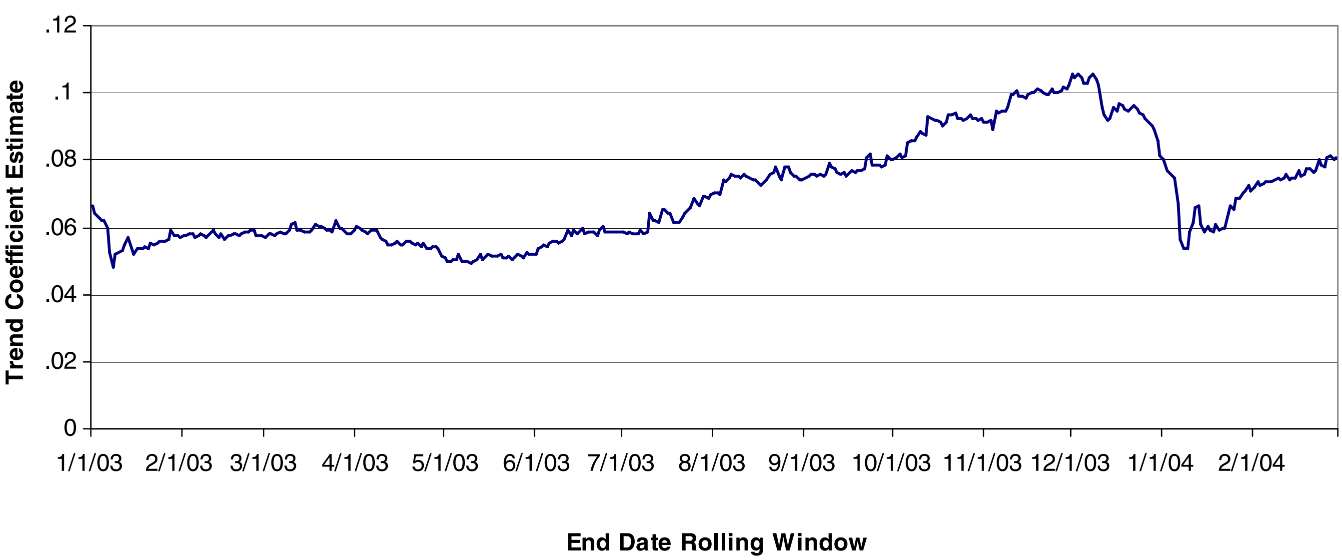
The interpretation of a stochastic trend (evolution) and its absence (stationarity) deserves further explanation. Stationarity, or mean reversion, implies that all observed fluctuations are temporary deviations from deterministic components, which may include mean, trend, and seasonal cycles (as in Equation 6). Thus, if an unexpectedly large number of people sign up today, we would not change our expectation of the number of new subscribers tomorrow. In contrast, evolution implies that no mean reversion occurs; that is, the performance series may wander widely apart from any previously held position. Therefore, if a large number of people sign up today, this "shock" substantially changes our expectation of the number of people who will sign up tomorrow. In the case of such positive evolution, the performance series has momentum (i.e., better performance today generates better performance tomorrow). The augmented Dickey–Fuller test investigates the presence of a stochastic trend as follows:

$$(7)\quad \Delta y_t = \gamma y_{t-1} + \delta t + \alpha + \sum_{i=1}^{p} + \beta_i dy_{t-i} + \sum_{j=2}^{7} \lambda_j DoW_j + \gamma Holiday + \varepsilon_t,$$

where dy_t is the first difference of the series and the number of lags, p, selected by the Bayesian information criterion (Hamilton 1994). We add the deterministic time trend to isolate the stochastic trend (Enders 2003), and the seasonal dummies provide good size estimates of the Dickey–Fuller test in seasonal series (Ghysels, Lee, and Noh 1994). The coefficient of interest is γ; the t-statistic testing $\gamma = 0$ is the Dickey–Fuller test for a unit root (evolution) against a trend-stationary alternative. The critical value for this test specification at the 5% significance level is –3.41; t-statistics below this value indicate trend stationarity, and t-statistics above this value indicate evolution. Again, we estimate Equation 6 in rolling windows of 365 daily observations to investigate the stochastic trend across periods and relate it to the timing of the move from free to fee.

