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# The role of seeding in multi-market entry

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**Abstract**

Firms introducing new products into multi-markets often face the dilemma of how to dynamically allocate their marketing resources during penetration. The aim of this study is to examine which responsive allocation strategy is more effective for these firms. We explore three major resource allocation strategies: *uniform strategy*, in which the firm distributes the marketing efforts evenly among its regions regardless of market development; *support-the-strong* strategy, under which the firm invests its efforts proportional to the number of adopters in that region (at least up to a certain market coverage); and *support-the-weak* strategy, in which the firm invests its efforts proportional to the remaining market potential.

Using both formal analysis and complex systems simulations, we find that strategies that disperse marketing efforts, such as support-the-weak and uniform strategies, are generally superior to support-the-strong strategy. Not only is this finding surprisingly robust to market conditions and variations on these strategies, but it also runs counter to conventional wisdom prevailing in international marketing. The conditions under which support-the-strong policy might become more effective include: (a) fixed entry or operation costs above a certain level; and (b) substantial variance between regions in responsiveness to marketing efforts. However, variance in intrinsic innovativeness between regions does not imply the superiority of support-the-strong strategy.


*Keywords:* International marketing; Diffusion; Multi-market entry; Complex systems; Advertising

## 1. Introduction

A senior executive in a leading firm in the digital printing industry shared with us the following dilemma: in the early 1990s, the company introduced a set of innovative products to the European market. The company already had some customers in several countries, and the marketing team had to decide how to allocate its marketing resources. One alternative was to focus marketing efforts on countries where they already had initial installations, reach a significant presence there, and then move on to other countries. A second option was to invest in the weaker countries, trying to encourage the adoption process with extensive advertising. A third option was to ignore market status and evenly distribute the marketing budget across the entire market.

The company was unable to make a decision. In this specific case, they focused initially on the early adopting countries, but then printing houses from other countries began to show interest. Management was confused: if they continued to focus on the al-

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ready active countries, they would miss business opportunities. On the other hand, if they dispersed their marketing efforts, they might slow the penetration process in the countries where they already had indications that business was developing in the desired direction.

This firm in the example above is not alone in this dilemma. In a series of interviews that we conducted with executives of a few dozen global high-tech firms, most admitted that after years of experience, they still do not have a good sense as to the right response to this situation. Overlooking the specific idiosyncrasies of the cases, these firms had to choose from among three distinct strategies: *support-the-strong* strategy, under which the firm invests its efforts proportionately to the percentage of adopters in each region; and *support-the-weak* strategy in which the firm invests its efforts proportionately to the remaining market potential, i.e., proportional to the percentage of individuals in the region who have *not yet adopted* the new product. A firm could also allocate its budget regardless of market development and choose the *uniform strategy*, wherein it distributes marketing efforts evenly among its regions (in proportion to region size).

The question becomes critical when reactions from the market begin to appear and the differences between regions become apparent. In these circumstances, it is not clear how market reaction in various regions should affect budgeting decisions. Thus, for example, if one region has achieved a penetration of 90% while others achieved only 10%, the firm is better off adopting a support-the-weak strategy by diverting marketing resources to the less developed regions, relying on word-of-mouth to increase the rate of adoption in the more highly developed region. Yet it is not intuitively clear if support-the-strong might not be a better strategy in other situations.

The aim of this paper is to examine the conditions under which each of the above three strategies yields more efficient diffusion. We depart from existing academic literature on this subject by focusing on strategies that dynamically respond to multi-market adoptions. Previous marketing modeling considered the choice among stationary strategies, i.e., the allocation of marketing efforts in multinational markets as a *pre-entry* decision (e.g., Kumar & Krishnan, 2002; Putsis, Balasubramanian, Kaplan, & Sen, 1997; Kalish, Mahajan, & Muller, 1995).

