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Marketing Science Institute
1000 Massachusetts Avenue
Cambridge, MA
02138–5396

Phone: 617.491.2060
Fax: 617.491.2065
www.msi.org

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Dynamic Marketing Investment Strategies for Platform Firms

Shrihari Sridhar, Murali K. Mantrala, Prasad A. Naik, and Esther Thorson

How should firms allocate marketing resources when demand from one customer group depends on demand from another customer group? This study looks at strategies for platform firms operating in two-sided markets.

Report Summary
In the marketing budgeting literature, few studies have addressed the problem of platform firms operating in two-sided markets with cross-market demand effects, where the firm's demand from one customer group depends upon the demand for the platform from the other customer group. Yet such firms—such as newspaper companies (with subscribers and advertisers) and shopping malls (with shoppers and retailers)—are pervasive in the business landscape and invest heavily in marketing.

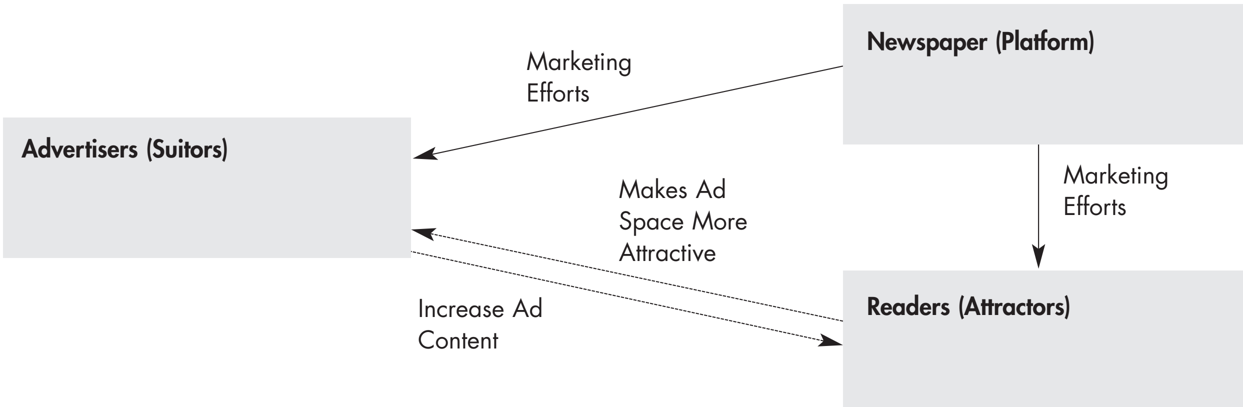
Here, the authors develop normative budgeting and allocation rules using a proposed two-sided dynamic sales response model, and test the model using data from a daily newspaper company whose two end-user groups of interest are readers and advertisers.

Three important findings emerge from their analysis. First, the market data furnish empirical support for the proposed two-sided market response model: a model that includes cross-market demand effects (CMEs) performs better than the one without CMEs. Second, this particular newspaper is a reinforcing platform: that is, the demand for the platform's offering from readers influences positively the demand from advertisers, and vice versa. Third, the significant CMEs imply that marketing efforts have both direct and indirect effects, i.e., efforts towards one end-user group also influence the other end-user group. In the context of the newspaper, the overall (direct + indirect) elasticity of investment in the newsroom, i.e., improving product (news) quality to attract readers, is 50% greater than the overall elasticity of marketing (salesforce) investments directed at advertisers.

These results have important implications for the daily newspaper industry. Many newspapers have made progressive cuts in their newsroom investments in an effort to improve their financial performance. Our results indicate that if marketing budgets have to be reduced then newspapers should be making cuts in their salesforce investments, which possess lower overall elasticity, rather than downsizing investments in newsroom staff, which have higher elasticity. ■

Shrihari Sridhar is Assistant Professor of Marketing, Eli Broad College of Business, Michigan State University.
Murali K. Mantrala is Sam M. Walton Distinguished Professor of Marketing, Trulaske College of Business, University of Missouri.
Prasad A. Naik is Chancellor's Fellow and Professor of Marketing, Graduate School of Management, University of California Davis.
Esther Thorson is Professor of Strategic Communication, Missouri School of Journalism, University of Missouri.

Figure 1
Newspaper Allocating Marketing Efforts



Introduction

Deciding the optimal levels and allocation of scarce marketing resources is a fundamental responsibility of marketing managers. Not surprisingly, a large volume of work in the marketing models literature has focused on developing normative rules for marketing resource allocation decisions, empirical analyses of the optimality of firms' marketing investments in practice, and building implementable model-based tools for optimizing marketing investment decisions in specific settings (Mantrala 2002). However, surveys of this literature (e.g., Leeflang et al. 2000; Hanssens Parsons, and Schultz 2001; Mantrala 2002; Gupta and Steenburgh 2008) reveal that most of the research to date has ignored marketing budgeting and allocation decisions by a substantial segment of firms in the economy, namely, *platform* firms that do business in "*two-sided*" markets.

Platform-firm markets are distinguished from "one-sided" firm markets in that they have two or more different groups of customers (that is, end-users of their products or service offerings) that businesses must seek to acquire and retain (Rochet and Tirole 2005). Examples include print media such as newspapers and magazines (readers and advertisers), TV broadcasting (viewers and advertisers), shopping malls (shoppers and retailers), payment cards (cardholders and merchants), and sports clubs (spectators and sponsors). More specifically, platform firms are characterized by: (1) the existence of two or more distinct groups of customers, (2) in which members of at least one group wish to access the other group, and (3) where the platform can facilitate that access more efficiently than bi-lateral relationships between the members of the groups (Evans 2003). Thus, in platform firms, demand from one customer group depends upon the demand for the platform from the other customer group, i.e., cross-market demand effects (CMEs) are present in such firms (e.g., Chen and Xie 2007). Intuitively, when CMEs are present, a platform firm's marketing efforts to stimulate demand from one customer group can have repercussions on its other customer group.

Hereafter, we shall refer to an end-user group who uses an offering of the platform itself, regardless of the presence or absence of any other end-user group, as *attractors* (e.g., readers of a newspaper). Further, we shall refer to the end-user group interested in accessing attractors via the platform as *suitors* (e.g., advertisers buying ad-space in a newspaper).

Figure 1 provides a diagrammatic representation of a newspaper firm allocating marketing efforts to its attractors and suitors. The newspaper's investment in marketing to increase its readership or circulation is by way of enhancing product (news content) quality. Its suitors (advertisers) are specifically interested in the number and composition of the newspaper's attractors (readers). Therefore, the newspaper firm also invests in communicating this information to the suitors (e.g., by employing a sales force to sell its ad-space). An increase in the number of suitors can, in turn, impact attractors' future demand for the newspaper. Specifically, an increase in the quantity of advertising in the newspaper can potentially increase/decrease demand from the attractors. (Advertising has been shown to have a positive effect on readers when the ad provides information deemed to be valuable by the readers, e.g., Bogart 1989; Sonnac 2000).Thus, these two sources of revenue for the newspaper are interrelated (Dewenter 2003).