The results of our timing analysis are informative. Granger-causality tests provided no evidence that the move from free to fee was caused by daily changes in new free subscriptions, so we proceed with our analysis of trends in new free subscriptions. Figure 5 shows the rolling-window test result for the deterministic trend coefficient, focusing on the period before and right after the move from free to fee (January 1, 2004). Throughout 2003, new free subscriptions grew (positive trend) and showed accelerated growth in fall 2003. However, there was a decline of the deterministic trend estimate in December 2003, representing the saturating-growth regime in the work of Pauwels and Hanssens (2007). Consistent with literature (e.g., Pauwels and Hanssens 2007; Schendel, Patton, and Riggs 1976), management makes a major change (the move from free to fee) when the deterministic trend estimate is declining (i.e., when the growth prospects from the traditional advertising income model are diminishing). Further tests confirm that the move from free to fee is affected by the rolling-window trend estimate and that the effect is negative (i.e., the trend decline significantly influences the move from free to fee). Afterward, we observe a further dip in the trend estimate, reflecting the loss of (potential) free subscriptions quantified in our VARX analysis.

FIGURE 5
Rolling-Window t-Statistic of Deterministic Trend of New Free Subscriptions



Notes: The trend coefficient is significantly different from zero in each rolling window.

FIGURE 6
Rolling-Window t-Statistic of Stochastic Trend of New Free Subscriptions