We examine *responsive* resource allocation strategies that take into account known intermediate success in various regions. In order to do so, we generalize the basic Bass model to multinational markets, and using analytical investigation, compare the performance of the stationary and responsive strategies. We also use *stochastic cellular automata*, a simulation method for modeling the dynamics of complex systems through interactions between individuals, to examine the question under more complex assumptions about market structure. We study symmetric market structures, as well as markets where regions differ in their levels of innovativeness and their influence on other regions. Our main findings are:

1. Absent entry costs, strategies that disperse marketing efforts (such as uniform or support-the-weak) perform better, in terms of the net present value (NPV) of number of adopters. This finding runs counter to conventional wisdom in international marketing. The result is surprisingly robust to market conditions and variations on these strategies.
2. Entry costs to a region or fixed regional operation costs, can change this pattern to favor support-the-strong strategy. The higher the entry costs into a region, or the fixed periodic operation costs in a region, the better support-the-strong strategy becomes.
3. Substantial variance between regions in responsiveness to marketing efforts can lead to a better performance of support-the-strong strategy. However, variance in intrinsic innovativeness between regions does not imply the superiority of support-the-strong strategy.

## 2. Multi-market resource allocation strategies

### 2.1. Pre-entry decisions

A number of studies have examined the preferred way for a firm to enter a multi-market environment, usually in the context of multinational diffusion of new products. Such studies usually investigate two types of pre-entry decisions: *sequential entry* in a pre-determined order, and *simultaneous entry*. Sequential entry, sometimes termed “waterfall”, implies that marketing efforts cascade from one country to another, while with simultaneous (“sprinkler”) entry, the firm enters its regions simultaneously.

Business literature suggests that firms often follow sequential entry patterns. Extensive research on US firms indicates that they usually start entry in countries that are similar to the home market, and then shift gradually to other countries (Davidson, 1983; Davidson & Harrigan, 1977). Mascarenhas (1992) checked data from the petroleum drilling industry and stated, "Simultaneous entry into multiple markets occurs infrequently and in mature stages of the product life-cycle". Ohmae (2000) claims that in the current hectic, competitive marketplace, wherein information flow is fast and global, the waterfall strategy is obsolete. "Successful companies would have to adopt a sprinkler business model: floating the key markets in all three triad regions simultaneously and spontaneously".

Academic recommendations as to which strategies to pursue vary. Some studies either assume or support sequential entry, based on the lead–lag effect (Eliashberg & Helsen, 1996) or the interaction among countries (Putsis et al., 1997). Sinha and Zoltners (2001) argue that concentration of marketing efforts is required in order to accelerate and enhance the internal regional dynamics. Ayal and Zif (1979) concluded that if the market is growing fast, sales are stable, and competitive pressure is low, then sequential entry is preferred. Kalish et al. (1995) suggested that when conditions in foreign markets are unfavorable (slow growth or low innovativeness), competitive pressure is low, and entry costs are high, then sequential entry is preferred. Ganesh and Kumar (1996) argue that when the lead effect between countries is strong, the sequential approach should be taken, while if diffusion in one region is independent of other regions, simultaneous entry is more effective.

Interestingly, while business practice and academic literature on this issue generally favor sequential entry, the limited empirical data that have actually examined its effectiveness support simultaneous entry. For example, Chryssochoidis and Wong (1998) found a positive relationship between the simultaneous launch of high-tech products and profitability. Mascarenhas (1997) found that larger initial advertising budgets do *not* result in higher performance in international markets, implying that the firm can disperse its advertising budget, instead of focusing it on a limited number of regions.

### 2.2. Responsive decisions

One limitation of the current academic approach to the manner of entry is that studies examine *stationary* strategies, in which the allocation of marketing efforts is made by the firm *prior* to the product's introduction into the market. In reality, firms often use *responsive* strategies, that is, they respond dynamically to the market, determining the allocation of marketing efforts based on the progress of the diffusion process. The most commonly used budget allocation method, the advertising-to-sales ratio (Bigne, 1995), is a responsive strategy. In the absence of repeat purchasing, when all sales stem from new adoption, advertising-to-sales ratio implies that the firm determines its advertising budget in proportion to the number of new adopters added during a given period.

Responsive advertising strategies have been examined in the advertising literature (Feinberg, 2001; Feichtinger, Hartl, & Sethi, 1994), and specifically regarding the question of optimal advertising during a new product diffusion process (Dockner & Jorgensen, 1988). These studies discussed "open-loop" responsiveness, in the sense that the decision variables are functions of time alone and do not contain an explicit response on the part of the firm to the product's adoption status in the market. "Closed-loop" equilibria, which consider explicit response of the firm to market state, have usually been discussed in a competitive context, though still in a single-market scenario (Wang & Wu, 2001; Chintagunta & Vilcassim, 1992; Erickson, 1992; Dolan, Jeuland, & Muller, 1986).

