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Integrated Marketing Communications at the Marketing-Sales Interface

Timothy M. Smith, Srinath Gopalakrishna, and Rabikar Chatterjee

A marketing/sales "disconnect" wastes expenditures, time, and energy. This study examines the complex relationship between marketing efforts, sales follow-up, and closing the deal. In collaboration with a major retailer, the authors develop a tool to assist managers in allocating resources across media channels

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Report Summary

In many organizations, there is a lack of coordination between the marketing and sales functions. Leads generated by the marketing department may be ignored by the salesforce, while marketing managers' lack of knowledge of the sales process often results in programs of, at best, variable quality. Such a divide can lead to wasted expense and energy as sales representatives chase after lesser quality leads (regardless of their origin), leaving many higher quality leads with delayed and potentially less effective selling approaches. An integrated marketing communications (IMC) framework, built on the synergy among different communication channels, has the potential to bridge the gap between marketing and sales.

Integration requires an understanding of how all communications influence each other. Here the authors address several questions, among them: What happens when expenditures on one media type are increased or reduced for another? Does a time lag in responding to customers' request for information have an impact down the line?

The authors develop a three-stage model to capture the effects of sequential marketing communications on generating leads, securing appointments with customers, and closing sales. Their results suggest strong and often complex relationships between marketing efforts (multiple-media that generate leads), delays in subsequent communications (time lag between inquiry and personal selling follow-up), and stresses placed on sales efficiencies (appointment and sales conversion). Their findings underscore the impact of multimedia communications spending on subsequent communications timing and effectiveness when addressing IMC resource deployment.

This study is a result of a collaborative effort with a large home improvement retailer with a national presence. A product of the study is a user-friendly decision support tool that managers can use to simulate the impact of varying communications budgets and media allocations and to do marketing and sales planning. It allows managers to assign media expenditures on a weekly basis for the year. Using the tool, the authors provide three hypothetical scenarios that illustrate the impact of changes in media allocations on the retailer's operations. ■

Introduction

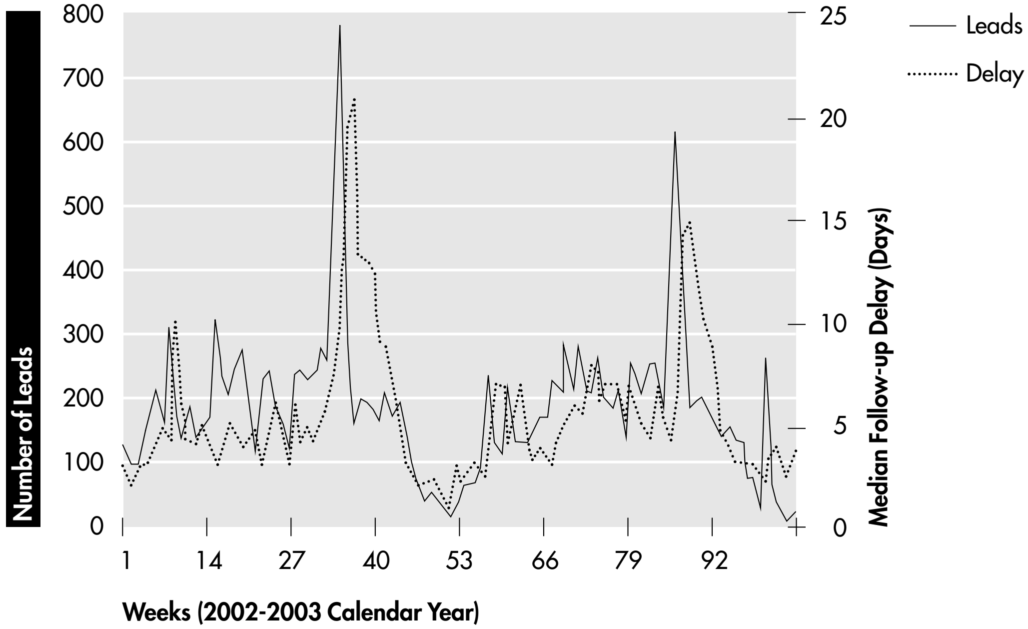
The effective integration of various elements of the marketing communications mix is an important challenge for practitioners and academics alike. Corporations spend heavily attempting to communicate with their current and prospective customers, often through multiple channels such as advertising, trade shows, and personal sales calls. Managers deploying scarce resources across different communication elements may intuitively hope to leverage complementarity (or synergy) across elements, in the sense that spending on one source has a positive impact on the effectiveness of another source (Gatignon and Hanssens 1987; Gopalakrishna and Chatterjee 1992). While this perspective, labeled integrated marketing communications (IMC), has received some attention in the academic literature; research in the area is scarce (Naik and Raman 2003).

In practice, the impact of communications activity on the buyer's purchasing process is often sequential, especially when the process involves multiple stages. An important issue in this context is the timing of exposure to sequential communications, an aspect that has not received research attention but is nevertheless central to effective resource deployment. Our research on this topic stems from a series of issues that emerged in our discussions with a major home improvement retailer, which we will refer to as HIR for reasons of confidentiality. The firm communicates with its target market for installed home improvement products through a variety of channels—direct mail, radio advertising, newspaper, trade shows, etc. Sales leads generated from these sources are followed up (by prior appointment) with a sales call. HIR management implicitly believes that all leads are important and require prompt follow up by the salesforce. Thus, customer appointments for sales visits are set up (through the call center) at the earliest available time slot, subject to mutual acceptance. However, the salesforce capacity is limited, which creates significant delays in the in-home visit by the salesperson, particularly in the busiest season. The result is a longer wait by the prospect with the possible consequence of a lost sales opportunity owing to the prospect's declining interest. HIR management recognizes that such declines in purchase likelihood bear some relationship to the lead-generating mechanism at the front end of the process.

The above scenario, which motivates our conceptual development and analysis, also lies at the heart of a hotly debated managerial topic—the marketing-sales disconnect. On the surface, the relationship between marketing and sales appears symbiotic and complementary; however, the coordination of the two functions is often sporadic. In many organizations, the integration of marketing and sales is limited merely to handing off information, creating tension over resources while bringing into question each function's role in enhancing customer experiences and their impact on the bottom line (Marketing Science Institute 2004). The business press has emphasized the critical importance of ensuring that marketing and sales work together, not against each other. A recent industry report suggests that as much as 70% of the leads generated by marketing efforts are simply ignored by the salesforce (Watkins 2003). In turn, salespeople argue that marketing managers have become so far removed from the sales process that they don't know what constitutes a good lead that is worthy of immediate follow-up. Such observations underscore the difficulties in achieving effective integration of communication activities in practice.

HIR management approached us with a complex problem that revolved around the development of an effective integrated communications mix. Sales leads generated through spending on marketing communications were creating stressful situations for the salespeople because the weekly lead volume was uneven. As shown in Figure 1, the average time to service leads closely follows weekly lead volume. Further, the data suggest that as the wait becomes longer, prospects are less likely to make a purchase.

Figure 1
Actual Lead Created and Follow-up Delay



While an intense marketing communications effort generates a large number of leads, high lead volume can create greater delays in servicing leads, which in turn may decrease the likelihood of sales conversion. Moreover, marketing's aggressive spending creates delays in servicing leads that can persist for several weeks (owing to a constraint on salesforce capacity). A side effect of such imbalances is the likely adverse impact of lower sales conversion rates on salesforce morale.

Our fundamental objective is to develop and estimate a model that captures the essential dynamics of the customer buying process, given the available information, and to employ the results obtained to simulate the impact of alternate marketing and sales budgets on HIR's performance. To help HIR managers run such simulations as an aid to marketing and sales planning, we develop a user-friendly decision support tool. In the process, we address the following questions:

- Which elements of the marketing communications mix are more effective than others in generating leads? What carryover and complementary (interactive) effects, if any, exist?
- What is the impact of lead volume on follow-up delay (the time lag between lead generation and sales appointment) for the prospect?
- What is the impact of delay on the likelihood of conversion of a lead to a sales appointment and to subsequent closure of the sale? Does this vary by lead source?
- What is the impact of seasonality at each stage of the buying process?
- How do such variables as salesperson quality and prospect characteristics affect the process?

We continue by briefly reviewing the relevant literature in the area of IMC, followed by a further discussion of the managerial context and data available. We then describe our model, based on a conceptual framework that examines the buying process as a sequence of three stages—lead generation, appointment conversion, and sales closure. Next, we discuss the results of our estimation of the various parameters of the multistage model and report on model validation. We then describe the decision support tool developed to help management simulate the impact of different media applications on outcomes (based on the model parameter estimates) and provide some illustrative simulations. Our concluding section summarizes research contributions, managerial implications, and avenues for future research.

Integrating Marketing Communications

While marketers intuitively embrace the IMC perspective, empirical research in this area is scarce. From a planning and budgeting perspective, practitioners have acknowledged the interaction among marketing communication elements for quite some time (Acheson 1993; Morrill 1970). However, the role of interactions and synergy remains largely unexplored. The IMC framework is built on the foundation that different communication media, if deployed appropriately, have the potential to enhance the contributions of other media (Belch and Belch 2003). Although there are several variations in the definition, IMC has been characterized as both a relational process and a business competency (Reid 2003). The goals and outcomes of IMC are often linked to building relationships with customers and other stakeholders through ongoing dialogue and subsequent effects on sales and profits (Duncan and Caywood 1996; Smith, Gopalakrishna, and Smith 2004). In addition, IMC as a business competency suggests that multiple communications can be integrated and managed to achieve synergistic outcomes (Duncan 2002; Naik and Raman 2003; Naik, Raman, and Winer 2005).