The paucity of research on optimal marketing resource allocation by platform firms is surprising, considering that such firms are among the largest in the economy, including Fortune 100 companies like Time Inc. (magazine) and FOX (television network). From a modeling viewpoint, two novel and challenging aspects of platform firms' marketing budgeting decisions are: (1) these decisions must account for the differential dynamic (carryover) effects of marketing on the demands from the dual or multiple sides of the platform firm's business, and (2) they must take into account the CMEs of marketing efforts towards multiple end-user groups. Evans and Schmalensee (2007) effectively summarize these challenges: "… its [platform's] customer groups form a dynamic system and live in a non-linear world. … Changes in customers of one type affect customers of the other type …" and the firm "… must consider the interdependence of these two groups of customers at every turn." Therefore, our objectives in this research are two-fold:

1. Extend extant marketing budgeting theory to platform firms based on a new model of dynamic two-sided market response to marketing efforts;
2. Estimate and validate empirically the proposed two-sided response model using market data from an archetypal platform firm, namely, a daily print newspaper company, and gain insights into the signs and magnitudes of dynamic CMEs and their impact on marketing elasticities.

The normative analysis that follows presents five new propositions that show how dynamic CMEs together with carryover effects modify the marketing-investment levels that are optimal in benchmark *classic firms* where CMEs are absent. These results indicate that, all else equal, optimal investment levels for two-sided platform firms could be set higher or lower than those of classic firms, depending on whether CMEs reflect *reinforcing* effects (CMEs in both directions are positive) or *counteractive* effects (when the CME in one direction is positive while the CME in the other direction is negative).

In our empirical analysis, using data from a local newspaper firm, we specify and calibrate a two-sided sales response model via state-space methods (e.g., Xie et al 1997; Naik, Mantrala, and Sawyer 1998). Three important findings emerge from this empirical analysis. First, these market data furnish empirical support for the proposed two-sided market response model: a model that includes CMEs performs better than the one without CMEs. Second, the attractor effect and the suitor effect are both significant and positive, revealing that this particular newspaper is a reinforcing platform. A positive suitor effect indicates that the newspaper's readers value advertising, unlike T.V. viewers who were found to be ad-averse by Wilbur (2008). Third, the significant CMEs imply that marketing efforts have both direct and indirect effects, i.e., efforts towards one end-user group also influence the other end-user group. In the context of the newspaper, the overall (direct + indirect) elasticity of investment in the newsroom or improving product (news) quality to attract readers is 50% greater than the overall elasticity of investments in marketing, i.e., sales force effort directed at advertisers.

Finally, we note that these results have important implications for the daily newspaper industry. Many newspapers have made progressive cuts in their newsroom investments in an effort to improve their financial performance (Rosentiel and Mitchell 2004). However, presuming budget reductions are warranted, our results indicate that newspapers should be making cuts in their sales force investments, which possess lower overall elasticity, rather than downsizing investments in newsroom staff, which have higher elasticity.

Platform Firms: Previous Research

Economic literature on two-sided markets

In recent years, the peculiar nature of the "two-sided" platform firm market has gained the attention of economists. However, this stream of research focuses on pricing strategies and does not address the marketing-mix problem.

For example, Eisenmann, Parker, and Alstyne 2006, Parker and Van Alstyne (2005), Rochet and Tirole (2005), Armstrong and Wright (2004), Jullien (2004), and Bolt and Tieman (2006) examine how standard pricing policies for profit-maximization should be restructured in the presence of two-sidedness, while Chakravorti and Roson (2004) and Caillaud and Jullien (2003) study how pricing rules should change in a setting of competing platforms. Roson (2004) provides a detailed review of pricing-related work on two-sided markets. He finds that when CMEs are present: (a) prices applied to the two market sides are both directly proportional to the price elasticity of the corresponding demand (Rochet and Tirole 2003); (b) socially optimal pricing in two-sided markets leads to an inherent cost recovery problem, inducing losses for the monopoly platform (Bolt and Tieman 2006); and (c) in a duopoly, the platform charging the lower fees could potentially capture *both* sides of the market and result in market monopoly (Caillaud and Jullien 2003).

Marketing literature

Ingene and Parry (1995), Urban (1975a, b), and Gensch and Welam (1990) examine the issues of how managers should allocate their marketing budget between multiple regions when marketing effort in one region impacts sales in another region. Similarly, Gijsbrechts and Naert (1984), Doyle and Saunders (1990), and Reibstein and Gatignon (1984) examine the issues of how managers in charge of selling multiple products should set their marketing budgets optimally, taking into account complementary and substitution effects. While this work may seem to be related to this study—since multi-region and multi-product models incorporate marketing spillover effects—they do not consider explicit demand interdependence (cross-marketing demand effects). That is, these extant models incorporate spillover effects from one region or product to another region(s) or product(s) bought *by the same end-user group*, whereas CMEs capture demand interdependence between *two different end-user groups*.

The small volume of marketing literature on platform firms has grown in recent years. For example, Chen and Xie (2007) examine the relationship between high levels of attractor loyalty and platform firm profits under competition. Wilbur (2008) estimates a structural model of suitor (advertiser) demand for viewers (attractors) and viewer demand for advertisers in the television industry and finds evidence for ad aversion among viewers. Gupta, Mela, and Vidal Sanz (2007) develop a model to calculate the customer lifetime value (CLV) of the buyers (attractors) and sellers (suitors) in an auction house and find that buyer CLV is higher than that of the seller. Mantrala, Naik, Sridhar, and Thorson (MNST) 2007 address the newspaper marketing budgeting allocation problem using a static model and empirically assess the optimality of short-term expenditures of a cross-section of firms in the newspaper industry. In contrast, this study focuses on marketing optimization over the long term by one firm, incorporating the dynamic effects of both CMEs and sales carryover.

In the next section, we specify a sales response function, formulate the budget allocation problem, and derive both general and specific insights into dynamically optimal marketing investments towards attractors and suitors in reinforcing and counteractive markets.

Normative Analysis

Sales response function

We consider a monopolist platform firm such as a local daily newspaper (98% of daily newspapers are the only ones published in their market (Picard 1993)). In addition, we assume that margins from both the attractor and suitor groups are constant because (1) newspaper retail prices are observed to stay fixed over four to seven years (Bils and Knelow 2002) and variable costs (e.g., newsprint costs) are constant after the first-copy costs (MNST 2007, p. 29), and (2) advertising rates for local newspapers, once published, are not negotiable and remain unchanged for long periods of time (Warner and Buchman 1991, p. 205).

Let A_t and S_t denote the dollar sales revenues at time t from the attractor and suitor sides of the market, respectively. Then we specify the platform's dynamic sales-marketing effort response system as follows:

$$\begin{bmatrix} A_t \\ S_t \end{bmatrix} = \begin{bmatrix} \lambda_A & \theta_{SA} \\ \theta_{AS} & \lambda_S \end{bmatrix} \begin{bmatrix} A_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} f(u_t) \\ g(v_t) \end{bmatrix} \tag{1}$$

In Equation 1, u_t and v_t denote marketing efforts allocated toward attractors and suitors respectively, while $f(u_t)$ and $g(v_t)$ denote the corresponding response functions, which are assumed to be concave to capture diminishing returns to marketing efforts such as investments in product quality (Rust, Zahorik, and Keiningham 1995) or marketing communications (e.g., Simon and Arndt 1980; Mantrala, Sinha, and Zoltners 1992). The sales realized in period t are then the sum of sales generated by current-period efforts and fractions of previous-period's sales that are carried over to the current period. In Equation 1, λ_A and λ_S denote these carryover fractions of attractor sales and suitor sales, respectively.