In this study, we analyze the effectiveness of various responsive strategies in a multi-market environment. We focus on three types of strategies commonly used by practitioners:

*Support-the-strong strategy*, in which the firm allocates the marketing budget for a region in proportion to the percentage of adopters in that region. In the formal analysis we will discuss this strategy in its pure form, whereas in the simulations we will investigate a more realistic approach, wherein the strategy is applied only until the country reaches a certain level of adoption.

*Support-the-weak strategy*, in which the firm invests its efforts proportional to the remaining market potential, i.e., to the percentage of individuals in the region who have *not yet adopted* the new product. Ohmae (1985) ironically labels this strategy the "United Nations Model".

One should note that the terms *strong* and *weak* relate to the percentage of adopters, and do not imply strength or weakness in other dimensions of the region.

*Uniform strategy*, in which the firm distributes its marketing efforts evenly among its regions, independent of penetration status. Note that this policy is uniform with respect to density, i.e., it is uniform in proportion to the region's total potential.

An allocation of resources in which the distribution of budget among regions does not change over time is called *stationary allocation*. Uniform strategy is thus a specific case of stationary allocation. Since we later prove that uniform strategy is the preferred stationary allocation, we use it as a benchmark for comparing performance to responsive strategies.

## 3. Modeling responsive multi-market allocation

Consider a firm, operating as a monopoly in a durable goods market, composed of $K$ regions of size $m_i$, for a total market potential of $M=m_1+m_2+\ldots+m_K$. Let $N_i(t)$ be the cumulative number of adopters at time $t$ in region $i$. $N(t)$, the total cumulative number of adopters, is $N(t)=N_1(t)+N_2(t)+\ldots+N_K(t)$. Let $x_i(t)$ be the cumulative proportion of adopters in the region. The total cumulative proportion is therefore $X(t)=N(t)/M$.

Let $p_i$ be a parameter representing the power of the firm's marketing efforts (such as advertising) while $q_i$ represents the power of influence among consumers (typically word of mouth and imitation) in the region. The diffusion literature (Mahajan, Muller, & Bass, 1990) sometimes uses the terms *external* and *internal* influences referring to $p_i$ and $q_i$, respectively, but since in a multi-national context these terms might be interpreted as inter-regional and intra-regional influences, we will, consistent with much of this literature, denote them as the coefficients of innovation and imitation, respectively.

We first assume that there is no inter-regional influence and relax this assumption later. Consistent with much of the marketing innovation diffusion literature, we have chosen to model the diffusion based on the Bass model (Bass, 1969). Hence the diffusion in a single region $i$ can be represented by:

$$\frac{dx_i(t)}{dt} = (p_i + q_i x_i(t))(1 - x_i(t)). \tag{1}$$

The firm has a total constant marketing budget $P$, which it allocates to the various regions according to the strategy. Consistent with much of the diffusion of innovations literature, we assume that the marketing expenses influence the diffusion through $p_i$ (Dockner & Jorgensen, 1988). The parameter $p_i$ is postulated to be a function of the marketing budget, as in Horsky and Simon (1983):

$$p_i = \alpha_i + \beta_i \cdot f_i(P_i) \tag{2}$$

The function $f(P_i)$ is usually considered an increasing function of the regional marketing expenses $P_i$. The second derivative of $f$ in respect to $P_i$ is either negative, to imply diminishing returns from advertising or marketing efforts (Horsky & Simon, 1983); zero, if $f(P_i)$ is linear (Thompson & Teng, 1984); or non-specified, if $f$ is S-shaped (Feinberg, 2001).

For the current analysis, we assume that $q_i$ is identical for all regions. We further assume that $\alpha_i=0$, $\beta_i=1$, and $f_i(P_i)=P_i$, that is, $p_i=P_i$. Hence, the marketing expenses of region $i$ are indicated by $p_i$, where $p_1+p_2+\ldots+p_K=P$. Note that in the above, we made some simplifying assumptions to enable an analytical formulation. We will later expand the formal analysis to include inter-regional influence. We will also use simulation methods for modeling the behavior of complex systems. This will help us relax many additional assumptions, study non-linear response functions, and deal with multiple regions that differ in their innovation and influence levels.

