



## Why the Generalized Bass Model leads to odd optimal advertising policies

Gila E. Fruchter<sup>a</sup>, Christophe Van den Bulte<sup>b,\*</sup>

<sup>a</sup> Graduate School of Business Administration, Bar-Ilan University, Ramat-Gan, 59000, Israel

<sup>b</sup> The Wharton School, University of Pennsylvania, Philadelphia, PA 19106-6340, USA

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### ABSTRACT

We show that the optimal advertising strategy under the Generalized Bass Model (GBM) involves beginning at an extremely low level (the lower the better) and then increasing spending throughout the planning period. This strategy remains optimal in the presence of decreasing prices that affect both margins and diffusion speed. We provide a simple explanation for why this happens. We further show that the intuitively appealing patterns of continuous decrease or increase-then-decrease (both with an uptick towards the end) identified in earlier research are also possible as optimal dynamic advertising paths under the GBM structure, but only if the advertising at launch is constrained to be higher than a particular threshold, which we identify. The constraint necessary to generate intuitively appealing strategies lowers overall profits. Therefore, the GBM generates advertising policy recommendations that most marketers would deem odd. This casts doubt on the value of the GBM for normative purposes. Other existing diffusion models are preferred when seeking normative guidance on optimal dynamic advertising policies for new products subject to word of mouth.

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### 1. Introduction

The diffusion of new products through the marketplace is often affected by both marketing communication efforts and social contagion from adopters to potential adopters. Managing the interplay between these two factors has gained renewed attention as novel findings about their relative importance have emerged (e.g., Iyengar, Van den Bulte, & Valente, 2011; Manchanda, Xie, & Youn, 2008; Van den Bulte & Lilien, 2001) and as marketers increasingly try to leverage word of mouth (WOM) and other contagion dynamics to boost the return on their marketing expenditures (e.g., Lehmann & Esteban-Bravo, 2006; Van den Bulte & Joshi, 2007). Even though referral programs and pure-play viral marketing campaigns allow the initial marketing effort to be quite minimal (e.g., De Bruyn & Lilien, 2008; Schmitt, Skiera, & Van den Bulte, 2011; van der Lans & van Bruggen, 2010), such campaigns form the core of very few marketing strategies. For the great majority of products and services, traditional paid-for marketing communications and free word of mouth are complements rather than substitutes (Armellini & Villanueva, 2010).

Over the years, several diffusion models incorporating both social contagion and marketing mix variables have been proposed. Such models are used not only to describe and predict how these two forces jointly drive new product sales but also to provide normative insights

into how to manage advertising to maximize profits while taking into account social contagion. The Generalized Bass Model, or GBM, proposed by Bass, Krishnan, and Jain (1994) has been especially popular in both descriptive and normative applications (e.g., Hariharan, Kwon, & Talukdar, 2010; Krishnan & Jain, 2006; Vakratsas & Kolarici, 2008). In a recent contribution, Krishnan and Jain (2006) have shown that in the GBM, the optimal evolution of advertising expenditures after launch,  $a(t)$  with  $t > 0$ , is highly dependent on the initial level of advertising,  $a(0)$ . This immediately raises the managerial question of what level of initial advertising maximizes the profit stream over the entire diffusion process, a key issue that Krishnan and Jain did not resolve.

Answering the call by Bass, Jain, and Krishnan (2000, p. 119) to find optimization approaches for the GBM that do *not* require fixing the initial levels of decision variables, we revisit the question of optimal dynamic advertising when a new product diffuses as specified by the GBM. Using a variational approach, we identify both the optimal initial level and the optimal subsequent trajectory of advertising. Because the amount of marketing support at launch is often deemed critical for market success (e.g., Sinha & Zoltners, 2001), finding its optimal level under the GBM is an important contribution. In addition, we identify conditions for the presence and location of turning points in the trajectory, as called for by Krishnan and Jain (2006), and we incorporate the effects that eroding margins, declining prices, and non-zero salvage values have on optimal advertising spending.

Identifying the optimal advertising strategy in the GBM is a technically difficult challenge because it involves a constraint on the control (decision) variable in the form of a differential equation. Krishnan

\* Corresponding author at: The Wharton School, University of Pennsylvania, 3730 Walnut St., Philadelphia, PA 19106-6340, USA. Tel.: +1 215 898 6532; fax: +1 215 898 2534.

E-mail addresses: [fruchtg@biu.ac.il](mailto:fruchtg@biu.ac.il) (G.E. Fruchter), [vdbulte@wharton.upenn.edu](mailto:vdbulte@wharton.upenn.edu) (C. Van den Bulte).

and Jain (2006) handled this challenge by transforming the objective function, turning the constraint on the control variable into a constraint on the state variable. This approach, however, does not allow the identification of the optimal level of marketing support at launch.

Our main result is that the optimal advertising policy under the GBM structure is to start at an extremely low level (the lower the better) and then to increase spending throughout the entire planning period. This result, which holds even when accounting for the presence of decreasing prices affecting both margins and diffusion speed, conflicts with the common intuition of using costly marketing communication mainly to “prime the WOM pump” and reducing marketing expenditures once the WOM is sufficiently strong to attract customers (e.g., Slywotzky & Shapiro, 1993). Furthermore, why would one want to keep increasing advertising expenses late in the process when the number of potential adopters still to be acquired keeps decreasing? Our main result also contrasts with prior analytical results derived from other extensions of the original Bass diffusion model (e.g., Dockner & Jørgensen, 1988; Horsky & Simon, 1983; Kalish, 1985) and other growth models (e.g., Sethi, Prasad, & He, 2008) that optimal advertising starts decreasing either immediately after launch or after the number of adoptions has peaked. Finally, the GBM-derived optimal policy is inconsistent with evidence that advertising and sales force elasticities decrease over time (e.g., Albers, Mantrala, & Sridhar, 2010; Lodish et al., 1995; Manchanda et al., 2008; Narayanan & Manchanda, 2009; Osinga, Leeflang, & Wieringa, 2010; Parsons, 1975).