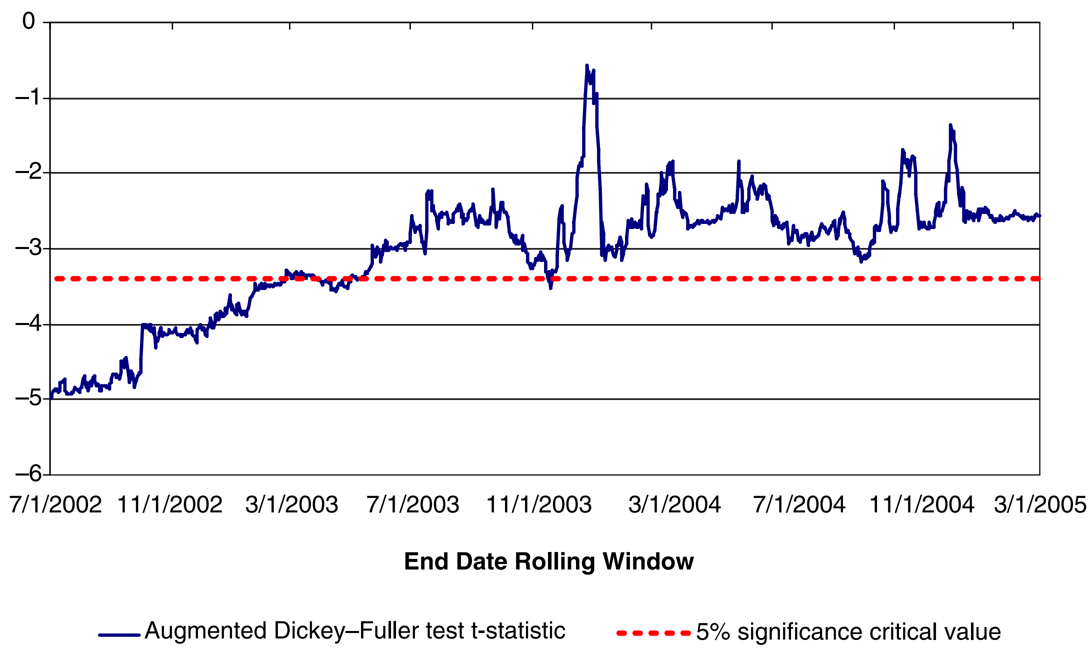


Figure 6 shows the rolling-window test results for the stochastic trend t-statistic. The stochastic trend analysis both confirms the deterministic trend assessment and highlights another aspect of the move's timing. First, the stochastic trend's t-statistic also declines in December 2003, the month before the move from free to fee. As a result, new free subscriptions are losing their classification as an evolving series and, thus, the ability to benefit permanently from a temporary subscription boost. Such change has been observed for the growth in online news consumers in Spain, marking the stabilization of consumer penetration and, thus, the need to tap other sources of growth for firms (Pauwels 2001). The move from free to fee (January 1, 2004) shows up as a return to the unit root classification because it represents a structural break in the series. Second, in contrast to previous work on growing brands (Bronnenberg, Mahajan, and Vanhonacker 2000), we do not observe a positive evolution from the start of our data set. Instead, new free subscriptions are initially classified as stationary, which changes only in spring 2003. Thus, it appears that the performance series gained "momentum" (ibid.) before management decided to move from free to fee. This influx of new free subscriptions increases the consumer value of joining the site, which enables (free and paid) users to exploit the joint expertise of the full installed base. This may be an important reason for the revenue success of the move for this particular company. It succeeded in first creating (in spring 2003) and then monetizing the positive evolution in new free subscriptions. We speculate that the paid-subscriber gains are lower and the free-subscriber losses are higher for companies that attempt to make the move before the momentum in free subscriptions has materialized. Evidently, data on such companies are needed to provide empirical evidence in this regard.

Conclusions and Avenues for Further Research

This research aims to contribute to filling an important gap in empirical research. When companies decide to move from free to fee, what is the role of marketing actions in the free- and fee-user response, and what sources of revenue loss might offset the paid subscription revenue gains? Although this trade-off is prevalent for online content, it is also likely relevant for many other marketing contexts in which users become accustomed to enjoying a product or service for free. Our analysis points specifically to the nature of the trade-offs firms face. Moving from free to fee has consequences for a firm's advertising revenues from free subscribers. The empirical results show that the move itself (plausibly through restriction of free content) slows down the growth of free users directly and reduces the effectiveness of marketing communications in generating new free users. Our content provider expected the former but not the latter, which is not readily revealed by inspection of the raw data, even after the move. In our empirical application, the revenue loss appeared minor: approximately 2% of the paid-subscriber revenue. Notably, the majority of this loss was due to the targeted e-mail blasts by the content provider aimed at convincing potential subscribers to commit to paid contracts. It appears that "content should be free" is still a powerful slogan on the Web; whereas some companies are trying to get surfers used to paying for content, other services, such as Congoo.com, are actively encouraging them to get beyond the "pay wall."

With subscription fees becoming the major revenue component for online content, the power of marketing actions to stimulate paid subscriptions is critical. Various marketing actions stimulate potential users to adopt specific pricing formats. In particular, price promotions are more effective in stimulating subscriptions for short-term contracts (in our case, monthly contracts) than for long-term contracts (in our case, yearly contracts). This finding is consistent with theoretical arguments that short-term contracts allow such users to try out the product at a minimal commitment, diagnose the extent to which the content is useful, and thus facilitate their adoption decision (Rogers and Shoemaker 1971).

In contrast to price promotions, both e-mails and search-engine referrals are more effective in generating new yearly subscriptions. The latter came as a surprise to our online provider, which suspected that the same-page display of competing content providers in search-engine results would reduce the commitment of subscribers gained though this route. However, this result is consistent with the notion that long-term commitments are riskier than short-term commitments because they involve a greater immediate economic investment. Prior research indicates that in conditions in which outcomes are risky, people look for cues that suggest that risk is minimal. One such cue is the credibility of the content provider, which may be derived through the search engine acting as a third party (Chu and Chu 1994). Likewise, the e-mails provide specific information on content, which tends to reduce perceived risk.

Finally, our moving-window trend analyses revealed that the move from free to fee occurred about a year after new free subscriptions became an evolving variable and about a month after its growth showed signs of saturation. The former is consistent with management intuition that the content site picked up momentum in signing on new users, which gave the firm the confidence to consider different ways to monetize user interest. Although such momentum may provide the opportunity to make the move from free to fee, the saturation in growth may have indicated the necessity to begin adding subscription revenues. In general, we speculate that (1) the success of the move from free to fee depends on the perceived content value of the site, which is indicated by momentum in free subscribers, and (2) management's decision to execute the move is more likely when this growth saturates. We note that saturating growth is still a relatively favorable regime in the framework of Pauwels and Hanssens (2007), who observe that packaged goods manufacturers tend to wait for dramatic changes until their performance is clearly in decline. Thus, management of a small company in a growth industry appears to act more proactively than management in established companies and mature industries (Schendel, Patton, and Riggs 1976).