Especially in dynamic settings, the added value associated with synergies created by strategically implementing and evaluating multiple media is not well understood. Naik and Raman (2003) have recently proposed a model incorporating synergistic effects in dynamic budgeting decisions. While they provide important and managerially relevant insights, their analysis is based on monthly data modeled at the market level, ignoring the *sequential* realities of communication exposure at the *individual* level. Naik, Raman, and Winer (2005) extend this work to rigorously incorporate competition in an extended Lanchester model specification that allows for interaction between advertising and promotion. Again, while their research makes an important theoretical and empirical contribution, it does not consider lead and lag effects or sequential interactions.

Discussion in the popular press has recently focused on "simultaneous media" in communications planning as justification for IMC and its concentration on communication synergies (Schultz 2004). While simultaneous exposure to communications may exist, even in the most technology-driven settings, multiple communications are most often processed sequentially. This aspect directly relates to the issue of timing. The time lag between two sequential communications has important implications on the interactive/synergistic effects between mix elements and the effectiveness of the overall deployment in terms of bottom-line outcomes.

Developing effective communications programs focusing on the allocation and timing of multiple media poses a significant challenge and raises additional questions: What happens to the number and quality of referrals if expenditures on one media type are increased and reduced for another? Does the time lag between communications in sequence impact the likelihood of response and does this vary with different combinations of communications employed? How do seasonality and firm-specific capacity constraints affect communications decisions? For example, a prospect identified at a company's trade-show booth may be of higher quality than one identified through a reply to a bingo card. However, if the bingo card prospect is exposed to a subsequent communication quickly (direct mail, salesforce, outbound telecommunications, e-mail, etc.), he or she may be of substantially greater value to the firm than the trade-show prospect contacted several weeks later. Therefore, management must consider not only the direct and interactive effects of the communications deployed, but also the impact of timing and time lag on the likely synergies created through sequential communications.

The interaction effects of advertising and sales efforts are not new to the marketing discipline. Since the introduction of the marketing mix concept, interactions among marketing variables have been acknowledged as important to the understanding of marketing effectiveness. While recent work in IMC has tended to focus on advertising, a number of researchers have explored the role of interactions across the marketing and sales divide. Several studies in the business press and academic literature have documented the role of advertising in terms of creating a favorable climate for the sales call (Couretas 1984; Levitt 1967; Morrill 1970). Indeed, the McGraw-Hill "man-in-chair" advertisement, considered a business marketing classic, suggests that advertising can have a positive impact on salesforce efficiency. Although a sequence of impersonal to personal communications makes intuitive sense, Swinyard and Ray (1977) report an increase in advertising effectiveness when there is prior salesperson contact, illustrating the importance of the order and/or relative timing of communications.

With regard to resource allocation, the literature is rich with studies exploring the mix of expenditures on personal and impersonal communications, but the analyses are often at the market level and limited to simple two-source systems (salesforce and advertising, direct mail and advertising, etc.). Gatignon and Hanssens (1987) explore the optimal ratio of personal and mass communications expenditures numerically within a static (single-period) case. Gopalakrishna and Chatterjee (1992) assess the joint impact of advertising and salesforce expenditures through the development of a dynamic sales response model. Smith, Gopalakrishna, and Smith (2004) assess the complementary effect of trade shows on salesforce performance and suggest normative implications for optimizing salesforce allocations based on previous communications exposure.

In summary, the literature offers limited empirical and theoretical insights on the process of integrating communications. Specifically, there is little help for marketing managers in planning communications strategies across multiple media and understanding their combined impact on salesforce effectiveness. We build on these gaps by exploring the dynamics of integrated marketing communications, including not only the carryover effects of media , but also the effects of delay (the time lag between media communications and salesforce deployments), decay (reduced selling effectiveness as delay increases), and seasonality on marketing resource deployment.

The Managerial Context

HIR is a large home improvement retailer with operations across the United States. The product in our study is quality replacement windows promoted through various channels of marketing communications and sold via a direct sales process. The firm provides a unique combination of product and service offerings in the industry, and communicates with its target market for installed home improvement products through a variety of channels—direct mail, radio advertising, newspaper, trade shows, etc. Sales leads generated from these sources are followed up, with prior appointment, by a sales visit. The nature of the product is such that the firm's salesperson must visit the prospect's home before a sale can be concluded. Typically, the salesperson visiting the prospect's home ascertains the specific needs, offers a quote for window replacement, and, if possible, tries to close the sale in that one visit.

The data pertain to HIR's lead-generation and sales processes in a major metropolitan market. Specifically, inquiries in the calendar years 2002–2003 frame the sample, representing 19,496 inquiries, 16,309 in-home sales visits, and 6,068 purchasing events. The disaggregated data set, at the prospective customer level, provides information about the date of initial customer inquiry, the marketing campaign prompting the inquiry, the number of units anticipated, and the date of the in-home sales visit. An important piece of information is the marketing program prompting the prospect's initial inquiry. Each communications medium specifically directs the prospective customer to call a toll-free number unique to that particular medium and campaign to "arrange for a free in-home estimate."

We examine nine separate sources of leads—print advertisements (newspaper print ads and newspaper supplements), direct mail (individual mailings and "marriage mail"), exhibition and event sponsorships (consumer-oriented home and garden shows and booths at various local events), radio advertisements, telephone directories, Internet communications, retail showrooms, referral programs, and repeat business. These sources account for more than 98% of the leads in our analysis and cover all the marketing communications expenditures incurred in this market.

Marketing communications expenditures were available (by media type), along with archival records of purchase transactions and demographic data at the zip-code level (provided by a third party). HIR manages marketing communications media expenditures weekly, with significant emphasis on key metrics such as media cost per lead and cost per appointment. Thus, we analyze weekly marketing communications expenditures by media type. Transactional data were available for all customer purchases at the individual (household) level. Data from this source include matching customer information, purchase date, units purchased, and purchase amount. Additionally, demographic data (estimates of home value, age of home, head of household age, household income, and length of residence) were available at the zip-code (not household) level.

These data allow us to explore a process that begins with impersonal marketing communications, generating a customer inquiry (contact with the call center), followed by a sales call (after a time lag), and culminating in a potential sale. The process is described in more detail in the next section. It is important to recognize the link between multimedia expenditures and the resulting delay between inquiry and sales appointment (see Figure 1). The delay adversely affects the purchase likelihood because consumer decisions to invest in home improvement tend to be transient, competing with alternative uses of the available funds. Significant delays in the sales visit, associated with high lead volume, warrant careful analysis of the allocation/timing of lead-generating communications that best complement the subsequent selling effort.

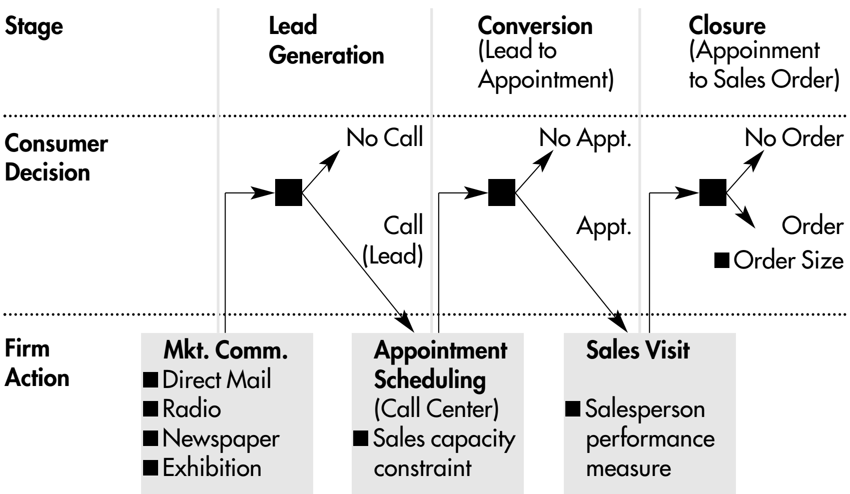
The Model

The sales process is modeled as a series of stages marked by concrete outcomes. They are (1) the generation of sales leads, (2) the conversion of leads into sales appointments, and (3) the conversion of appointments into sales. Figure 2 displays this sales process as a sequence of stages, marked by the actions of both the firm and its prospective customers. We briefly describe the dynamics of the process of conversion to the outcome—sales leads, appointments, or actual sales orders—for each stage. In adopting particular model specifications and underlying functional forms, we have been guided by the objective of capturing the essential relationships and dynamics consistent with the underlying phenomena and with the patterns exhibited by the data, in a reasonably parsimonious and robust manner. Several viable candidate forms were considered, and the final choices best met the criteria of "theoretical and descriptive soundness" (Lilien, Kotler, and Moorthy 1992, p. 674).

Stage 1: Lead generation

Sales leads are generated by phone calls to the company's call center from potential customers expressing an interest in HIR's products and (typically) scheduling an appointment for an in-home visit by a salesperson. These leads are

Figure 2
Sales Process as a Sequence of Stages Marked by Concrete Outcomes



triggered primarily by the company's marketing communications via radio and newspaper advertising, direct mail, and exhibitions (consumer -oriented home shows). Leads are also generated by a limited retail/showroom presence, telephone directories, the Internet, referrals, and repeat business. An examination of the data and insights from HIR managers suggest that:

- Exhibitions produce some carryover effect on the volume of leads generated, but the impact of other key media (for which expenditures are controlled by HIR and may be varied over time, specifically in the case of radio, newspapers, and direct mail) is instantaneous, with no discernable carryover to later weeks.
- There are interactive effects, in that the volume of leads generated by one source is affected by communications expenditure on other sources.
- The impact of communications expenditure on lead volume displays seasonal variation, given the highly seasonal nature of the product. Rather than a discrete step change from low to high season, there appear to be gradual "shoulders" at either end of the high season, such that the impact ramps up (from some low level) at the start of the season to the plateau of the high season and then ramps down at the end. The two shoulders or ramps each appear to be about 12 weeks long.