Next, we define the dynamic cross-market effects that constitute the novel features of a platform firm's markets. Specifically, in Equation 1, θ_{AS} denotes an *attraction effect* coefficient that captures the dynamic effect of increased attractor demand in period $t-1$ on suitors' demand in period t. We expect θ_{AS} to be positive because suitors seek access to attractors and their demand for the medium of the platform should increase when they observe a higher level of attractors' demand for the platform. Similarly, θ_{SA} denotes *suitor-repercussion* effect, which can be positive or negative depending on whether attractors value suitors' use of the platform, e.g., newspaper readers may be "ad-lovers" (Sonnac 2000) or TV viewers may be "ad-averse" (Wilbur 2008). Together, we refer to the platform market setting as *reinforcing* when $\theta_{AS} > 0$ and $\theta_{SA} > 0$, and as counteractive when $\theta_{AS} > 0$ and $\theta_{SA} < 0$. To determine how much the platform manager should spend on marketing efforts, we next analyze a dynamic profit maximization model incorporating the continuous-time form of the sales response system 1.

Marketing Decision Problem Formulation and General Solution. Let $u(t)$ and $v(t)$ denote the marketing investments toward attractors and suitors, respectively. We assume the platform firm's goal is to maximize discounted long-term profits and, therefore, its problem is expressed as

$$\text{Maximize } J(u, v) = \int_0^\infty e^{-\rho t}\pi(A(t), S(t), u(t), v(t))dt, \quad (2)$$

$$\text{where } \pi(A, S, u, v) = m_A A - m_S S - u - v, \quad (3)$$

and m_A and m_S represent the margins on unit sales to attractors and suitors, respectively. In determining the optimal effort levels, denoted u^* and v^*, the manager needs to account for CMEs and the dynamics of market response. Denoting $\dot{x} = dx(t)/dt$, we express Equation 1 in continuous-time as

$$\begin{bmatrix} \dot{A} \\ \dot{S} \end{bmatrix} = \begin{bmatrix} -(1-\lambda_A) & \theta_{SA} \\ \theta_{AS} & -(1-\lambda_S) \end{bmatrix} \begin{bmatrix} A \\ S \end{bmatrix} + \begin{bmatrix} f(u) \\ g(v) \end{bmatrix} \quad (4)$$

and solve the maximization problem defined by equations 2–4 by applying optimal control theory (see, e.g., Kamien and Schwarz 1992 or Sethi and Thompson 2006). We relegate the technical details of the solution to Appendix A. In the appendix, we also detail how our results relate to and extend some of the classic optimality results on static (Dorfman and Steiner 1954) and dynamic (Nerlove and Arrow 1962) marketing investments respectively.

Next, we utilize the optimality conditions (Equation A10 in Appendix A) to provide general insights into how CMEs affect optimal investment levels in different types of platforms. We present the proofs of our results in Appendix B.

General results on optimal investment levels in platform firms compared to classic firms

Applying the gradient condition in Equation A11, we compare the optimal investment levels in two types of platforms against the benchmark classic firm with the same sales carryover dynamics and discount rate but no CMEs ($\theta_{SA} = \theta_{AS} = 0$) and obtain the following result:

Result 1. All else equal, optimal marketing efforts by reinforcing platform firms (θ_{AS} and $\theta_{SA} > 0$) directed at both attractors and suitors are greater than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$).

An example of a reinforcing platform is a local newspaper with ad-loving readers (e.g., Sonnac 2000). Result 1 offers the insight that when CMEs are mutually reinforcing, a profit-maximizing platform firm's marketing spending should be *more* than that of its counterpart classic firm, *not less* as intuition might suggest.

Result 2. All else equal, optimal marketing efforts by counteractive platforms ($\theta_{AS} > 0$, $\theta_{SA} < 0$) directed at attractors are greater than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$) provided the margin ratio m_S/m_A exceeds a critical value, m^*.

This result reveals that an important managerial trade-off is required in counteractive platforms. Increasing marketing towards attractors (u) leads to an increase in attractor revenue (A) and, subsequently, an increase in suitor revenue (S) through the attraction effect (θ_{AS}). However, an increase in suitors and, therefore, in suitor revenues deters the long-term revenue from attractors, such as in a setting with ad-avoiding newspaper and magazine readers (Sonnac 2002). The amount of loss depends on the magnitude of the negative suitor-effect θ_{SA} and the long-term purchase reinforcement effect of attractors (λ_A). The critical point m^*, given by $|\theta_{SA}|/(\rho + 1 - \lambda)$, is the margin ratio m_S/m_A at which the long-term profit contribution of the suitor revenue exceeds the lost contribution due to lower attractor revenues. The critical margin ratio increases as the suitor-effect or the carryover effect increases, and it decreases with the discount rate.

Result 2 suggests that rather than indiscriminately adding attractors, managers of counteractive platforms should tailor their marketing messages to gain attractors who may be more tolerant to suitors. For example, past research reveals significant ad-avoidance heterogeneity among the potential readers of magazines and newspapers (Sonnac 2002, p. 251). In such situations, managers may find it useful to target market segments that are less ad-avoiding.

Result 3. All else equal, optimal marketing efforts by counteractive platforms ($\theta_{AS} > 0$, $\theta_{SA} < 0$) directed at suitors are smaller than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$).

Result 3 reveals that marketing investment toward the suitors (v^*) should be lower in counteractive platforms. That is, although the effect of v in increasing the number of suitors may be large, the negative value of θ_{SA} reduces its overall long-term effectiveness, which reduces its optimal spending level. Result 3 has implications for investments in ad-selling effort of platforms like radio broadcasters. News radio stations commonly employ salespeople to sell *piggyback* slots to retailers, i.e., multiple slots that are scheduled back-to-back. While these significantly increase revenue for the station, they increase the units of ads heard during a program and increase the clutter of messages (Warner and Buchman 1991, p. 229). Increased clutter may contribute to wasted coverage (i.e., listeners not buying from the advertisers) or even lead to a high turnover (i.e., listeners switching stations). Increasing investment in the salesforce may not be optimal for the station as a whole in such situations, even if the salesforce is effective in selling piggyback slots to retailers.

Moderating role of "other market" sales carryovers

In the absence of CMEs ($\theta_{AS} = \theta_{SA} = 0$), it can be shown that a firm's optimal marketing effort level toward one end-user group is unaffected by the magnitude of the sales carryover factor in the second end-user group or "other-market." In contrast, other-market sales carryover does influence the optimal level of marketing investment in the first group when CMEs are present. We characterize the nature of this influence in the following two results.