This article investigated one company. Although this company is representative of the U.S. online content industry, further studies are needed to establish whether our findings generalize to other content providers and other countries. In particular, because the online provider appears to have successfully migrated to a paid-content format, it is useful to consider which factors drove these results. Consumer, competitive, and company considerations may all play a role (see Table 9).

TABLE 9
Potential Drivers on the Revenue Effects of Moving from Free to Fee

	Subscription Revenue: Paying Subscribers	Advertising Revenue: Free Subscribers
Customer growth momentum	+	+
Customer perceived value free content	– (?)	+
Customer perceived value fee content	+	– (?)
Customer price sensitivity	–	–
Competitive intensity	–	–
Competitive price level	+	?
Company content restriction extent	+	–
Company price level	–	+ (?)
Company communication effectiveness	+	+
Company free-to-fee conversion efforts	+	–
Company revenue flow management	+	+

First, the customer base growth at the time of the move from free to fee matters. Our rolling-window analysis revealed that the move occurred after the free subscription series showed a strong growth trend (i.e., momentum). Management believed that investment in search-engine optimization well before the move from free to fee was a strong driver of subscription growth, and indeed we find permanent effects of search-engine referrals. As a result, the fee subscription membership was marketed to a large and rapidly growing group of free subscribers. Other content providers may have made this switch too early (e.g., before a substantial free membership base was created), consistent with the difficulty faced by some of the earliest movers for fee-based content. For example, Microsoft entered the online magazine business with *Slate*, which unsuccessfully tried to charge subscriptions and now exists as a free site. In addition, the subscription-based nature of the industry may matter; whereas 97% of online business content is subscription based compared with single sales, this situation differs for other categories, such as online music and greeting cards. Customer reaction to the move from free to fee may well differ in transactional versus subscription-oriented markets. Finally, individual customer considerations include price sensitivity and the perceived value of free content and fee content, which are all likely to be distributed heterogeneously in the (potential) customer population.

Second, competition may be an important driver of the revenue results of moving from free to fee. Negative effects follow from a high perceived value of competitive content and its overlap with the free and fee content of the focal company, whereas a high competitive price may actually benefit the focal company. Our data provider faces a large number of competitors, some with substantial financial resources, even within the niche of marketing content. Most of these competitors follow an advertising income model, and one competitor recently announced a subscription model at a price that is an order of magnitude higher than that in our data. Several price cuts followed, presumably because of market resistance, whereas our content provider has succeeded in upgrading many consumers to higher price levels. It is unclear whether our empirical results of net revenue gains would generalize to situations with a different focal firm position (e.g., a marginal versus dominant player), substantially more versus fewer major competitors, and the choice of free versus for-fee content.

Third, the company's marketing-mix decisions may exert an important influence on the revenue outcome of moving from free to fee. Our results already point to the loss in free subscribers due to marketing actions aimed at converting free subscribers into paying ones. In addition, the small loss in new free subscriptions may be due to the content restriction decision; our content provider restricted only a portion (approximately one-seventh) of the content and maintained a steady flow of interesting free content. Furthermore, the price structure and level should matter; our data provider focuses on winning long-term (yearly) contracts and charges a yearly price close to the industry average for online business content. In contrast to the aforementioned competitor, the focal company managed to maintain prices while growing paid subscriptions. Further research is needed to confirm and operationalize the recommendation that "the key is for companies [providing Internet services] to set realistic fees and then gradually raise them" (*USA Today* 2002). Moreover, the growth in paid subscriptions is fairly well explained by several model variables, such as search-engine referrals and e-mail advertising, which are widely used. However, the extent to which these are effective depends, in large part, on how well they are executed. In addition, firms use various other techniques to move free users to paid users, such as nonprice promotional offers and advertising-based "day passes," which our content provider does not employ. These can be the subject of further research. Finally, other possible reasons for our content provider's success include its effectiveness in hiring the right people to manage the transition and to manage the resultant cash flows.