Based on these observations, we propose the following model specification for lead generation:[1]

$$L_{it} - \lambda_i L_{i(t-1)} = \alpha_{0i}(\alpha_{1i})^{S_t}(X_{it})^{\beta_{ii}} \sum_{\substack{j=1,\\ j\neq i}}^{N} (1 + X_{jt})^{\beta_{ij}}; \tag{1a}$$

$$S_t = \begin{cases} 13 - t & \text{if } 1 \le t \le 12 \\ 0 & \text{if } 13 \le t \le 40 \\ t - 40 & \text{if } 41 \le t \le 52 \end{cases} \tag{1b}$$

where i indexes the communications source ($i = 1, \ldots, N$) and t indexes the time period (in weeks, $t = 1, \ldots, 52$, with $t = 1$ denoting Week 1 of the calendar year) respectively, and:
L_{it} = lead volume (number of customer calls) attributed to source i in week t;
X_{it} = communications expenditure (in dollars) for source i in week t;
and α_{0i}, α_{1i}, β_{ii}, β_{ij}, λ_i, are the lead-generation model parameters (to be estimated).

The parameter α_{0i} captures the scale effect in the sense that, all else equal, a higher value of this parameter implies a proportionately higher number of leads generated by the particular source in a given week. The slope of the off-season ramps in the lead-generation function on either side of the high season is captured via α_{1i}—to have downward sloping ramps, $0 < \alpha_{1i} < 1$, with smaller values of α_{1i} indicating steeper declines in the ability of communications to generate leads. The β parameters allow for nonlinearity in the main and interactive effects. Specifically, $0 < \beta_{ii} < 1$ would suggest a concave response function for the main effect, positive but with declining marginal impact due to saturation. The term $(1 + X_{ij})^{\beta_{ij}}$ captures the interactive or synergistic effect of source j on leads generated by source i; $\beta_{ij} > (<)\ 0$ would imply positive (negative) synergies, while $\beta_{ij} = 0$ would signal no interactive effect. Note that adding the 1 in the interaction terms—$(1 + X_{ij})^{\beta_{ij}}$—ensures that the main effect $(X_{it})^{\beta_{ii}}$ remains intact even if X_{jt} is zero. Finally, the carryover effect, λ_i, is estimated in the case(s) where such an effect might exist (exhibitions), but is assumed to be zero for media sources where there is no carryover.

Furthermore, we observe that HIR's presence in certain major exhibitions (which occur in specific months) is significantly larger in terms of expenditures and scope compared to its involvement in other (minor) shows. The impact of these major exhibitions in lead generation appears to be qualitatively different from that of the minor ones. Accordingly, we modify Equation 1a in the case of exhibitions to reflect this possible difference as follows:

$$L_{it} - \lambda_i L_{i(t-1)} = \alpha_{0i}(\alpha_{1i})^S (\beta_E)^{E_t} (X_{it})^{\beta_{ii}} \prod_{\substack{j=1, \\ j \neq i}}^{N} (1 + X_{jt})^{\beta_{ij}} \tag{1′a}$$

for i = exhibitions,

where E_t is a dummy variable indicating the type of exhibition; E_t = 1 if the exhibition in week t is a major, 0 otherwise.[2] The parameter β_E captures the differential impact of a major (versus minor) exhibition on lead generation. We would expect $\beta_E > 1$ if major exhibitions do indeed have a greater impact.

Stage 2: Conversion of leads to appointments

The sales lead in the form of a phone call from the customer (outcome of Stage 1) provides the call center with an opportunity to schedule an in-house sales visit. Of course, not all leads are converted to sales appointments. Attrition (non-conversion) may occur because the customer may not be ready to schedule an in-house sales visit, the time lag between the call date and the earliest sales appointment date (delay) is unacceptable to the customer, or the customer cancels a sales visit after it has been scheduled. The latter two factors suggest that attrition increases with delay. Data suggest that the rate of attrition is specific to the communications source. Further, the attrition rate is likely to be different in the off-season relative to the high season (although the effect of seasonality on leads-to-appointments conversion should not be source-related). Given these considerations, we specify the following model for sales appointments:

$$A_{it} = \gamma_{0i}(\gamma_1)^{S_1}(\gamma_2)^{S_2}(L_{it})^{\delta_{1i}}(\overline{Lag}_t)^{\delta_{2i}} \tag{2}$$

where L_{it} is as defined earlier, and:
A_{it} = number of sales appointments converted from leads in week t attributed to source i;
$\overline{Lag}_t$ = median lag time between the leads generated in week t and the resulting sales appointments;
S_1, S_2 = seasonality indicators; S_1 = 1 if week $0 \le t \le 12$, 0 otherwise; and S_2 = 1 if week $41 \le t \le 52$, 0 otherwise; and γ_{0i}, γ_1, γ_2, δ_{1i}, and δ_{2i} are the conversion model parameters (to be estimated). The high-season scale effect, captured by γ_{0i}, is modified to $(\gamma_{0i} \times \gamma_1)$ for the 12-week off-season period prior to the high season and to $(\gamma_{0i} \times \gamma_2)$ for the 12-week off-season period following the high season. Note that the off-season adjustment parameters γ_1 and γ_2 are assumed to be independent of the lead source. The (possible) nonlinearity in the effects of L_{it} and $\overline{Lag}_t$ on conversion is captured by δ_{1i}, and δ_{2i}. Since these effects should be positive for L_{it} and negative for $\overline{Lag}_t$, we would expect $\delta_{1i} > 0$ and $\delta_{2i} < 0$.

Stage 3: Sales closure

During the sales appointment (outcome of Stage 2), the salesperson collects the information necessary to prepare a quote for the customer, after which the customer places an order for supply and installation. A sales appointment may or may not result in a sales order for HIR. We model this stage in two parts: (1) the probability of closure (in the form of an order), given that the sales appointment has taken place, and (2) the size of the order placed by the customer, given that an order has been placed.

The probability of closure decreases as the time lag between the initial customer contact (sales lead) and the scheduled sales visit increases, similar to the dynamics in Stage 2. Again, the initial probability and decay rate may vary by communication source. Our initial examination of the data suggests this. Similarly, seasonality affects the probability of closure. Furthermore, the effectiveness of the particular salesperson calling on the household can also influence the probability of closure.

Unlike the sales lead-generation and appointment conversion models in Stages 1 and 2, the availability of appropriate data (household-level variables) makes it possible to model the probability of sales closure at the individual household level. Finally, rather than the median lag (between sales lead and appointment), we can now consider household-specific lags. An examination of the data (and discussions with managers at HIR) suggests that individual cases of lags that are greater than the corresponding median lag (for that week) tend to be customer-driven in nature, in the sense that the customer requests a specific appointment date beyond that offered by HIR. Obviously, such customer-driven lags will not have the same adverse effect on the probability of closure as HIR-driven lags arising due to the salesforce capacity constraint.

Based on the above considerations, we employ the following logit specification to model the probability of closure at the individual household level:

$$\ln\left(\frac{P_{h|it}}{1-P_{h|it}}\right) = \theta_{0i} + \theta_1 S_1 + \theta_2 S_2 + \eta Y + \phi_{1i}\min(Lag_{hit}, \overline{Lag}_t) + \phi_{2i}[\max(Lag_{hit}, \overline{Lag}_t) - \overline{Lag}_t] + \sum_{l=1}^{L} \lambda_l Z_{lh}, \tag{3}$$

where h indexes the individual household, l indexes the household descriptor variable, i and t index the communications source and time period respectively as before, S_1, S_2, and $\overline{Lag}_t$ are defined as before,[3] and:

$P_h|_{it}$ = probability that household h places an order, given that the initial lead was generated by source i in week t;

Y = dummy variable indicating salesperson type ($Y = 1$ if salesperson is above the median effectiveness level, 0 otherwise);

Lag_{hit} = lag time for household h between the initial lead in week t attributed to source i and the resulting sales appointment;

Z_{lh} = value of l^{th} household descriptor variable for household h; and

θ_{0i}, θ_1, θ_2, η, ϕ_{1i}, ϕ_{2i}, and λ_l are parameters (to be estimated).

The effects of seasonality, salesperson, and the set of household-level descriptor variables are modeled in a straightforward manner, via the parameters θ_1, θ_2, η, and λ_l. Note that these effects are not hypothesized to be specific to the media generating the lead. We model the impact of the lag by assuming that any household-level lag beyond the corresponding median lag is initiated by the customer, as captured by the two terms with the lag variables. If $Lag_{hit} < \overline{Lag}_t$, these two terms reduce to ϕ_{1i}; if $Lag_{hit} > \overline{Lag}_t$, they reduce to $\phi_{1i}\overline{Lag}_t + \phi_{2i}$ $(Lag_{hit} > \overline{Lag}_t)$. Thus, ϕ_{1i} measures the impact of the HIR-driven lag, while ϕ_{2i} captures the impact of the part of the lag beyond the median value, assumed to be customer-initiated.

The size of the order (given that an order is placed) is influenced by the potential size of the order based on the anticipated number of units of the potential order (ascertained during the initial phone call), the effectiveness of the salesperson, and household characteristics. Further, the communications source that generated the initial lead may affect the order size. Given these considerations, we specify the order-size model as follows:

$$S_{h|i} = \kappa_i (V_h)^{\nu} (\mu)^{Y} \prod_{l=1}^{L} (Z_{lh})^{\tau_l}, \tag{4}$$

where Y and Z_{lh} are as defined earlier, and:

$S_{h|i}$ = size of the order from household h given that an order is placed following a lead generated by source i;

V_h = potential size of order from household i (as ascertained during sales lead); and

κ_i, ν, and τ_l are parameters (to be estimated).

The source-specific effect on the order size is captured by κ_i, while ν and τ_l measure the impact of salesperson effectiveness and household-level descriptors, respectively.

The "Linking" Model. The above stage-wise models capture the adverse impact of the lag between the initial phone call (lead) and the sales appointment on the conversion of leads to appointments and then on the closure of appointments to orders. As discussed earlier, a key decision on the part of HIR management is the timing of the communications effort via the various available channels. Greater effort will generate more leads, but, given salesforce capacity constraints, a larger number of leads will likely translate into a longer delay between the lead and a possible sales visit, potentially causing attrition in conversion and closure rates.

Thus, in addition to the stage-wise response models represented by equations 1-4, we need a model that links the leads generated in Stage 1 to the lags that may affect conversion and closure in stages 2 and 3. Conceptually, the extent of lag in period t would depend on the current backlog, captured by the extent of lag in period $(t-1)$, and the new leads generated in that period. If the volume of these new leads exceeds some "steady-state" level, then the backlog may increase from the current level. This conceptualization translates into the following model specification:

$$\overline{Lag}_t = \psi_0 + \psi_1 \overline{Lag}_{(t-1)} + \psi_2 \left(\sum_{i=1}^{N} L_{it} - \overline{L} \right), \tag{5}$$

where $\overline{Lag}_t$ and L_{it} are as defined earlier, $\overline{L}$ is the average volume of weekly leads generated (over the two years of available data), to capture the "steady state" level, and ψ_0, ψ_1, and ψ_2 are parameters to be estimated from the data.

Versions of the models used for parameter estimation

For estimation, models 1, 2, and 4 are linearized by taking logs on both sides. Furthermore, models 2, 3, and 4 have some parameters that are source-specific and others that are common across sources. The estimation versions of the models are specified as follows. First, the lead-generation model 1 is restated as:

$$\ln(L_{it} - \lambda L_{i(t-1)}) = \ln\alpha_{0i} + \ln(\alpha_{1i})\, S + \beta_{ii}(\ln X_{it}) + \sum_{\substack{j=1,\\ j\neq i}}^{N} \beta_{ij} \ln(1 + X_{jt}) + e_{1it}. \tag{1E}$$

and estimated separately for each source, $i = 1, \ldots, N$. The error terms e_{1it} are assumed to be distributed $N(0, \sigma_{1i})$, with the possibility of serial correlation (i.e., e_{1it} and $e_{1i(t-1)}$ are correlated). In the case of exhibitions, the restated lead-generation model (1′) will have an additional term to accommodate the dummy variable, E_t, indicating exhibition size, as follows:

$$\ln(L_{it} - \lambda L_{i(t-1)}) = \ln\alpha_{0i} + \ln(\alpha_{1i})\, S_t + \ln(\beta_E) E_t + \beta_{ii}(\ln X_{it}) + \sum_{\substack{j=1,\\ j\neq i}}^{N} \beta_{ij} \ln(1 + X_{jt}) + e_{1it}. \tag{1′E}$$

The appointment conversion model is estimated across sources as:

$$\ln A_{it} = \ln\gamma_{0N} + \sum_{i=1}^{N-1} D_i \ln\gamma_{0i} + \ln(\gamma_1)S_1 + \ln(\gamma_2)S_2 + \sum_{i=1}^{N} D_i\left[\delta_{1i}(\ln L_{it}) + \delta_{2i}(\ln(\overline{Lag}_t))\right] + e_{2it}, \tag{2E}$$

where the dummy variable $D_i = 1$ if the media source is i ($i = 1, \ldots, N-1$), 0 otherwise, and the error terms e_{2it} are assumed to be distributed $N(0, \sigma_2)$, with the possibility of serial correlation. The estimation version of the closure model (estimated across sources and households) is:

$$\ln\left(\frac{P_{h|it}}{1-P_{h|it}}\right) = \theta_{0N} + \sum_{i=1}^{N-1} D_i\theta_{0i} + \theta_1 S_1 + \theta_2 S_2 + \eta Y + \sum_{i=1}^{N-1} D_i\left[\phi_{1i}\min(Lag_{hit}, \overline{Lag}_t) + \phi_{2i}\left[\max(Lag_{hit}, \overline{Lag}_t) - \overline{Lag}_t\right]\right] + \sum_{l=1}^{L}\lambda_l Z_{lh} + e_{3h}, \tag{3E}$$

where D_i is defined as before, and the error terms e_{3h} are assumed to be independent across h and have the extreme value distribution, so that 3E is the familiar logit model. The estimation version of the order size model 4 is:

$$\ln S_{h|i} = \ln\kappa_N + \sum_{i=1}^{N-1} D_i(\ln\kappa_i) + \nu(\ln V_h) + (\ln\mu)Y + \sum_{i=1}^{L}\tau_l(\ln Z_{lh}) + e_{4h}, \tag{4E}$$

where $D_i = 1$ is again defined as before and the error terms e_{4h} are assumed to be independently distributed $N(0, \sigma_4)$. Finally, the linking model 5 used for estimation is specified as:

$$\overline{Lag}_t = \psi_0 + \psi_1\overline{Lag}_{(t-1)} + \psi_2\left(\sum_{i=1}^{N} L_{it} - \overline{L}\right) + e_{5t} \tag{5E}$$

with the error terms e_{5t} assumed to be distributed N $(0, \sigma_5)$, with the possibility of serial correlation.

Estimation Results

We next report on the coefficient estimates obtained for the various models discussed above, based on the data for 2002–2003 described earlier in "The Managerial Context" section, and also discuss the implications of the estimates obtained.

Stage 1: Lead generation

The parameter estimates of the lead-generation model (1E) are presented in Table 1. In this case, we estimated the models separately for each of the four sources (media types) where expenditures and allocations are actively managed—direct mail, newspaper advertising, exhibitions, and radio advertising. For each source-specific sub-model, we note that the fit is quite good, with R^2 values between .45 and .49. Also, we observe that the preseason build-up and the post-season decay in sales, captured through the ramp coefficient α_1, is statistically significant in the case of direct mail, newspaper, and radio. It is quite interesting to note that the ramp effect is different across sources. To illustrate, the ramp coefficient in the case of direct mail is .868 ($e^{-.142}$). Thus, six weeks before the start of the high season, the leads generated through direct mail are $(.868)^6$ or 43% of the lead volume in the high season, all else remaining equal. In the case of newspapers and radio,

Table 1

Coefficient Estimates for Lead-Generation Models (1E)

Model and Variable	Coefficient Estimate	Standard Error	*p*-value*
Direct Mail (R^2 = .486)			
Intercept	3.103	.591	.000
Seasonality ramp	–.142	.032	.001
Ln(Direct mail)	.082	.015	.000
Ln(Newspaper)	.0038	.044	.933
Ln(Exhibition)	.0217	.026	.408
Ln(Radio)	–.0239	.046	.606
Newspaper (R^2 = .491)			
Intercept	.923	.756	.225
Seasonality ramp	–.149	.047	.002
Ln(Direct mail)	.075	.043	.084
Ln(Newspaper)	.110	.033	.001
Ln(Exhibition)	.0246	.038	.520
Ln(Radio)	.135	.066	.046
Exhibition (R^2 = .479; λ = .54)			
Intercept	–2.709	2.075	.195
Seasonality ramp	–.065	.109	.552
Large show effect	2.536	1.44	.081
Ln(Direct mail)	.069	.098	.482
Ln(Newspaper)	.017	.150	.910
Ln(Exhibition)	.327	.049	.000
Ln(Radio)	.192	.154	.215
Radio (R^2 = .450)			
Intercept	–.988	1.352	.466
Seasonality Ramp	–.350	.081	.000
Ln(Direct mail)	.028	.076	.714
Ln(Newspaper)	.027	.115	.812
Ln(Exhibition)	–.087	.067	.197
Ln(Radio)	.199	.058	.000

*All *p*-values are reported for two-tailed tests of significance.

the corresponding fractions are 41% [$(.862)^6$]; and 12% [$(.705)^6$], all else remaining the same.

In the case of exhibitions, the seasonality effect is not significant; instead the impact of large exhibitions relative to minor shows is statistically significant. Specifically, we note that a major exhibition generates about 12 times greater lead volume than a smaller show, all else equal. Any seasonality effect would indeed be subsumed in this big-show effect, given the peak-season timing of the major shows. In addition, we find a carryover effect only in the case of exhibitions (λ = .54), suggesting strong carryover.

Next, we observe that current period expenditures have a significant effect on lead volume in each of the four sources. Note that all the β_i coefficient estimates are less than 1 (.08 for direct mail, .11 for newspaper, .19 for radio, and .32 for exhibitions), suggesting diminishing returns. We also observe some significant interaction effects. Expenditures on radio advertising as well as on direct mail in the current period enhance lead generation through newspapers in the current period. In addition, radio advertising appears to have a positive impact on exhibition leads, although the statistical significance is marginal (p = .107, one-tailed test).[4] As a practical matter, this suggests that during a week when a trade show is to be held, radio advertising may be used to boost attendance at the show (and a visit to the firm's booth). Under these circumstances, it is easy to observe that the trade-show effect dominates the radio-advertising effect, which may explain the negative interactive effect of exhibitions on radio leads.

These observations highlight the fact that the expenditure levels on each of the various communication sources provide differing degrees of leverage to other sources in the mix. These indirect effects have significant implications on the number of leads generated in a particular week. To illustrate, consider a scenario in the high season where the firm budgets $30,000, with $15,000 spent on exhibition, $1,000 on radio, $8,000 on newspaper and $6,000 on direct mail in a particular week. Applying the parameter estimates derived for our model, this spending pattern results in a total of 250 leads for the week. However, the same budget reallocated, with $15,000 spent on the trade show, $10,000

Table 2
Coefficient Estimates for "Linking" Model 5E

Variable	Coefficient Estimate	Standard Error	*p*-value*
Intercept	7.8573	.238	.000
Previous week lag, $\overline{Lag}_{i(t-1)}$	.5751	.012	.000
Leads – Steady state, $L_{it} - \overline{L}_i$	.0538	.020	.007

Adjusted R^2 = .744
*All *p*-values are reported for two-tailed tests of significance.

on radio, $3,000 on newspaper, and $2,000 on direct mail, results in a total lead volume of 314. While the shift to more radio advertising produces little direct effect on radio advertising leads (.5 leads over the previous budget), the indirect effects of increased radio spending on the level of response to newspaper advertisements and exhibition is substantial. Newspaper advertising leads increase by 5.3 leads under a reduced budget of $5,000, and 65.6 additional leads are created through the exhibition channel with no change to its budget (direct-mail leads drop with the reduction in its budget, but only marginally). From a managerial perspective, this example underscores the value of integrative planning of expenditures at the front end of the process. We next describe the critical role of total lead volume in defining the amount of delay that is generated within the system.

Delay: Linking marketing efforts and salesforce capacity

Leads generated in Stage 1, while central to maintaining the downstream productivity of sales personnel, contribute to delays when the sales organization's capacity is exceeded. Such delays may affect conversion and closure in stages 2 and 3. The parameter estimates of the linking model 5E are presented in Table 2. We note a strong model fit (adjusted R^2 = .744) and statistical significance for all parameter estimates. Specifically, 56.7% of the lag in the previous period ($t-1$) carries over into the current period, all else equal (Ψ_1=.567), and new leads generated in the current period in excess of the "steady-state" level ($L_{it} - \overline{L}_i$) are positively related to the lag present in the sales system in any given week (Ψ_2=.016). Based on these findings, the implications of generating too many leads become evident. Leads generated beyond the capacity of the sales organization result in increased lag time between inquiry and salesforce follow up. Moreover, these delays remain in the system beyond the period in which they are created. For example, consider an effective home show that generates more leads than the salesforce can handle during that week. Leads not serviced during the week of the show are scheduled in subsequent weeks, displacing leads generated in those weeks further into the future. This cycle continues until lead generation falls below the steady-state level in an amount, or for a time, sufficient to allow the sales organization to catch up.

Stage 2: Appointment conversion

To consider the conversion of leads to appointments, we estimate the log-linear equation 2E. In Stage 2, we begin to observe issues of lead quality and decay. With regard to appointment conversion, some leads are better than others. However, identifying the better leads is not straightforward. Estimation results for the Stage 2 model are presented in Table 3. Overall model fit is strong (adjusted R^2 = .96). Parameter estimates indicate that leads are converted to appointments at different rates across many of the sources examined (δ_{1i}) and that a predominantly negative delay effect (δ_{2i}) exists at the appointment conversion stage. With regard to the source-specific relationship between leads and appointments, coefficient estimates of δ_{1i} ranged from .849 to .994, all of which are statistically significant, with significant differences between them (α = .10). To illustrate the magnitude of these differences, assuming negligible delay in the system ($\overline{Lag}_{Nt}$ = 2 days), we would expect to convert nearly all (99%) of the leads generated by newspaper advertising in the high season to sales appointments. By contrast, under the same time lag and seasonality conditions, radio advertising is

Table 3

Coefficient Estimates for Appointment Generation Model 2E

Variable	Coefficient Estimate	Standard Error	*p*-value*
Intercept	.008	.082	.921
Early season	–.049	.021	.0211
Late season	–.077	.024	.001
Direct mail	.285	.109	.009
Newspaper advertising	.081	.115	.478
Radio advertising	.140	.115	.224
Directories	.073	.127	.565
Referrals	.145	.105	.169
Repeat customers	.137	.123	.265
Retail showrooms	.073	.128	.565
Webpage	–.447	.118	.000
Ln(Leads) * Direct mail	.849	.024	.000
Ln(Leads) * Exhibition	.941	.017	.000
Ln(Leads) * Newspaper advertising	.994	.024	.000
Ln(Leads) * Radio advertising	.899	.039	.000
Ln(Leads) * Directories	.982	.036	.000
Ln(Leads) * Referrals	.967	.034	.000
Ln(Leads) * Repeat customers	.967	.043	.000
Ln(Leads) * Retail showrooms	.978	.039	.000
Ln(Leads) * Webpage	.911	.041	.000
Ln(Lag) * Exhibition	–.039	.056	.488
Ln(lag) * Newspaper advertising	–.111	.043	.010
Ln(lag) * Radio advertising	–.079	.051	.117
Ln(lag) * Directories	–.086	.047	.065
Ln(lag) * Referrals	–.081	.048	.094
Ln(lag) * Repeat customers	–.042	.048	.279
Ln(lag)*Retail showrooms	–.056	.046	.220

Adjusted R^2 = .960

*All *p*-values are reported for two-tailed tests of significance.

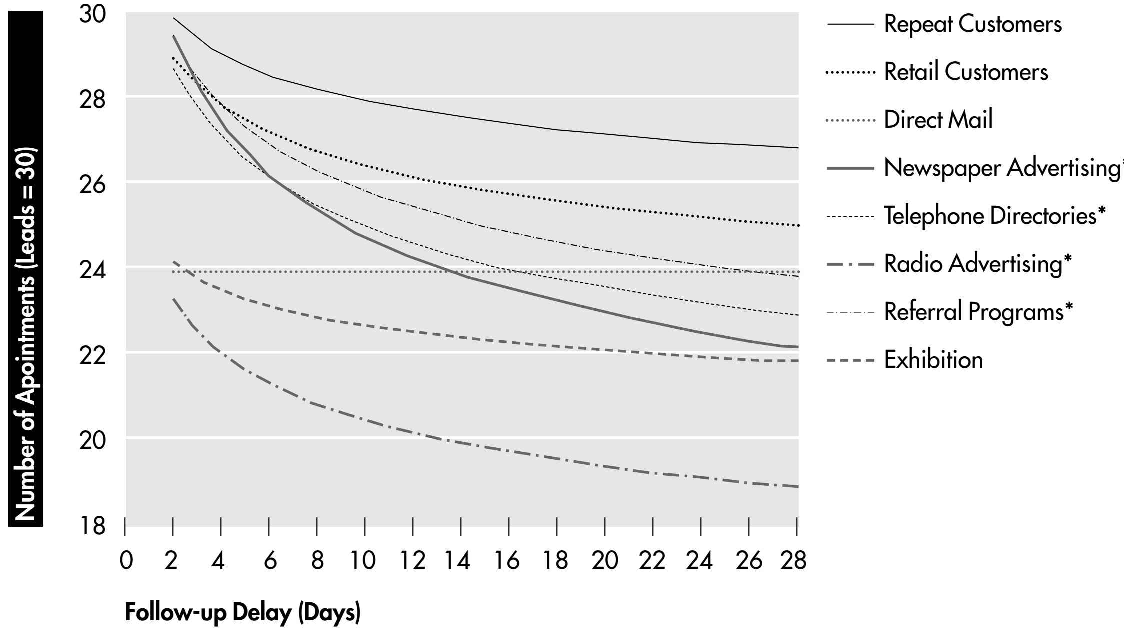
expected to convert 77% of leads to appointments. This scenario is graphically presented in Figure 3, where two distinct clusters of initial lead quality are evident. Prior to any substantive time-lag effect, leads generated from repeat business, newspaper advertising, referral programs, retail showrooms, and telephone directories convert to appointments at very high rates. Leads generated by exhibitions, direct mail, and radio advertising convert at significantly lower rates. Finally, Internet leads convert at even lower rates and are not shown in the figure.

It is rare, especially in the busiest season, for a sales appointment to be scheduled quickly. We therefore explore the potentially negative relationship between appointment conversion and time lag (the number of days from lead creation to sales visit). Our results suggest that seven of the nine sources display a directionally negative lag coefficient, with four of them (newspaper advertising, radio advertising, telephone directories) statistically significant at the .10 level or better (one-tailed test) and a fifth (retail showrooms) marginally so (one-tailed p = .11)[5] Direct mail and Internet leads produced positive, but not significant, lag coefficients. Therefore, the lag coefficients were set to zero for these sources. Figure 3 continues our previous example by plotting predicted appointment conversion of 30 hypothetical high-season leads from all sources (Internet leads were excluded since they convert at very low rates and do not show significant time-lag effects). As noted previously, with a delay of two days, almost all high-season newspaper leads convert to appointments (99%). If the delay increases to seven days, the conversion rate drops to 86%, and at three weeks (common during high season), it drops to 76%. Similar results hold true for referral programs and telephone directories, where we note that four weeks after the inquiry, these once high-quality leads decay to, at best, average levels. Finally, we note a significant late-season effect ($\lambda_2 = -.053$). Leads obtained in the last 12 weeks of the calendar year convert 5.2% fewer appointments than those obtained in the high season.

Stage 3a: Sales closure

Estimation results for the sales closure model 3E are presented in Table 4. Unlike earlier models, this is an individual (household)-level specification. We estimate the log-likelihood of sales closure as a function of quality of the sales representative, the season, the source generating the lead, the time lag, and several household-level variables. The overall model fit is reasonable, given its disaggregate nature. The model chi-square (likelihood ratio test) is highly significant (p < .0001), and the corresponding Nagelkerke R^2 is .145.