Result 4. Optimal marketing efforts toward attractors increase as (a) λ_S increases in reinforcing platforms and (b) λ_S increases in counteractive platforms provided m_S/m_A exceeds the critical value m^*.

This result has direct implications for media-selling strategies. For example, many retailers who advertise in print news platforms (newspapers, magazines) plan their calendars for extended periods of time and rely on "past media usage" patterns while placing recurring ads in a platform (Warner and Buchman 1993, pp. 258–9). From the platform's perspective, this situation represents a setting with high sales carryover (λ_S) due to purchase reinforcement effects from its suitors (advertisers). To be able to procure ads from the retailers, the platform should increase its marketing spending to its attractors since a large attractor base is valued by retailers who stay with the same platform for longer periods of time. In counteractive platforms, the platform should increase its marketing toward attractors only after ensuring that its margin ratio m_S/m_A exceeds m^* as per the logic in Result 2.

Result 5. Optimal marketing efforts toward suitors (a) increases as λ_A increases in reinforcing platforms and (b) decreases as λ_A increases in counteractive platforms (regardless of the margin ratio).

Result 5 implies *opposite* investment policies toward the suitors in reinforcing versus counteractive platforms. Specifically, a high value of λ_A represents high purchase reinforcement effects on the attractor side of the platform, e.g., renewed subscriptions to magazines or pay-per-view channels. In a situation where attractors with higher long-term revenue potential actually like suitor presence, marketing efforts toward suitors should be increased. However, marketing efforts toward suitors should be decreased when attractors avoid suitors because then increasing suitor presence leads to loss of attractors with long-term revenue potential as well as subsequent loss in suitor revenue due to loss of attractors.

In sum, results 1 through 5 highlight the fact that optimal budgeting rules not only differ for platform firms relative to classical one-sided markets, but also vary across different kinds of platform firms (e.g., reinforcing or counteractive). Because different investment strategies hold for different platform firms, managers should estimate parameters of the market response functions to determine whether their platform is reinforcing or counteractive. In the next section, we describe an econometric estimation approach to estimate and validate the proposed two-sided market response model using data from a daily newspaper firm.

Empirical Analysis

This section illustrates how managers can establish empirically, using historical sales data, whether their firm is a reinforcing or counteractive platform by estimating CMEs. To this end, we first describe the data, then the Kalman filter estimation approach, followed by model selection and diagnostics, and, finally, present the empirical results.

Data

We obtained data from one newspaper owned by a privately held media company that has diversified holdings in newspaper and magazine publishing as well as radio broadcasting. The company wishes to remain anonymous. Medium-sized newspapers (subscriptions < 85,000) form the core business of the company. The particular print newspaper we analyze is a monopolist in its city-region, producing somewhat differentiated news content overall due to its local flavor. A third-party audit bureau verifies this newspaper's subscription figures, and it also provides demographic information (age, gender, income, home ownership) about the newspaper's readers (attractors) to its advertisers (suitors) who wish to purchase ad space in the future. The newspaper appeals mainly to advertisers who seek to reach audiences older than 50, and these advertisers include financial companies and assisted living centers. Because the newspaper invests heavily in marketing to these advertisers, its share of local advertisers' print advertising budgets is quite high.

The dataset spans the decade January 1997 through December 2006 and contains information on revenues from attractors (readers) and suitors (advertisers). In addition, the monthly marketing efforts toward these two revenue sources, namely, dollar spending on newsroom and ad-space sales force, are provided. Prior work in the journalism literature suggests that investments in the newsroom are akin to investments in product quality (Litman and Bridges 1986), as the newsroom department is responsible for providing accurate and engaging news stories to its diverse local readers. The field salesforce's main task is to provide recent figures on the size and composition of the attractor base to the suitors as well as to inform them about the potential benefits of purchasing ad-space in certain sections of the newspaper that their targeted attractors might read.

Table 1 shows that the company spends about equally in the newsroom (49% of budget) and on the salesforce (51% of budget). As is typical in the mature daily newspaper business, subscription and ad-space prices changed only a few times over the 10-year time span of the data. Margins on sales were high (mean = .45) but very stable (standard deviation = .03) during this 10-year period. To calibrate the model using these data, we next describe an approach for estimation, inference, and model selection.

Kalman Filter estimation

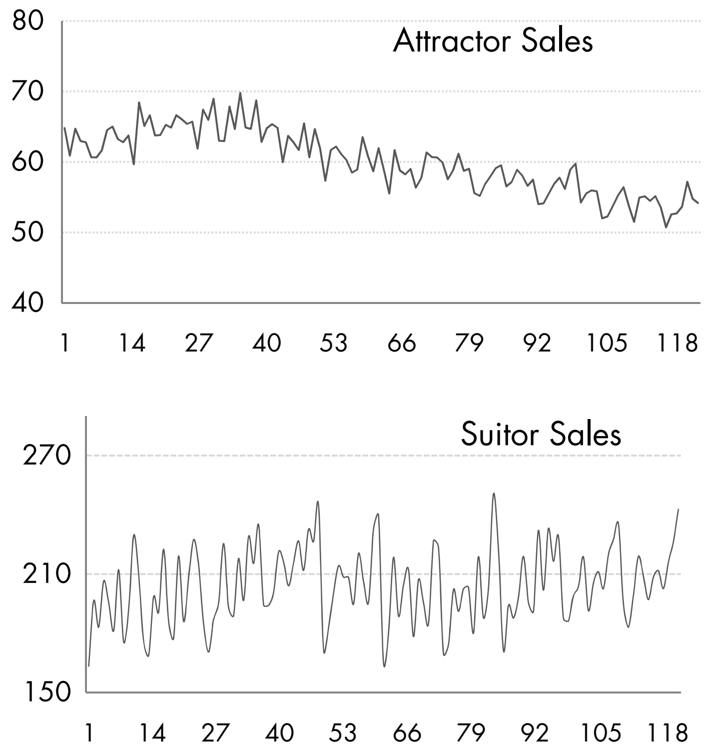
Equation 1 represents a system of stochastic difference equations with non-linear decision variables, inter-temporal dependence of demand, and potentially correlated error structures. Because ordinary least squares

Table 1
Descriptive Statistics

Variables*	Means	Std. Deviations
Attractor Revenues (Subscription)	60.04	4.43
Suitor Revenues (Advertising)	202.4	19.45
Newsroom Department Investments	22.14	1.30
Salesforce Department Investments	21.02	2.56

* All variables in 10,000 U.S. dollars per month.

Figure 2
Observed Attractor and Suitor Sales Patterns



approach can yield biased estimates when estimating dynamic models (Naik, Schultz, and Srinivasan 2006), we apply state-space methods (e.g., Harvey 1994). Specifically, we use a multivariate Kalman Filter (KF) to estimate Equation 1 via the following three steps:

Step 1 Transition Equation. The transition equation specifies the model dynamics and captures the influence of marketing efforts. We obtain the transition equation by allowing the de-seasonalized attractor and suitor revenues to be influenced by their own past values through carryover effects (λ_A, λ_S) as well as each other's past sales values through CMEs (θ_{AS} and θ_{SA}). In addition, we allow the revenues to be influenced by marketing efforts; specifically, we chose square-root functional forms based on their simplicity and popularity in the marketing-sales response literature (e.g., see Naik, Prasad, and Sethi 2008 for a recent application). The transition equation is thus specified as

$$\begin{bmatrix} A_t \\ S_t \end{bmatrix} = \begin{bmatrix} \lambda_A & \theta_{AS} \\ \theta_{SA} & \lambda_S \end{bmatrix} \begin{bmatrix} A_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_A \sqrt{u_t} \\ \beta_S \sqrt{v_t} \end{bmatrix} + \begin{bmatrix} \omega_{A,t} \\ \omega_{S,t} \end{bmatrix} \quad (5)$$

where A_t and S_t represent the attractor and suitor revenue; u_t and v_t represent the investments towards the attractors and suitors respectively; β_A and β_S represent marketing effectiveness parameters of u and v, respectively; and $\alpha = (\alpha_{At}, \alpha_{St})'$ is the transition error vector that follows $N(0, Q)$, where Q is the 2×2 covariance matrix.

Step 2 Observation Equation. We link the transition equation to the observation equation, which includes factors like trends and seasonality. Figure 2 displays the actual sales observations over time. Attractor sales exhibit a general downward trend, reflecting the general decline in print newspaper readership due to the growth of online newspapers in the U.S. To account for this decline, we construct a time-trend variable. Additionally, to capture the role of the Internet in this general decline of print newspaper readership, we obtain annual ad revenues of online newspapers from the State of the News Media database (www.stateofthenewsmedia.org) and interpolate these data to get monthly online ad revenues via the Biyalogorsky and Naik (2003) approach, which is based on the theory of cubic splines. We also construct two dummy variables to account for seasonality in the suitor revenue (see Figure 4), i.e., a rise in the year-end Christmas season and a dip in the

Table 2
Best Error Structure

Models	Transition Noise Covariance	Observation Noise Covariance	AIC	AICc	BIC
1	***No***	***No***	***1044.94***	***1050.94***	***1087.54***
2	No	Yes	1026.97	1033.74	1072.35
3	Yes	No	1042.91	1049.68	1088.29
4	Yes	Yes	1028.41	1036.01	1076.58

Table 3
Presence of CMEs

Models	CMEs Included?	AIC	AICc	BIC
1	No	1033.78	1039.06	1073.59
2	***Yes***	***1026.97***	***1033.74***	***1072.35***

beginning of the year. Thus, the observation equation is given as

$$\begin{bmatrix} Y_{At} \\ Y_{St} \end{bmatrix} = \begin{bmatrix} A_t \\ S_t \end{bmatrix} + \begin{bmatrix} \gamma_1 t + \gamma_2 OAD_t \\ \gamma_3 D_1 t + \gamma_4 D_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{A,t} \\ \varepsilon_{S,t} \end{bmatrix} \tag{6}$$

where Y_{At} and Y_{St} represent the actual observed values of attractor and suitor revenues, OAD represents the total ad revenue of online newspapers in the U.S., γ_1 and γ_2 capture the trend and online ad-revenue effects on Y_{At}, while γ_3 and γ_4 control for the seasonal year-end and beginning effects via the dummy variables D_{1t} and D_{2t} defined as follows:

$$D_{1t} = \begin{cases} 1 & \text{if } t = (11,12), (23,24), \ldots \\ & (119,120) \quad \text{for t} \in (1,120) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$D_{2t} = \begin{cases} 1 & \text{if } t = (1,2), (13,14), \ldots \\ & (109,110) \quad \text{for t} \in (1,120) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

Finally, the observation error vector $\varepsilon = (\varepsilon_A, \varepsilon_S)'$ follows $N(0, H)$, where H represents a 2 × 2 diagonal matrix for observation variances.

Step 3 Likelihood Function. Using the KF recursions (Harvey 1994, p. 88) and denoting Y_t as $(Y_{At}, Y_{St})'$, we compute the log-likelihood function,

$$\mathrm{LL}(\Psi; Y_T) = \sum_{t=1}^{T} \mathrm{Ln}(p(Y_t \mid \Im_{t-1}) \tag{9}$$

where $p(.|.)$ denotes the conditional density of Y_t given the history of information up to the previous period $\Im_{t-1}$. The parameter vector Ψ contains the model parameters $(\lambda_A, \lambda_S, \theta_{AS}, \theta_{SA}, \beta_A, \beta_S, \gamma_1, \gamma_2, \gamma_3, \gamma_4)'$ together with the observation and transition covariance matrices and the initial means $(A_0, S_o)'$. By maximizing the likelihood function in Equation 9, we obtain the maximum-likelihood estimates and follow the standard procedure for statistical inference.

Model selection and diagnostics

Model Selection. To compare various models by balancing fidelity and parsimony, we use the three information criteria: Akaike Information Criteria (AIC), Bias-corrected AIC (AIC), and Bayesian Information Criteria (BIC). First, we compare models with and without correlated errors terms in the attractor and suitor transition and observation equations. Table 2 shows that the best model—the one that attains the lowest values on information criteria—has correlated observation noise, but uncorrelated transition noise. Second, we compare models with and without CMEs. Table 3 indicates that the model with CMEs performs the best. Thus, based on all three criteria, market data lend support to the presence of CMEs. Next, we test for exogeneity of marketing investments.

Exogeneity of Marketing Investments. Applying the approach developed by Engle, Hendry, and Richard (1983), we test for exogeneity of newsroom and salesforce investments. Let $p_1(A, u)$ be the joint density of attractor revenues and newsroom investments, $p_2(A|u)$ denote the conditional density of attractor revenues given newsroom investments, and $p_3(u)$ represent the marginal

Table 4
Estimation Results

Parameters	Estimates	t-values
Observation Equation Parameters		
Control Variables		
Trend in Attractor Revenue (γ_1)	–.83	–1.77
Online Ad Revenue Growth (γ_2)	9.71	.65
Year End Ad Revenue Rise (γ_3)	23.72	8.26
Year Beginning Ad Revenue Drop (γ_4)	–24.09	–8.36
Variance Parameters		
Attractor Revenue Std Deviation (Observation Noise) (σ_A)	.78	4.68
Suitor Revenue Std Deviation (Observation Noise) (σ_S)	.0001	.03
Observation noise covariance (σ_{AS})	11.88	15.20
Transition Equation Parameters		
Carry-Over Terms		
Attractor Revenue Carry-over (λ_A)	.25	2.39
Suitor Revenue Carry-over (λ_S)	.81	12.19
CME's Attractor Cross-Market Effect (θ_{AS})	.42	2.54
Suitor Repercussion Cross-Market Effect (θ_{SA})	.11	1.74
Marketing Effectiveness Effectiveness of Attractor–Directed Marketing (β_A)	4.69	3.40
Effectiveness of Suitor-Directed Marketing (β_S)	2.95	1.84
Variance Parameters Attractor Revenue Transition Noise Std Deviation (ν_A)	–1.90	–15.15
Suitor Revenue Transition Std Deviation (ν_S x 10^8)	.001	.001
Maximized Log-Likelihood = –495.48		

density. Then we factorize $p_1(A, u) = p_2\ (A|u)\ x\ p_3(u)$, and weak-exogeneity means that a precise specification of $p_3(\cdot)$ is not needed and no loss of information occurs when we proceed with estimation using the condition density $p_2(\cdot)$. Engle et al. (1983) develop a test for exogeneity, which we applied and found support that newsroom and salesforce investments are weakly exogenous. If this test were to reject exogeneity, then we would apply instrumental variables method to control for the presence of endogeneity.

Predictive Accuracy. We conduct a cross-validation study to assess predictive accuracy. Specifically, we estimate our model using 96 observations and forecast the remaining 24 observations in the hold-out sample using the estimates from the calibrated model. Numerical metrics indicate reasonable predictive accuracy. Specifically, the mean absolute deviation of the attractor revenues was 4% and that of suitor revenues was 8%, both suggesting a small deviance from the actually observed values in the hold-out sample.

In sum, these diagnostic tests furnish evidence that the proposed model not only is a parsimonious specification, but also fits the in-sample data well and forecasts the out-sample data satisfactorily. We close the section by presenting the empirical results.

Estimation results

Control Variables. Table 4 presents the parameter estimates and t-values from the KF estimation. The estimated $\gamma_1 = -.83$ ($p < .10$) indicates a declining trend in attractor revenues. The coefficient γ_2 capturing the influence of the online ad-revenue growth on the firm's attractor revenues is not significant, possibly because the older target audience of the newspaper (> 50 years) are less influenced by the Internet. The significant estimates γ_3 and γ_4 ($p < .01$) suggest seasonality in suitor revenues. Specifically, we find a statistically significant increase in suitor revenue in the Thanksgiving and Christmas season followed by a drop-off in the beginning of the year. This finding comports with the experience of many small newspapers in the U.S.; for example, the *Monroe County Advocate* designs a "Christmas Carol" supplement to accommodate more ad-space during holiday months because about 41% of news readers find ads most helpful during shopping sales (Newspaper Association of America Report 2006).

Cross-market Effects. We find that the attraction effect (θ_{AS}) and the suitor effect (θ_{SA}) are *both positive*, suggesting that this particular newspaper is a *reinforcing platform*. Positive suitor effects suggest that, unlike T.V. viewers who have been found to be ad-averse (Wilbur 2008), our newspaper's readers value advertising. This finding could be explained by several factors: (1) newspapers are a high-attention medium not suitable for multi-tasking; (2) the newspaper ads are "keepable" since they can be cut out and used at a later period; and (3) newspapers are viewed as a less-intrusive and more trustworthy source of information (Conaghan 2006). Additionally, the magnitude of the attractor effect (θ_{AS} = .42) is almost four times that of the suitor effect (θ_{SA} = .11), suggesting that a larger pool of attractors is highly valued by the suitors.

Sales Carryover Effects. Both parameters representing sales carryover effects, i.e., the attractor carryover coefficient (λ_A) and the suitor carryover coefficient (λ_S) are positive and significant ($p < .05$). Higher carryover values imply that current marketing efforts generate revenues for extended periods of time. A high value of sales force carryover λ_S (.81) is explained by the fact that many local retailers and department stores buy weekly ad space for an extended period of time, aiming to inform readers about different sales during the season (Center for Entrepreneurship 2008). A low value of λ_A = .25 suggests that newly acquired attractors do not stay with the newspaper for extended periods of time. This finding is consistent with the general trend of local readers not finding enough community content in the newspaper. Local community news is the main differentiating advantage of a local newspaper; but it has gone down by 8% in the last year in U.S. newspapers (Project for Excellence in Journalism Report 2008).

Marketing Effectiveness and Elasticities. The effectiveness of newsroom investments on attractor revenues (β_A) and sales force on suitor revenues (β_S) are both positive and significant. Furthermore, the magnitude of β_A (4.69) is about 1.6 times that of β_S (2.95).

How do these estimates contribute to the magnitudes of their respective elasticities? Due to the presence of the two CMEs (θ_{AS} and θ_{SA}), marketing investments towards one end-user group (e.g., attractors) has a direct effect (on attractor demand) and indirect effect (on suitor demand). Thus, our analysis provides empirical support for *cross-market indirect elasticities*, which are distinct from indirect elasticities due to interaction effects between marketing variables (e.g., Naik and Raman 2003; Narayanan et al. 2004).

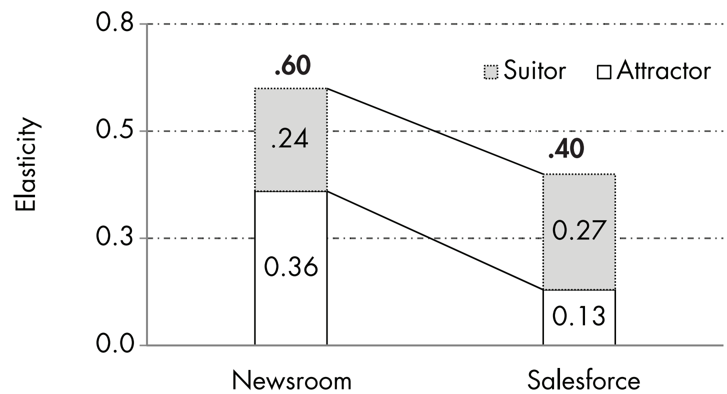
Table 5 presents the direct and indirect long-term elasticities of newsroom and salesforce investments, respectively. As Figure 3 shows, the direct elasticity of newsroom investments (.36) is 1.33 times that of the direct elasticity of salesforce effort (.27), and the indirect elasticity of newsroom investments (.24) is 1.84 times the indirect elasticity of salesforce effort (.13). Finally, the overall elasticity of the

Table 5
Direct and Indirect Elasticities of Marketing

Marketing Variable	Revenue	Nature of Effect	Elasticity Expression	Elasticity*
Newsroom	Attractor	Direct	$\dfrac{(1-\lambda_S)\beta_A\sqrt{u}}{2A[(1-\lambda_A)(1-\lambda_S)-\theta_{AS}\theta_{SA}]}$	.36
	Suitor	Indirect	$\dfrac{\theta_{AS}\beta_A\sqrt{u}}{2S[(1-\lambda_A)(1-\lambda_S)-\theta_{AS}\theta_{SA}]}$	.24
Salesforce	Attractor	Indirect	$\dfrac{\theta_{SA}\beta_S\sqrt{v}}{2A[(1-\lambda_A)(1-\lambda_S)-\theta_{AS}\theta_{SA}]}$	.13
	Suitor	Direct	$\dfrac{(1-\lambda_A)\beta_S\sqrt{v}}{2S[(1-\lambda_A)(1-\lambda_S)-\theta_{AS}\theta_{SA}]}$	.27

* Elasticities evaluated by using the mean values of *u*, *v*, *A*, and *S*, and the estimated parameter values.

Figure 3
Direct and Indirect Elasticities



newsroom investment (.60) is 1.5 times that of the salesforce (.40). These results are not only valuable to the newspaper firm in question, but also have some important implications for the daily newspaper industry in general. While newspapers may need to make cutbacks in spending, they should do so in areas that have lower overall elasticity. However, the current trend of newsroom cutbacks suggests that managers may be the cross-market consequences that can be detrimental to total revenues and profit.

In sum, this empirical analysis shows that the proposed platform sales response model is supported by the market data, furnishes strong evidence of the presence of CMEs, and sheds light on indirect marketing elasticities induced by CMEs. Thus, based on the theoretical and empirical results, newspaper managers should systematically estimate response models that incorporate cross-market effects to make informed marketing investment decisions.

Managerial Implications

Since many firms rely heavily on marketing, managers have the responsibility to plan their investment budget and its allocation optimally and demonstrate that these investments generate appropriate returns for the firm. Although considerable research on this topic exists, the literature so far has largely ignored the marketing budgeting allocation problem of platform firms operating in two-sided markets characterized by cross-market effects (CMEs). This gap in research exists despite the reality that platform firms are not only pervasive across the modern business landscape, but also invest heavily in marketing (Evans and Schmalensee 2007).

Our research contributes to the domain of marketing budgeting and allocation planning by investigating two-sided platform firms' marketing decisions both theoretically and empirically. Specifically, we develop normative budgeting and allocation rules using a proposed two-sided dynamic sales response model, and estimate and validate the proposed model using data from an archetypal platform firm, namely, a daily newspaper company whose two end-user groups of interest are readers and advertisers. We derive five new propositions that show how optimal marketing investment strategies toward each end-user group of a platform firm depend on the carry-over dynamics of both markets as well as cross-market effects (CMEs). These results complement the findings and managerial guidance obtained on pricing in two-sided markets (Eisenmann, Parker, and Alstyne 2006). Empirically, our analysis of the longitudinal data from the daily newspaper firm reveals the presence of dynamic CMEs between the readers and advertisers of this newspaper. Our findings imply that CMEs are important in the estimation of marketing effort-sales elasticities in platform firm settings. To summarize, we present the key takeaways for managers and academics from our analytical and empirical findings.

Takeaway 1: It is crucial for platform managers to take both effects—CMEs and carry-over—into account while making decisions. CME structures may imply higher marketing investments in the case of reinforcing platforms (Result 1) or, in counteractive platforms, a conservative approach that carefully weighs the gain from adding suitors against the loss of some attractors when setting marketing investment levels (Result 2).

Takeaway 2: Due to the interplay between own-market and cross-market effects, there may be situations where platform firms should invest heavily in marketing to an end-user group even when it provides low sales margins (Result 2).

Takeaway 3: In the newspaper industry, the presence of CMEs substantially increases the net worth of the newspaper's spending on newsroom quality as this investment attracts readers and in turn higher advertiser revenues. Thus, our findings support the case for increasing investments in news quality, which is contrary to what many troubled newspaper companies are doing today.

In sum, we hope that managers use our proposed model-based approach to determine the marketing budget and its allocations in both reinforcing and counteractive platform markets. We also hope that the newspaper managers in troubled newspaper companies could use the substantive findings to potentially improve performance.

Appendix A. Analytical Derivation of Optimality Conditions

We assume the platform firm's goal is to maximize discounted long-term profits and, therefore, its problem is expressed as

$$\text{Maximize } J(u, v) = \int_0^\infty e^{-\rho t}\pi(A(t), S(t), u(t), v(t))\,dt, \tag{A1}$$

$$\text{where } \pi(A, S, u, v) = m_A A + m_S S - u - v, \tag{A2}$$

$u(t)$ and $v(t)$ denote the marketing investments toward attractors and suitors, respectively, and m_A and m_S represent the margins on unit sales to attractors and suitors, respectively.

In determining the optimal effort levels, denoted u^* and v^*, the manager needs to account for CMEs and the dynamics of market response. Denoting $\dot{x} = dx(t)/dt$, we express Equation 1 in continuous-time as

$$\begin{bmatrix} \dot{A} \\ \dot{S} \end{bmatrix} = \begin{bmatrix} -(1-\lambda_A) & \theta_{SA} \\ \theta_{AS} & -(1-\lambda_S) \end{bmatrix} \begin{bmatrix} A \\ S \end{bmatrix} + \begin{bmatrix} f(u) \\ g(v) \end{bmatrix} \tag{A3}$$

and solve the maximization problem defined by equations 2-4 by applying optimal control theory (see, e.g., Kamien and Schwarz 1992, or Sethi and Thompson 2006). To this end, we first define the current-value Hamiltonian

$$H = m_A A + m_S S - u - v + \mu_1(-(1-\lambda_A)A + \theta_{SA}S + f(u)) + \mu_2(-(1-\lambda_S)S + \theta_{AS}A + g(v)) \tag{A4}$$

where μ_1 and μ_2 represent the co-state variables corresponding to $\dot{A}$ and $\dot{S}$, respectively. By applying the Pontryagin's maximum principle, we obtain the first-order conditions:

$$\frac{\partial H}{\partial u} = 0 \Rightarrow \mu_1 \frac{\partial f}{\partial u} = 1 \quad \text{(A5)}$$

$$\frac{\partial H}{\partial v} = 0 \Rightarrow \mu_2 \frac{\partial g}{\partial v} = 1 \quad \text{(A6)}$$

and

$$\dot{\mu}_1 = \rho\mu_1 - \frac{\partial H}{\partial A} = \rho\mu_1 - m_A + \mu_1(1-\lambda_A) - \mu_2\theta_{AS} \quad \text{(A7)}$$

$$\dot{\mu}_2 = \rho\mu_2 - \frac{\partial H}{\partial S} = \rho\mu_2 - m_S + \mu_2(1-\lambda_S) - \mu_1\theta_{SA} \quad \text{(A8)}$$

Next, using the transversality conditions (Kamien and Schwartz 1992, p.175), we obtain the stationary μ_1^* and μ_2^* given below:

$$\begin{bmatrix}\mu_1^* \\ \mu_2^*\end{bmatrix} = \frac{1}{[(\rho+1-\lambda_A)(\rho+1-\lambda_S) - \theta_{AS}\theta_{SA}]}\begin{bmatrix} m_A(\rho+1-\lambda_S) + m_S\theta_{AS} \\ m_A\theta_{SA} + m_S(\rho+1-\lambda_A)\end{bmatrix} \quad \text{(A9)}$$

Finally, we substitute μ_1^* and μ_2^* from (10) into (6) and (7) to obtain the gradient condition,

$$\begin{bmatrix} \left.\frac{\partial f}{\partial u}\right|_{u=u^*} \\ \left.\frac{\partial g}{\partial v}\right|_{v=v^*}\end{bmatrix} = \begin{bmatrix} \frac{(\rho+1-\lambda_A)(\rho+1-\lambda_S) - \theta_{AS}\theta_{SA}}{m_A(\rho+1-\lambda_S) + m_S\theta_{AS}} \\ \frac{(\rho+1-\lambda_A)(\rho+1-\lambda_S) - \theta_{AS}\theta_{SA}}{m_A\theta_{SA} + m_S(\rho+1-\lambda_A)}\end{bmatrix} \quad \text{(A10)}$$