In summary, compared with the results for our data provider, we would expect lower revenue benefits for companies that (1) make the move from free to fee before momentum in free subscriptions has materialized, (2) set prices too high compared with consumer willingness to pay for their content, (3) are up against a dominant competitor with better (perceived) content and/or lower price levels, (4) charge fees for all (previously free) content, and (5) fail to ramp up marketing communication efforts and execute them effectively.

Apart from the generalizability conditions, we note several areas for further research. First, our proxy search-engine referrals should be replaced with marketing control variables that drive this outcome variable. Data limitations also prevent us from analyzing the actions of competing content providers and their effects on the focal company, a situation typical for these kinds of company data sets. Second, we do not have usage data, which would allow us to assess whether the move from free to fee also reduces the frequency with which free users visit the site and the number of pages they view. Likewise, we lack data on renewal and switch patterns for online content providers. As to our modeling approach, its focus on the aggregate level precludes an analysis of customer heterogeneity (e.g., in willingness to pay for content). Finally, our models are reduced form, and thus the long-term impact calculations are subject to the assumption that the basic data-generating process does not change. Although this is appropriate for "innovation accounting" (i.e., an account of what happened with the move from free to fee within our data sample; see Franses 2005; Van Heerde, Dekimpe, and Putsis 2005), the modeling approach is not suited for revealing structural aspects of customer and firm behavior.

A great deal of marketing research has examined how customers react to pricing when they have a reference price greater than zero. This has been valuable to our understanding of how customers react to products and services for which they expect to pay. However, it is possible that future generations may expect certain products and services, especially those delivered by the Internet, to be free, and thus they will have a reference price of zero. As content providers on the Internet have found, this is a daunting possibility. Researchers can help further illuminate how to move people from free to fee. This research is just a first step in that direction.

REFERENCES

Abraham, Magid M. and Leonard M. Lodish (1987), "Promoter: An Automated Promotion Evaluation System," *Marketing Science*, 6 (2), 101–123.

Ailawadi, Kusum L., Donald Lehmann, and Scott Neslin (2001), "Market Response to a Major Policy Change in the Marketing Mix: Learning from Procter & Gamble's Value Pricing Strategy," *Journal of Marketing*, 65 (January), 44–61.

Ariely, Dan and Kristina Shampan'er (2004), "Tradeoffs Between Costs and Benefits: Lessons from 'the Price of 0,'" working paper, Massachusetts Institute of Technology.

Bakos, Yannis and Erik Brynjolfsson (2000), "Bundling and Competition on the Internet," *Marketing Science*, 19 (1), 63–82.

Bawa, Kapil and Robert Shoemaker (2004), "The Effects of Free Sample Promotions on Incremental Brand Sales," *Marketing Science*, 23 (3), 345–63.

Bradley, Efron and Robert Tibshirani (1993), *An Introduction to the Bootstrap*. London: Chapman and Hall.

Brehm, Jack W. (1966), *A Theory of Psychological Reactance*. New York: Academic Press.

Bronnenberg, Bart J., Vijay Mahajan, and Wilfried Vanhonacker (2000), "The Emergence of Market Structure in New Repeat-Purchase Categories: The Interplay of Market Share and Retailer Distribution," *Journal of Marketing Research*, 37 (February), 16–31.

Brynjolfsson, Erik, Yu Hu, and Michael D. Smith (2003), "Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers," *Management Science*, 49 (11), 1580–96.

Bucklin, Randolph E. and Catarina Sismeiro (2003), "A Model of Web Site Browsing Behavior Estimated on Clickstream Data," *Journal of Marketing Research*, 40 (August), 249–67.

Chu, Wujin and Woosik Chu (1994), “Signaling Quality by Selling Through a Reputable Retailer: An Example of Renting the Reputation of Another Agent,” *Marketing Science*, 13 (2), 177–89.

Cooke, Alan D.J., Harish Sujan, Mita Sujan, and Barton A. Weitz (2002), “Marketing the Unfamiliar: The Role of Context and Item-Specific Information in Electronic Agent Recommendations,” *Journal of Marketing Research*, 39 (November), 488–97.