Figure 3
The Effect of Intercommunication Time Lag on Appointment Conversion for Select Lead-Generating Media



* Significant delay effect ($\alpha = .10$).

As expected, the quality of the sales representative has a significant positive effect on the likelihood of closure. Based on a median split of previous-period sales performance, high-performing sales representatives significantly impact sales conversion (captured by the parameter η), increasing the odds of a sale by 9% ($e^{.087}$), all else held constant. We find significant seasonality effects in this stage of our model (captured by θ_1 and θ_2). The odds of closing a sale are reduced by 8.5% ($e^{-.089}$) in the early season and by 11.2% ($e^{-.119}$) in the late season. Two household-level descriptors (Z_{lh}) also have a significant impact on sales closure: length of residency (positive impact) and age of the home (negative impact).

We note significant differences exist between the lead-generating sources in this stage. We observe significant lead-source dummy coefficients (θ_{0i}), indicating deviation from the exhibition reference source (θ_{0N}). While appointments from leads generated by exhibitions, newspaper, radio advertising and telephone directories result in a sale at roughly the same rate, all else equal, direct-mail appointments are less likely to convert to a sale, while appointments generated by referral programs, retail showrooms, and repeat business convert at higher rates.

As in Stage 2, time-lag effects are estimated with regard to their impact on sales closure. As noted earlier, appointment dates are negotiated with individual prospects based on their needs and salesforce availability. The time lag between inquiry and sales visit can be *capacity-driven* or *customer-driven*. Capacity-driven lag is operationalized as the time lag up to the median lag observed in the system at the time the lead was created $\{\min(Lag_{hit}, \overline{Lag}_{it})\}$. Therefore, any additional time lag $\{\max(Lag_{hit}, \overline{Lag}_{it}) - \overline{Lag}_{it})\}$ is customer-driven in that the additional delay is "created" by the customer. Controlling for customer-driven lag effects, we observe significant negative impacts of increased capacity-

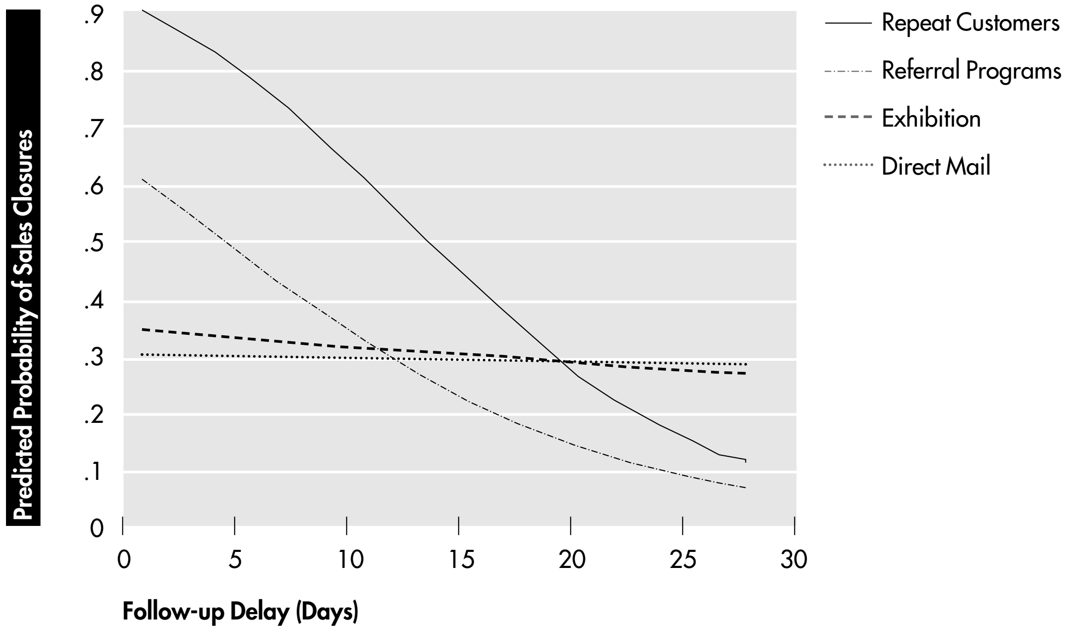
Table 4
Coefficient Estimates for Logit Model of Sales Closure 3E

Variable	Coefficient Estimate	Wald Stat	*p*-value*	Exp(B)
Intercept	–.4256	3.684	.055	.653
Early season	–.0894	3.241	.072	.915
Late season	–.1187	4.408	.036	.888
High-performing sales representative	.0866	5.561	.018	1.090
Direct mail (DM)	–.2174	3.012	.083	.805
Newspaper advertising (NA)	–.1573	1.764	.184	.854
Radio advertising (RA)	–.3865	2.028	.154	.679
Telephone directories (TD)	–.1862	2.304	.129	.830
Referral programs (RP)	1.1485	64.656	.000	3.153
Repeat customers (RC)	2.6799	393.725	.000	14.584
Retail (RT)	.3713	8.959	.003	1.450
Internet communications (IC)	.2325	1.318	.251	1.262
Capacity-driven lag * DM	–.0034	.041	.840	.997
Capacity-driven lag * EX	–.0143	3.357	.067	.986
Capacity-driven lag * NA	–.0018	.013	.910	.998
Capacity-driven lag * RA	–.0052	.012	.913	.995
Capacity-driven lag * TD	–.0189	1.466	.226	.981
Capacity-driven lag * RP	–.1154	29.269	.000	.891
Capacity-driven lag * RC	–.1507	68.417	.000	.860
Capacity-driven lag * RT	.0087	.346	.556	1.009
Capacity-driven lag * IC	–.0354	1.109	.292	.965
Customer-driven lag * DM	.0143	3.950	.047	1.014
Customer-driven lag * EX	.0048	2.475	.116	1.005
Customer-driven lag * NA	.0046	1.204	.272	1.005
Customer-driven lag * RA	.0521	1.658	.198	1.054
Customer-driven lag * TD	.0153	3.263	.071	1.015
Customer-driven lag * RP	–.0096	.561	.454	.990
Customer-driven lag * RC	–.0315	5.637	.018	.969
Customer-driven lag * RT	.0008	.041	.839	1.001
Customer-driven lag * IC	.0020	.203	.652	1.002
Length of residency	.0267	6.248	.012	1.027
Home age	–.0036	9.118	.003	.996
Home value	–.0172	.552	.458	.983
Head of household age	–.0420	2.136	.144	.959
Household income	–.0068	.466	.495	.993

Model chi-square = 1656.24 (df = 34, sig. = .000). Nagelkerke R^2=.145.
*All *p*-values are reported for two-tailed tests of significance.

driven lag among appointments from exhibitions ($\phi_{1(exhibition)} = -.014$), referral programs ($\phi_{1(referral)} = -.115$), and repeat business ($\phi_{1(repeat)} = -.151$). The other sources (with the exception of retail) exhibit ϕ_1 coefficients that are negative but not significant. While customer-driven lag

Figure 4
Effect of Capacity-Driven Delay on Sales Closure



is really not under direct management control, it is interesting to note that accommodating additional customer-driven lag has a generally positive relationship to the likelihood of sales, except among repeat customers ($\phi_{2(repeat)} = -.032$, $p = .012$).

Sales closure (the rate of conversion of sales visits to orders) is typically a key sales-organization performance metric. Figure 4 shows predicted probabilities of sales closure, by lead-generating source, with varying capacity-driven lag. In this illustrative example, we assume that leads are generated in the high season, households are average (in terms of their background characteristics), prospects are called on equally by high- and low-performing salespeople, and customer-driven lag is ignored. Focusing on exhibition and direct-mail appointments, when the capacity-driven lag is negligible [$\min(Lag_{hit}, \overline{Lag_{it}}) = 1$], direct-mail appointments are converted at a lower rate—29.6% versus 34.2% for exhibition leads. However, when the sales organization is stressed (i.e., incoming leads exceed capacity) to the point where the inquiry-sales visit lag approaches three weeks, an exhibition appointment converts into a sale at the same rate (28.3%) compared to its once weaker direct-mail counterpart.

Of potentially greater concern is the impact of capacity-driven delay on seemingly unrelated sources. If marketing activities create enough stress on the salesforce to generate even minor levels of capacity-driven lag, the predicted sales conversion rates for repeat customer and referral program appointments are adversely affected. A sales visit conducted within a day of a referral lead is expected to convert to a sale 60.7% of the time, but if that lead has to wait for 15 days, it converts only 22.6% of the time, dropping below the rates for exhibition appointments after 11 days and direct mail appointments after 12 days. Similarly, repeat customer appointments close 90% of the time when capacity-driven lag is one day, but the closure rate falls to 44.8%, when the lag is 15 days.

Stage 3b: Order size

Estimates of the parameters of the order-size model 4E are shown in Table 5. These results suggest that overall model fit is strong with an

Table 5
Coefficient Estimates for Order-Size Model 4E

Variable	Coefficient Estimate	Standard Error	*p*-value*
Intercept	7.8573	.238	.000
Direct mail	.0257	.035	.467
Newspaper advertising	.0409	.033	.213
Radio advertising	.0568	.080	.477
Directories	.0222	.036	.542
Referrals	.1187	.041	.004
Repeat customers	–.1890	.081	.019
Retail showrooms	.0788	.034	.019
Webpage	.0039	.062	.950
Ln(Potential units)	.5751	.012	.000
High-performing sales representative	.0538	.020	.007
Ln(Length of residency)	.0523	.078	.500
Ln(Home age)	–.2253	.024	.000
Ln(Home value)	.0070	.108	.948
Ln(Head of household age)	.0006	.098	.995
Ln(Household income)	.2073	.082	.012

Adjusted R^2 = .449
*All *p*-values are reported for two-tailed tests of significance.

adjusted R^2 of .449. Potential order size, given the number of units expected to be purchased by the prospect (collected by the call-center representative at the time of the initial inquiry) is a major predictor of the realized order size ($\nu = .575$, $p < .001$). High-performing representatives produce 5.5% ($e^{.054}$) higher levels of revenue from a sale than low-performing sales staff. The lead-generating source (κ_i) continues to be relevant. While many sources did not differ significantly from the exhibition reference source, retail leads and referral leads tend to create significantly higher levels of revenue, whereas repeat customers generate lower levels of revenue per sale. Finally, sales to customers living in older homes tended to produce lower revenues ($\tau_{(homeage)} = -.225$) and sales to high-income households produce higher levels of revenues ($\tau_{(highincome)} = .207$).

Model validation

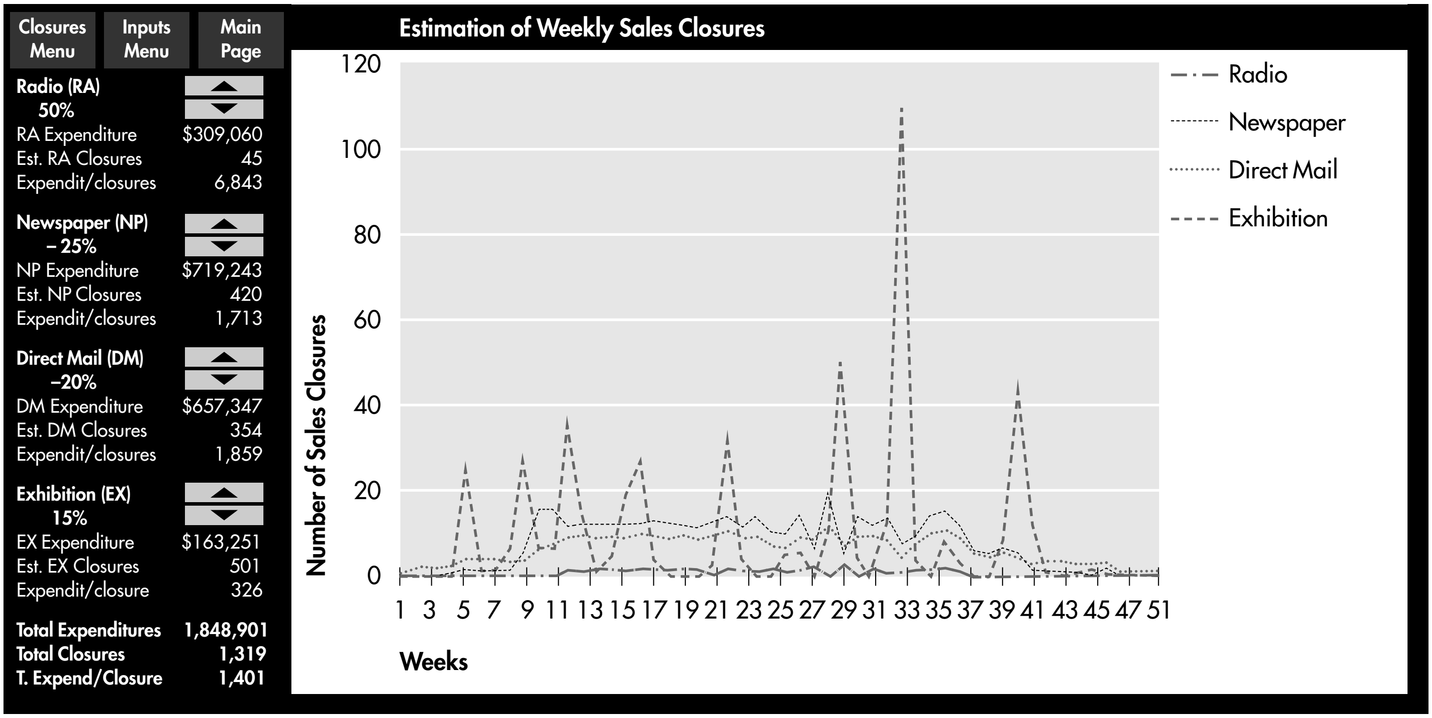
To examine the predictive accuracy of the model, we use data available for the first 21 weeks of 2004 as our holdout sample (note that the model was estimated on 2002–2003 data) and compare the predicted versus actual outcomes. In Stage 1, 1,790 leads were predicted during this holdout period, compared to 1,810 actual leads generated—a 1.1% error. In Stage 2, our model predicts 2,793 appointments from all nine lead-generating sources, while actual appointments are 3,053 (an error of 8.5%). For sales closure (Stage 3a), we predict a 37.8% closure rate, compared to the observed 39.9% (5.3% error). Finally, we note an actual average order size of \$8,464 versus a predicted value of \$7,604 (lower by 10.2%).

While the model performs reasonably well in predicting these out-of-sample observations, we note that it does underpredict both the sales closure rate and the average order size. The 2004 actuals reflect the improved economic conditions over 2003, an aspect not reflected in the model parameters, estimated on 2002–2003 data.[6]

Simulation and Normative Implications

Following discussions with HIR management over a two-year period, we developed a decision support tool that was implemented in the fall of 2004. This user-friendly interface allows management to assign media expenditures, on a weekly basis, for the calendar year. It also allows inputs for salesperson allocations, household-level attributes, and gross margin. From a practical standpoint, the tool provides a series of outputs to "what if" types of questions and addresses the impact of changes in communications budgets and/or allocations. As an example, Figure 5 shows the sales closure stage of the tool (Stage 3a). The weekly closure estimates incorporate the complex multimedia interactions and carryover (Stage 1), effects of delay and decay on appointment generation and closure (stages 2 and 3a), and effects across the

Figure 5
Illustrative Decision Support Tool Output: Stage 3 —Sales Closure Results



stages, such as seasonality. While this is a single-screen shot, other diagnostic capabilities in the tool permit analysis at each of the three stages in the sales process and at varying levels of aggregation. Data in Figure 5, for instance, are aggregated to provide yearly projections of media expenditures at 5% increments, altered proportionately based on initial inputs.

Using the decision support tool, we provide three hypothetical scenarios in Table 6 to illustrate the impact of changes in media allocations on HIR's operations. Results and time-lag diagnostic statistics for weekly budgeted 2004 media expenditures are shown in column 2. Note that the budget allocations were created in fall 2003, prior to the development of the tool. Based on these allocations (across a budget of about $2.1 million), the model estimates the number of leads, appointments, and sales orders, as well as estimated sales dollars and total profit (approximately $4.1 million, assuming a gross margin of 30%). In addition, the average (over 52 weeks of the 2004 budget year) weekly median lag is predicted by the model to be 8.2 days, with a minimum and maximum over the year of 2.0 and 17.5 days, respectively (standard deviation = 3.62).

Given the complexity of media planning and the external constraints associated with these decisions (such as media availability, price variability, timing of exhibitions, etc.), we explore deviations from established media-spending patterns to better understand the implications of changes in spending across sources. We develop three stand-alone scenarios by first exploring the lead-generating efficiency of media expenditures in scenarios 1 and 2, and then examining the sales conversion efficiency in scenario 3.

In theory, it is possible to employ an optimization methodology to develop a "zero-based" profit-maximizing communications budget. However, in practice, such an optimization might imply radical deviations from current expenditure levels and/or allocations that fall

Table 6

Budget Timing and Allocation Simulations

Simulation Stages	2004 HIR Budget Allocation	Scenario 1 Media Timing Lead Focus	Scenario 2 Media Allocation Lead Focus	Scenario 3 Media Reduction Sales Focus
Communication budget				
Direct mail	$821,684	$821,684	$779,354	$492,025
Newspaper advertising	$958,991	$958,991	$914,321	$1,013,931
Radio advertising	$206,040	$206,040	$287,040	$269,079
Exhibitions	$141,957	$141,957	$147,957	$136,732
Total	$2,128,672	$2,128,672	$2,128,672	$1,911,767
Leads (Stage 1)				
Direct mail	1,731	1,721	1,682	1,543
Newspaper advertising	1,749	1,804	1,957	1,756
Radio advertising	82	81	83	86
Exhibitions	1,780	2,615	2,861	1,839
Other source	4,320	4,320	4,320	4,320
Total	9,662	10,540	10,902	9,544
Appointments (Stage 2)				
Direct mail	1,319	1,313	1,284	1,194
Newspaper advertising	1,435	1,468	1,592	1,447
Radio advertising	71	71	72	76
Exhibitions	1,225	1,754	1,910	1,269
Other source	3,610	3,596	3,591	3,614
Total	7,660	8,201	8,450	7,600
Orders (Stage 3a)				
Direct mail	376	374	366	341
Newspaper advertising	435	444	480	437
Radio advertising	18	18	18	19
Exhibitions	368	524	568	386
Other source	1,475	1,452	1,438	1,500
Total	2,672	2,811	2,870	2,682
Total sales (Stage 3b)	$20,747,236	$21,843,327	$22,315,021	$20,814,939
Total profit	$4,095,499	$4,424,326	$4,565,834	$4,332,715
Delay statistics				
Mean	8.2	8.9	9.1	8.1
Stand. dev.	3.62	3.51	3.63	2.64
Range	2.0 – 17.5	2.0 – 17.4	2.0 – 19.2	2.0 – 12.0

outside the range of values over which the model was estimated—casting serious doubts about the validity of the optimization. We have therefore refrained from suggesting an optimization routine to HIR, and discussing a similar approach in this paper.

Scenario 1: Media timing

In this scenario, no changes to the overall media budget or the allocation across media sources are considered. We simply alter the timing of media spending, shifting spending levels of radio advertising, newspaper advertising, and direct-mail efforts from one week to another. We conservatively focus on these media because they tend to be most flexible with regard to time. Exhibitions are largely predetermined events; thus any changes in the timing would be unrealistic. Column 3 of Table 6 shows the impact of these timing shifts in each stage of our model. In Stage 1, the new spending pattern results in 878 additional leads, 541 additional appointments, 117 additional sales orders, and $328,827 in incremental profit (an 8.0% increase). Performance improvements are attributed to leveraging interaction effects in Stage 1 of the model. In many cases, HIR alternates the use of media, often spending heavily in one medium in a given week and shifting the emphasis to a different medium the next week. By moving expenditures into common weeks, especially those with heavy exhibition and newspaper spending, we allow the interaction effects of Stage 1 to be better utilized. Specifically, we tried to better support exhibitions by moving more radio spending into weeks involving major exhibition events. Similarly, we tried to leverage radio and direct-mail efforts by moving them into weeks with heavy newspaper advertising. While these shifts have very little impact on the number of leads generated directly by either radio advertising or direct mail (in fact, leads decrease slightly), the impact on exhibition leads and newspaper leads are substantial (890 additional leads from these sources). Further examination of the baseline scenario indicates that 44% of leads estimated by Stage 1 are generated directly by their respective media sources, independently and in the absence of other media spending (2,377 leads), whereas 56% of leads (2,965) are generated indirectly by spending in other categories. By better leveraging media interactions through shifts in media timing, 62% of leads are generated indirectly [(2,965 + 890)/6,220] in this scenario. In other words, we observe considerable scope for leveraging the potential interactions between communication elements without altering either the total budget or the allocation but with merely shifting the timing of expenditures.

Scenario 2: Media allocation

In this scenario, we continue to focus on improving media-driven lead generation but relax the constraint of maintaining the existing allocation. Similar to the first scenario, column 4 represents a potential allocation to illustrate the stage-wise impacts associated with changes in media timing and allocation. Again, focusing primarily on the interactive effects of radio advertising on exhibitions and newspaper advertising, the radio advertising budget is increased by $81,000 (39.3%) and is spent in weeks that better leverage exhibitions and newspaper ads. The budget for exhibitions has a modest increase (4.25%) while direct-mail and newspaper budgets are marginally reduced (by 5.2% and 4.7%, respectively) to balance the overall budget at current levels. Based on these alterations in allocation and timing, the expected annual total leads increase by 12.8 %. While leads from exhibitions increase significantly due to more spending in this category as well as support from radio, we note that newspaper leads also increase even though its allocation is reduced. Expected newspaper leads increase by 11.9% with a budget reduced by nearly $45,000. Following these efficiency improvements through stages 2 and 3 (appointment generation and sales conversion), overall sales dollars increase by nearly $1.6 million, creating over $470,000 of incremental profit (11.5%).

The improvements over HIR's original allocation (scenarios 1 and 2) come at a price—significantly increased stresses placed on the salesforce and potentially detrimental service levels to prospects and customers. The average time lag between customer inquiry and sales appointment increases from 8.2 days to 8.9 days in Scenario 1 and to 9.1 days in Scenario 2. The expected median lag in some weeks reaches 19.2 days in Scenario 2. The increased delay may have a negative impact on customer sentiment, but it also has an adverse impact on the selling efficiency. The reallocation in Scenario 2 focuses heavily on creating more exhibition leads, which convert to sales at a lower rate than other sources. Also, these leads are created when delay is greatest in the system, further reducing their potential of conversion. Thus, not only are the incremental leads themselves less likely to convert to sales, but the increased lag time also hampers all other leads in the system at that time. The overall conversion rate (orders/leads) drops by nearly 5% under this scenario. Therefore, while marketing may seem to "gain" by the reallocated budget (greater leads), the salespeople face serious disadvantages, potentially creating friction within the organization. Thus, we explore a third scenario to address the integration of lead generation and sales conversion in allocation decisions.

Scenario 3: Integrating media and selling communications

In this scenario (column 5, Table 6), the overall media budget is reduced by approximately 10%, reallocated across media and redistributed across weeks to further improve possible synergistic effects. The reallocation involves direct-mail expenditures being reduced relative to the baseline (HIR's 2004 budget) by 40.1%; radio advertising is increased by 30.6%; and minor changes are made to newspaper advertising (increased by 5.7%) and exhibition efforts (reduced by 3.7%). These spending patterns are expected to generate 9,544 leads, 118 fewer than the original 2004 budget; however, slight improvements in the number of closures (10) and the overall sales dollar volume ($67,703) are also expected. Expected profitability improves by $237,216 (5.8%) in this scenario. The improved conversion efficiency is due to two reasons: a slight reduction in intercommunication time lag (from 8.2 to 8.1 days) and a significant drop in the variation in delay across weeks. In fact, the standard deviation drops by 27.1%, and the upper bound of the range reduces from 17.5 days to 12.6 days.

While it is somewhat inappropriate to compare the above scenarios directly, they do highlight distinct relationships between the number of leads created, the resulting time lag, and the entire system performance. They also suggest multiple strategies for improving overall performance. The classic marketing perspective of communications media typically stops at the lead-generation stage, with the objective of maximizing the number of leads, given a budget, assuming that more leads provide increased opportunity for downstream sales. Scenarios 1 and 2 illustrate how an improved understanding of the synergies between media can help to achieve this objective. But, integration of marketing communications is not restricted to advertising or direct communications. Integration, from an IMC planning perspective, requires an understanding of how all communications influence each other, in this case, simultaneously (between media in a given week) and sequentially (between media and selling activities). Scenario 3 illustrates how an improved understanding of the impact of media spending and lead generation on sales conversion can further improve system performance. In this scenario, a case can be made for reducing the number of leads created by media spending in favor of increased service quality (in the form of response time) and selling efficiencies (higher closure rates) downstream.

Conclusions and Future Research

A report by the Aberdeen Group confirms that there has been a crippling disconnect between the marketing and sales functions within many organizations (Watkins 2003). Such a divide can lead to large amounts of wasted expenditures and energy for the firm. In addition, inconsistent customer messaging, poor or delayed sales preparation, and less effective selling dialogues can result. The IMC framework is a useful way to bridge this gap. Despite its intuitive appeal, the concept continues to evolve as researchers and practitioners explore its central principles—that communications through any medium are part of an on-going dialogue with customers, and that one mode of communication can contribute to the performance of other elements in the mix. In the context of this research, the above observations imply that engaging and managing the customer's experience requires targeted contacts with effective support from the right elements of the mix (Schmonsees 2005). Marketing and sales expenditures can then be seen as delivering tangible returns and contributing effectively to the bottom line. Such accountability seems to be the order of the day (Marketing Science Institute 2004).

We model the effectiveness of communications in three distinct stages: lead generation, appointment conversion, and sales closure. We provide empirical evidence of interactive and carryover effects between communication elements in the lead-generation stage. We show that communications spending directly contributes to delays in salesforce follow-up, thus linking media spending more directly to sales process. We observe that increases in delay lead to detrimental effects within the sales process, reducing the likelihood of converting a lead into an appointment and thereafter the closure of the appointment to a sale. Using individual (household) level data from a major home improvement retailer, our estimation results indicate that individual communications media (print advertising, radio advertising, exhibitions, etc.) have differing impacts on the various sales process stages and are affected differently by the follow-up time lag (delay). These findings have useful implications for media planning and budgeting. Through scenarios and utilizing a decision support tool, we show that the effectiveness of the *entire system* can improve through two distinct but interrelated mechanisms: interactive effects between lead-generating media and complementary effects between these media and subsequent follow-up selling activities influenced by capacity-driven delay.

Our study has several limitations that also serve as useful avenues for future research. First, we believe that more detail on the prospect's exposure could be collected when the inquiry comes into the call center. In our case, prospects indicated only the one source that was most responsible in influencing them to inquire about the firm's product. Clearly, we recognize that multiple communication sources are in operation at a given time; thus, future research could look at which other sources the prospect was exposed to and when. Second, our analysis assumes that time lags above the median value were likely driven by the customer; however, it would be desirable to collect more refined data on the extent to which the agreed-on appointment date with a customer was customer- versus firm-driven. Third, our sponsor is clearly a major player in the industry and the market we studied; however, incorporating the effect of competition would be a useful dimension. Further, a replication of these results in other markets served by the firm would be valuable.

While we have noted the practical problems with using an optimization methodology to recommend profit-maximizing communications budgets, such an approach may be useful if the methodology incorporates (user-specified) constraints that ensure realistic allocations and also avoids expenditure levels too far beyond the range of values on which the model was estimated. This is an issue that we will consider in our next phase of work with our sponsor. ■

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Notes

1. For ease of exposition, the error terms are suppressed in our initial specification of the mathematical models.

2. Based on an inspection of the data, an exhibition was classified as large when weekly expenditures on this medium exceeded $10,500 (HIR expenditures correlate with the size of the exhibition).

3. In this household-level model, we track the median lag $\overline{Lag}_t$ by a specific day rather than by week.

4. While the *p*-values reported in tables of coefficient estimates are all two-tailed, in this case we have a clear prior hypothesis that the interactive effect will be positive and hence the one-tailed test of statistical significance is appropriate.

5. See footnote 4. In this case, we expect a decline in conversion over time, i.e., our prior hypothesis is that these coefficients are negative.

6. Given the available data, our model does not include the impact of macroeconomic conditions. Such adjustments would have to be made exogenously.

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