This gradient condition can be applied to obtain exact solutions for u^* and v^* upon specifying the sales response functions f and g. For instance, let us suppose they have the square-root form as in Naik and Raman (2003), i.e., $f(u) = \beta_1\sqrt{u}$ and $g(v) = \beta_2\sqrt{v}$. Then the gradient condition in Equation A10 becomes:

$$\begin{bmatrix}\sqrt{u^*} \\ \sqrt{v^*}\end{bmatrix} = \frac{1}{2[(\rho+1-\lambda_A)(\rho+1-\lambda_S) - \theta_{AS}\theta_{SA}]}\begin{bmatrix} \beta_1(m_A(\rho+1-\lambda_S) + m_S\theta_{AS}) \\ \beta_2(m_A\theta_{SA} + m_S(\rho+1-\lambda_A))\end{bmatrix} \quad \text{(A11)}$$

We can now see that previous solutions for optimal investment levels in classic firms are special cases of Equation A11). Specifically, we can obtain the static Dorfman and Steiner (1954) result by setting the carry-over parameter values $\lambda_S = \lambda_A = 0$ (No Dynamics) and $\theta_{AS} = \theta_{SA} = 0$ (No CMEs). That is,

$$\begin{bmatrix}u^* \\ v^*\end{bmatrix} = \frac{1}{4}\begin{bmatrix}(\beta_1 m_A)^2 \\ (\beta_2 m_S)^2\end{bmatrix}. \quad \text{(A12)}$$

Similarly, we can obtain the dynamic Nerlove-Arrow (1962) result from Equation A11 by setting $\theta_{AS} = \theta_{SA} = 0$ (No CMEs). That is,

$$\begin{bmatrix}u^* \\ v^*\end{bmatrix} = \begin{bmatrix}\frac{(\beta_1 m_A)^2}{4(\rho+1-\lambda_A)^2} \\ \frac{(\beta_2 m_S)^2}{4(\rho+1-\lambda_S)^2}\end{bmatrix} \quad \text{(A13)}$$

Comparing Equation A12 and Equation A13, we learn that the optimal spending levels $(u^*, v^*)'$ in Equation A13 are larger than those in Equation A12 as a result of accounting for sales dynamics. Intuitively, marketing spending levels should be increased to take advantage of the carryover effects (λ_A, λ_S) when they are present (e.g., Sinha and Zoltners 2001).

Appendix B. Proofs of Analytical Results

We refer the reader to the equations in Appendix A and notation described in the text.

Result 1. Optimal marketing efforts by reinforcing platform firms (θ_{AS} and $\theta_{SA} > 0$) directed at both attractors and suitors are greater than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$).

Proof. The gradient condition (A10) reveals that $df/du|_{u=u^*}$ for reinforcing platforms is less than $df/du|_{u=u^*}$ for classic firms. Furthermore, for any concave function f, $df/du|_{u_1^*} < df/du|_{u_2^*}$ implies $u_1^* > u_2^*$, thus proving the claim for attractors. Similarly, $dg/dv|_{v=v^*}$ for reinforcing platform is less than $dg/dv|_{v=v^*}$ for classic firms, indicating that suitors v^* (reinforcing platform) > v^* (classic firms).

Result 2. Optimal marketing efforts by counteractive platforms ($\theta_{AS} > 0, \theta_{SA} < 0$) directed at attractors are greater than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$) provided the margin ratio m_S/m_A exceeds a critical value, m^*.

Proof. The gradient condition (A10) reveals that $df/du|_{u=u^*}$ for counteractive platforms is less than $df/du|_{u=u^*}$ for classic firms when $m_S(\rho + 1 - \lambda_A) + \theta_{SA}m_A > 0 = m_S/m_A > m^*$, where the critical value $m^* = \dfrac{|\theta_{SA}|}{\rho + 1 - \lambda_A}$ and $|x|$ denotes the absolute value of x. Furthermore, $df/du|_{u_1^*} < df/du|_{u_2^*}$ implies $u_1^* > u_2^*$, indicating that u^* (counteractive platform) > u^* (classic firm) when $m_S/m_A > m^*$, as posited.

Result 3. Optimal marketing efforts by counteractive platforms ($\theta_{AS} > 0, \theta_{SA} < 0$) directed at suitors are smaller than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$).

Proof. From the gradient condition in (A10), $dg/dv|_{v=v^*}$ for a counteractive platform is greater than $dg/dv|_{v=v^*}$ for classic firms. Furthermore, $dg/dv|_{v_1^*} > dg/dv|_{v_2^*}$ implies $v_1^* < v_2^*$, indicating that v^* (counteractive platform) < v^* (classic firm), which proves the claim.

Result 4. Optimal marketing efforts towards attractors increase as (a) λ_S increases in reinforcing platforms and (b) λ_S increases in counteractive platforms provided m_S/m_A exceeds the critical value m^*.

Proof. A decrease in $df/du|_{u=u^*}$ implies an increase in u^*. Furthermore, the change in $df/du|_{u=u^*}$ with respect to λ_S is given by

$$\left.\frac{\partial^2 f}{\partial u \partial \lambda_S}\right|_{u=u^*} = \frac{-\theta_{AS}[m_S(\rho - 1 - \lambda_A) - \theta_{SA}m_A]}{[m_A(\rho + 1 - \lambda_S) + m_S\theta_{AS}]^2}$$

which is negative in reinforcing platforms because $\theta_{SA} > 0$ and $\theta_{AS} > 0$.

Consequently, u^* in reinforcing platforms increases with λ_S. Additionally, $\left.\dfrac{\partial^2 f}{\partial u \partial \lambda_S}\right|_{u=u^*}$ is negative in counteractive platforms ($\theta_{AS} > 0, \theta_{SA} < 0$) when $m_S(\rho + 1 - \lambda_A) + \theta_{SA}m_A > 0 = m_S/m_A$ exceeds m^*, the critical margin ratio. This completes the proof.

Result 5. Optimal marketing efforts towards suitors (a) increases as λ_A increases in reinforcing platforms and (b) decreases as λ_A increases in counteractive platforms (regardless of the margin ratio).

Proof. A decrease in $dg/dv|_{v=v^*}$ implies an increase in v^*. Furthermore, the change in $dg/dv|_{v=v^*}$ with respect to λ_A is given by

$$\frac{\partial^2 g}{\partial v \partial \lambda_A} = \frac{-\theta_{SA}[m_A(\rho + 1 - \lambda_S) + \theta_{AS}m_S]}{[m_S(\rho + 1 - \lambda_A) + m_A\theta_{SA}]^2}$$

which is negative in reinforcing platforms ($\theta_{SA} > 0$, $\theta_{AS} > 0$). This implies a reduction in $dg/dv|_{v=v^*}$ and thus an increase in v^* in reinforcing platforms as λ_A increases. Additionally, $\dfrac{\partial^2 g}{\partial v \partial \lambda_A}$ is positive in counteractive platforms because $\theta_{AS} > 0$ and $\theta_{SA} < 0$, implying v^* increases as λ_A increases. This completes the proof.

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