Danaher, Peter J. (2002), “Optimal Pricing of New Subscription Services: Analysis of a Market Experiment,” *Marketing Science*, 21 (2), 119–38.

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

——— and ——— (2004), “Persistence Modeling for Assessing Marketing Strategy Performance,” in *Cool Tools in Marketing Strategy Research*, Donald Lehmann and Christine Moorman, eds. Cambridge, MA: Marketing Science Institute.

Diehl, Kristin, Laura J. Kornish, and John G. Lynch (2003), “Smart Agents: When Lower Search Costs for Quality Information Increase Price Sensitivity,” *Journal of Consumer Research*, 30 (June), 56–71.

Dyson, Esther (1995), “Intellectual Value,” *Wired Magazine*, (July), (accessed December 10, 2007), [available at http://www.wired.com/wired/archive/3.07/dyson.html].

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

Fitzsimons, Gavan J. and Donald R. Lehmann (2004), “Reactance to Recommendations: When Unsolicited Advice Yields Contrary Responses,” *Marketing Science*, 23 (1), 1–16.

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

Gedenk, Karen and Scott A. Neslin (1999), “The Role of Retail Promotion in Determining Future Brand Loyalty: Its Effect on Purchase Event Feedback,” *Journal of Retailing*, 75 (4), 433–59.

Ghysels, E., H. Lee, and J. Noh (1994), “Testing for Unit Roots in Seasonal Time Series,” *Journal of Econometrics*, 62 (2), 415–42.

Granger, Clive W. and Paul Newbold (1986), *Forecasting Economic Time Series*, 2d ed. New York: Harcourt Brace Jovanovich.

Haga, Susan (2005), “Readers’ Opinions,” USC Annenberg Online Journalism Review, (accessed December 12, 2005), [available at http://www.ojr.org/ojr/blog/comments.cfm?id=771].

Hamilton, J. (1994), *Time Series Analysis*. Princeton, NJ: Princeton University Press.

Hanssens, Dominique M. and Ming Ouyang (2001), “Hysteresis in Market Response: When Is Marketing Spending an Investment?” working paper, Anderson School of Management, University of California, Los Angeles.

Jain, Sanjay and P.K. Kannan (2002), “Pricing of Information Products on Online Servers: Issues, Models, and Analysis,” *Management Science*, 48 (September) 1123–42.

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

Kwiatkowski, Dennis, Peter Phillips, Per Schmidt, and Yongcheol Shin (1992), “Testing the Null Hypothesis of Stationary Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?” *Journal of Econometrics*, 54 (1–3), 159–78.

Lambrecht, Anja and Bernd Skiera (2006), “Paying Too Much and Being Happy About It: Existence, Causes, and Consequences of Tariff-Choice Biases,” *Journal of Marketing Research*, 43 (May), 212–23.

Laurent, Gilles and Jean-Noel Kapferer (1985), “Measuring Consumer Involvement Profiles,” *Journal of Marketing Research*, 22 (February), 41–53.

Leeflang, Peter S.H., Dick R. Wittink, Michel Wedel, and Philippe A. Naert (2000), *Building Models for Marketing Decisions*. Dordrecht, the Netherlands: Kluwer Academic Publishers.

Lewis, Regina (1995), “Relation Between Newspaper Subscription Price and Circulation, 1971-1992,” *Journal of Media Economics*, 8 (1), 25–41.

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

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

Neslin, Scott A. and Robert W. Shoemaker (1983), “Using a Natural Experiment to Estimate Price Elasticity: The 1974 Sugar Shortage and the Ready-to-Eat Cereal Market,” *Journal of Marketing*, 47 (Winter), 44–57.

Online Publishers Association (2003), *Online Paid Content: U.S. Market Spending Report*, (accessed January 18, 2006), [available at http://www.online-publishers.org/pdf/opa_paid_content_report_mar03.pdf].

——— (2005), *Online Paid Content: U.S. Market Spending Report*, (accessed January 18, 2006), [available at http://www.online-publishers.org/pdf/opa_paid_content_report_fullyear05.pdf].