### 3.1. Modeling the strategies

In support-the-strong strategy, the relative marketing expenditures are proportional to the percentage of adopters. As we start with the case of two regions, or $K=2$, it follows that $p_i/P=x_i/(x_1+x_2)$, i.e., the advertising proportion devoted to the region is equal to a fraction where the numerator is the proportion of adopters in region $i$, and the denominator is the total number of adopters in the two markets.[1] Along the lines of Kumar and Krishnan (2002), the equations for two regions in support-the-strong strategy have the form:

$$\begin{cases} \frac{dx_1}{dt} = \left(\frac{P \cdot x_1}{x_1+x_2} + q \cdot x_1\right)(1 - x_1) \\ \frac{dx_2}{dt} = \left(\frac{P \cdot x_2}{x_1+x_2} + q \cdot x_2\right)(1 - x_2) \end{cases}. \tag{3}$$

Note that these equations can be applied only to $x_1$, $x_2>0$. Therefore, the strategy can be applied only to $t>0$. Equation system (3) can be solved analytically, by dividing the equations by each other, and canceling the common term $(P/(x_1+x_2)+q)$. The symmetry of the resulting term is used in order to express $x_1$ in terms of $x_2$. The solution is given in terms of a transcendental function and is available from the authors at: www.seeding.homestead.com.

[1] Note that if the market potentials of the two regions are the same, then $p_i/P=N_i/(N_1+N_2)$. If the market potentials differ, then there are two distinct strategies: one relies on relative number of adopters, and the other uses relative densities. In this research we relate only to relative densities.

In support-the-weak strategy, the relative marketing expenditures are proportional to the remaining region potential, thus $p_i/P=(1-x_i)/((1-x_1)+(1-x_2))$, where the term in the denominator is the total remaining potential of the two regions. For this strategy, the growth equations for a two-region market take the form:

$$\begin{cases} \frac{dx_1}{dt} = \left(\frac{P(1-x_1)}{(1-x_1)+(1-x_2)} + q \cdot x_1\right)(1-x_1) \\ \frac{dx_2}{dt} = \left(\frac{P(1-x_2)}{(1-x_1)+(1-x_2)} + q \cdot x_2\right)(1-x_2) \end{cases}. \tag{4}$$

This equation system is valid for every $x_i, t_i \geq 0$, and can only be solved numerically.

Assume that at time $t^*>0$, the adoption proportions in the regions are $x_1^*$ and $x_2^*$. If $x_1^*=x_2^*$, then for support-the-strong and for support-the-weak strategies, $dx_1/dt=dx_2/dt$ at $t=t^*$. Since both regions start with the same value of $x_i$, have the same slope at $t=t^*$, and develop according to the same equations, they will clearly continue to be identical, receiving $p_i=P/2$ for all cases of $t>0$ for both strategies. Thus, in the case of equal initial conditions, support-the-strong and support-the-weak are equivalent to uniform strategy.

However, in many cases we can expect that regions will develop differently in early periods, either because of exogenous constraints, the allocation policy of the firm in the period $0<t<t^*$, or simply due to the stochastic nature of the diffusion process (this is well demonstrated in the simulations formulation of Section 4). In such a case, regions develop differently in early periods, resulting in $x_1^* \neq x_2^*$. Hence at $t^*$, marketers will have to respond to regions with varying numbers of adopters. For such a case, Equation systems (3) and (4) should be solved with the initial conditions $x_1^* \neq x_2^*$.

Although, as shown above, Equation system (3) can be solved analytically, the analytical solution adds little to our intuition, as the result does not lend itself to straightforward manipulation. Therefore, both equation systems were solved numerically. For the numerical analysis, we conducted a full factorial design experiment over the entire range of the parameters $P$ and $q$, and over all options for initial conditions. Parameter ranges were set as follows:

1. $q$ — coefficient of imitation from $1 \times 10^{-6}$ to 1.0
2. $P$ — total advertising budget from $1 \times 10^{-6}$ to 1, $P<q$
3. $x_1^*$ — initial condition for region 1 from 0.1 to 0.99
4. $x_2^*$ — initial condition for region 2 from 0.1 to 0.99, $x_1^* \neq x_2^*$.

Time $t^*$, which indicates the point at which the strategies start to be applied, was arbitrarily set to 1. Since the entire range of values for $x_1^*$ and $x_2^*$ was tested, this choice has no significance. