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Optimal targeting of advertisement for new products with multiple consumer segments

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ABSTRACT

Armed with improved targeting technology, firms are increasingly interested in optimizing their advertising dollars through consumer segment-specific targeting, particularly while introducing new products. That task becomes especially important in markets with distinct consumer segments—the early market and the main market—that affect each other's adoption behavior. In this study, in contrast to prior normative studies that assume a single-segment market structure, we derive dynamic optimal advertising and segment-specific targeting strategies for firms facing a two-segment market structure. We allow for mutual demand interactions between the two segments, and for the diffusion parameters, advertising sensitivity, and cost of targeting to differ across the segments. We model the effect of advertising as a logarithmic function that accounts for diminishing marginal returns. Among our key findings: From profit optimization perspective, our two-segment model outperforms the single-segment model under multiple diffusion dynamics contexts—especially for the 'bimodal chasm' and the 'early dip followed by bell-shaped' type diffusion patterns—even when the cost of targeting the early market is relatively high. Our numerical analyses indicate that the optimal share of advertisement targeted to the early market segment at launch needs to be much higher than the share of the early market segment in the population. Advertising sensitivity, relative cost of targeting the early market, and the proportion of early market consumers in the population have the greatest effects on the optimal time to transition the targeted advertising spending from the early to the main market segment.

1. Introduction

Firms today have the technology to locate and target individual consumers (Green, 2008; Vascellaro, 2011), and not surprisingly, such targeting leads to better conversion (Farahat & Bailey, 2012). For example, during the launch of its new Bluetooth headset in 2013, Motorola approached Klout, a social media analytics firm, to target influential consumers that are passionate about technology and sports (Robehmed, 2013). This helped Motorola to gain 62 million earned impressions. Further, consumers driven to Motorola's webpage through Klout spent about 2.5 times longer than a standard visitor. However, as one would expect, such targeted advertising comes at a higher cost. A recent study sponsored by the *Network Advertising Initiative* has estimated the cost of targeted advertising to be about 2.7 times more than the cost of regular advertising (Beales, 2009).

With the advent of technology-enabled, more effective but costlier options of finely targeted marketing, a critical challenge faced by business managers when introducing new products is how best to target their advertising dollars. Specifically, this decision context raises several interesting questions that are of importance to both managers and researchers: What should be the optimal advertising and segment-specific targeting strategies of a firm under different patterns of new product diffusion dynamics? Under what key market conditions should the firm target its advertising spending for its new products based on consumer types rather than mass advertise to the entire market? How do key diffusion dynamics parameters alter the optimal time to transition from targeting the *early market* segment to the *main market* segment?[4] The goal of our paper is to investigate these important and interesting questions from both theoretical and practical perspectives.

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[4] This terminology is adopted from Goldenberg et al. (2002). The early market adopters and the main market adopters are conceptually similar to "influentials" and "imitators" used by Van den Bulte and Joshi (2007).

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Although there exist several normative dynamic models of advertising for new product diffusion (Dockner & Jorgensen, 1988; Horsky & Simon, 1983; Krishnan & Jain, 2006; Teng & Thompson, 1983; Thompson & Teng, 1984), the extant literature suffers from the following strong limitations. First, in spite of empirical diffusion studies pointing to multi-segment diffusion dynamics in reality (e.g., Goldenberg, Libai, & Muller, 2002; Van den Bulte & Joshi, 2007), none of the prior normative studies derive dynamic optimal advertising strategies using a multi-segment diffusion model. As a consequence, they cannot be used to evaluate the firm's decision to optimally target advertising based on consumer types. Neither could they be used to obtain optimal advertising strategies when the diffusion dynamics follow non-unimodal diffusion patterns, even though such patterns are empirically common (e.g., Goldenberg et al., 2002; Moe & Fader, 2001). Moreover, the prior studies can generate empirically observed advertising patterns (monotonically decreasing or increase–decrease) as optimal advertising strategies only when they impose unrealistic constraints on the shape of the diffusion dynamics pattern or on the initial advertising spending. For instance, Dockner and Jorgensen (1988) constrain the adoption pattern to be monotonic to derive monotonically decreasing optimal advertising strategy; in another case, Krishnan and Jain (2006) derive increase–decrease and monotonically decreasing optimal advertising strategies by constraining the initial advertising to be a priori higher than a particular threshold level.

As highlighted in Table 1, our study contributes to the relevant existing literature in several important ways. It is the first study to develop dynamic optimal advertising and segment-specific targeting strategies for a new product that diffuses simultaneously across two distinct consumer segments—a typical real-world market context. Our diffusion dynamics allows for mutual influence between the segments, and for the diffusion parameters, advertising sensitivity, and cost of targeting to differ across the segments. Our two-segment model structure enables us to analyze firm's optimal advertising and targeting strategies across the four major empirically observed diffusion dynamics patterns—viz., 'unimodal bell-shaped', 'bimodal chasm', 'early dip followed by bell-shaped', and 'exponential decline'.

2. Proposed model

2.1. Market's diffusion dynamics with two segments and targeted advertising

The adoption behaviors of the two segments ($i = 1$ refers to the early market, and $i = 2$ refers to the main market) are given as follows:

$$\dot{F}_1(\mathrm{t}) = (1 - F_1(\mathrm{t}))(p_1 + q_{11}F_1(\mathrm{t}) + q_{12}F_2(\mathrm{t}))[1 + \beta_1 \log(1 + \delta(\mathrm{t})u(\mathrm{t}))], \tag{1}$$

and

$$\dot{F}_2(t) = (1 - F_2(t))(p_2 + q_{21}F_1(t) + q_{22}F_2(t))[1 + \beta_2 \log(1 + (1 - \delta(t))u(t))], \tag{2}$$

where $\dot{F}_i(t)$ denotes the rate of adoption of segment i at time t, $F_i(t)$ denotes the proportion of consumers in segment i that have adopted at time t, p_i denotes the external influence in the adoption behavior of segment i, q_{ii} denotes the within-segment influence in the adoption behavior of segment i, $q_{ij}\ \forall\ j \neq i$ denotes the cross-segment influence of segment j on segment i's adoption, $u(t)$ is the total advertising spending at time t, $0 \leq \delta(t) \leq 1$ is the proportion of total advertising spending targeted at the early market at time t, and β_i denotes the advertising sensitivity of segment i.

Since the early market is more in touch with new developments, its external influence is likely to be higher than that of the main market (i.e., $p_1 > p_2$). In line with prior research (e.g., Steffens & Murthy,

Table 1
Scope of prior studies that derive dynamic optimal advertising strategies for new product diffusion and our study.

Study	Number of segments	Diffusion pattern(s)	Advertising functional form	Advertising affects	Price/cost/margin function(s)	Optimal advertising pattern(s)
Horsky and Simon (1983)	One	Unimodal	Logarithmic	Only the external influence of the entire market	Constant or decreasing margin	Monotonically decreasing
Teng and Thompson (1983)		Unimodal	Linear	Both external and internal influences of the entire market	Constant prices; decreasing cost	Min–max–min
Thompson and Teng (1984)		Unimodal	Linear		Price is modeled as a control variable with decreasing cost. It is optimal to monotonically decrease or increase-then-decrease prices.	Min–max–min
Dockner and Jorgensen (1988)		Monotonic	Logarithmic		Constant prices; decreasing cost	• Monotonically increasing • Monotonically decreasing
Krishnan and Jain (2006)		Unimodal	Time-derivative		Constant or decreasing prices; constant marginal cost	• Increase–decrease • Decrease–increase • Monotonically decreasing • Monotonically increasing
Our study	Two	• Unimodal bell-shaped • Bimodal chasm • Early dip followed by bell-shaped • Exponential decline (Major diffusion patterns observed in the empirical literature)	Logarithmic (Decreasing returns to advertising are observed in empirical studies)	External influence, within-segment influence, and cross-segment influence of both segments	Decreasing margin	• Increase–decrease • Monotonically decreasing • Longer period of medium spending, then decrease