We provide a simple explanation for this discrepancy. The GBM was originally developed not to help managers make better decisions but to explain why the original Bass model tends to fit empirical diffusion trajectories quite well despite the absence of price, advertising, and other demand influencing variables (e.g., Bass & Srinivasan, 2002, p. 301; Bass et al., 1994, pp. 203–204). This purpose requires the GBM to have a closed-form solution that is observationally equivalent to that of the regular Bass model when prices decline exponentially. To achieve this objective, the GBM assumes that new product sales are not influenced by the *level* of marketing mix variables but by *proportional changes* in these variables. This assumption, for which a behavioral rationale has never been articulated, becomes quite problematic when the model is combined with a standard profit function, as suggested by Krishnan and Jain (2006). Sales increase with proportional changes in advertising, while costs are linear in the level of advertising. As a result, the model structure allows firms to have their cake (fast diffusion) and eat it too (negligible advertising costs throughout the planning period provided the initial level is close to zero). Intuitively more appealing patterns of continuous decrease or increase-then-decrease (with an increase at the end) are also possible as optimal dynamic advertising paths under the GBM structure – even with constant margins over time – but only if the advertising at launch is constrained to be higher than a particular threshold, which we identify. Note that the constraint necessary to generate intuitively appealing strategies lowers overall profits.

As we discuss next, other normative models imply patterns of optimal advertising that not only have more face validity but also are consistent with prior research suggesting that the effectiveness of marketing expenditures declines over time. We expect that most readers will find these models preferable to the GBM for normative applications.

## 2. Literature review

### 2.1. Analytical results using models other than GBM

Obtaining informative analytical results on the optimal level of marketing spending over time for a new product subject to social contagion has proven to be a difficult task. Only a small number of

studies have taken up the challenge.<sup>1</sup> Kotowitz and Mathewson (1979) and Horsky and Simon (1983) find that when social contagion is at work, the optimal policy is to advertise heavily at launch and then to consistently reduce the level of spending as the product diffuses. Monahan (1984) finds the same result in a stochastic model, provided that the effectiveness of advertising is not much higher than that of contagion.<sup>2</sup> Dockner, Feichtinger, and Sorger (1989) extend the model of Horsky and Simon with price and again find (for the undiscounted case) that optimal advertising levels decrease over time. Using different model structures incorporating both price and advertising, Kalish (1985), Jedidi, Eliashberg, and DeSarbo (1989), Swami and Khairnar (2006), and Sethi et al. (2008) all come to the same conclusion. Horsky and Mate (1988) and Krishnamoorthy, Prasad, and Sethi (2010) obtain monotonic decline as the optimal strategy in the case of a duopoly rather than a monopoly. Nguyen and Shi (2006) obtain the same result in a structural-type empirical analysis of the rivalry between Kodak and Polaroid. The common result is intuitively appealing to marketers: spend heavily at first to get the word-of-mouth snowball rolling and then cut back as social contagion takes over and generates “free” adoptions. It is also consistent with the “launch hard” prescription of Sinha and Zoltners (2001) based on their experience in identifying optimal sales force policies for pharmaceutical products.

Teng and Thompson (1985) and Mesak and Clark (1998) obtain a somewhat more nuanced result where monotonicity depends on advertising effectiveness. For the undiscounted case, they find that the optimal advertising level increases whenever the elasticity of the number of adoptions with regard to cumulative adoptions increases with advertising (i.e., whenever the contagion elasticity is boosted by advertising) and that the optimal advertising level decreases whenever the elasticity decreases with advertising. Because new products notably affected by contagion have bell-shaped adoption curves, in which adoptions first increase and then decrease with the cumulative number of adoptions, the latter results imply optimal advertising policies where spending first increases and then decreases over time. Dockner and Jørgensen (1988, pp. 119–120) similarly find that, generally, “it pays to increase (decrease) advertising over time if [adoptions] increase (decrease) as penetration increases.” Teng and Thompson (1983) present a model where, depending on how advertising boosts the effectiveness of contagion, the optimal advertising policy is identified to be one of three types: (i) zero advertising throughout, (ii) advertising at first followed by zero advertising, or (iii) zero advertising early on, followed by maximum advertising at an intermediate stage, then followed by zero advertising later in the diffusion cycle. Thompson and Teng (1984) obtain similar results when the model is extended with price as a decision variable. This set of increase-then-decrease results is somewhat less intuitive than the continuous decrease results discussed earlier. However, the recommendations are certainly not devoid of intuitive appeal from an optimization point of view because they imply that firms should advertise the most when contagion and advertising have the greatest joint effect on generating new adoptions.

Comparing eighteen different model specifications, Mesak and Clark (1998) conclude that the optimal dynamic advertising paths depend on how exactly one incorporates the advertising and contagion effects into the diffusion model. As a result, researchers and managers may prefer to conduct their analysis using a model that is empirically well validated (e.g., Dockner & Jørgensen, 1988; Little,

<sup>1</sup> Our literature review focuses on monopoly results and does not consider models without contagion or models where advertising is taken to essentially be a contagion phenomenon (e.g., Feinberg, 2001; Sethi, 1979). We do not consider studies focusing on allocation across multiple segments or markets (e.g., Lehmann & Esteban-Bravo, 2006).

<sup>2</sup> Without the proviso, Monahan (1984) shows that optimal advertising decreases once half of the market has adopted the new product.

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