Pauwels, Koen (2001), “The Drivers of Online Readership: A Decomposition Approach,” *Social Science Research Network* Working Paper No. 01-08.

——— (2004), “How Dynamic Consumer Response, Competitor Response, Company Support and Company Inertia Shape Long-Term Marketing Effectiveness,” *Marketing Science*, 23 (4), 596–610.

——— (2007), “How Retailer and Competitor Decisions Drive the Long-Term Effectiveness of Manufacturer Promotions for Fast-Moving Consumer Goods,” *Journal of Retailing*, 83 (3), 297–308.

——— and Enrique Dans (2001), “Internet Marketing the News: Leveraging Brand Equity from Marketplace to Marketspace,” *Journal of Brand Management*, 8 (4–5), 303–314.

——— and Dominique M. Hanssens (2007), “Performance Regimes and Marketing Policy Shifts,” *Marketing Science*, 26 (3), 1–19.

———, ———, and S. Siddarth (2002), “The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity,” *Journal of Marketing Researc*h, 34 (November), 421–39.

———, Shuba Srinivasan, Jorge Silva-Risso, and Dominique M. Hanssens (2004), “New Products, Sales Promotions, and Firm Value: The Case of the Automobile Industry,” *Journal of Marketing*, 68 (October), 142–56.

Perron, Pierre (1989), “The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis,” *Econometrica*, 57 (6), 1361–1401.

——— (1990), “Testing for a Unit Root in a Time Series with a Changing Mean,” *Journal of Business & Economic Statistics*, 8 (2), 153–62.

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

——— and Yongcheol Shin (1998), “Generalised Impulse Response Analysis in Linear Multivariate Models,” *Economics Letters*, 58, 17–29.

Peterson, Robert A., Sridhar Balasubramanian, and Bart J. Bronnenberg (1997), “Exploring the Implications of the Internet for Consumer Marketing,” *Journal of the Academy of Marketing Science*, 25 (4), 329–46.

Rogers, Everett M. and Floyd F. Shoemaker (1971), *Communication of Innovations: A Cross-Cultural Approach*. New York: The Free Press.

Saba, Jennifer (2005), "Dispelling the Myth of Readership Decline," *Editor & Publisher* (online edition), (November 28), (accessed January 3, 2006), [available at http://www.editorandpublisher.com/eandp/news/article_display.jsp?vnu_content_id=1001571463].

Schendel, Dan E., Richard G. Patton, and James Riggs (1976), "Corporate Turnaround Strategies: A Study of Profit Decline and Recovery," *Journal of General Management*, 3 (Spring), 3–11.

Scott, Carol A. (1976), "The Effects of Trial and Incentives on Repeat Purchase Behavior," *Journal of Marketing Research*, 13 (August), 263–69.

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

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

Telang, Rahul, Peter Boatwright, and Tridas Mukhopadhyay (2004), "A Mixture Model for Internet Search-Engine Visits," *Journal of Marketing Research*, 41 (May), 206–214.

USA Today (2002), "Internet Firms Fish for Revenue from Fees," (June 11), (accessed December 10, 2007), [available at http://www.usatoday.com/money/covers/2002-06-11-tech-sell.htm].

Van Heerde, Harald J., Marnik G. Dekimpe, and William P. Putsis Jr. (2005), "Marketing Models and the Lucas Critique," *Journal of Marketing Research*, 42 (February), 15–21.

———, Sachin Gupta, and Dick Wittink (2003), "Is 75% of the Sales Promotion Bump Due to Brand Switching? No, Only 33% Is," *Journal of Marketing Research*, 40 (November), 481–91.

Varian, Hall (1995), "The Information Economy," *Scientific American*, (September), 200–202.

Wertenbroch, Karl (1998), "Consumption Self-Control by Rationing Purchase Quantity of Virtue and Vice," *Management Science*, 17 (4), 317–37.

Zeithaml, Valarie A. (1988), "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence," *Journal of Marketing*, 52 (July), 2–22.

Zellner, Arnold and Henri Theil (1962), "Three-Stage Least Squares: Simultaneous Estimation of Simultaneous Equations," *Econometrica*, 30 (1), 54–78.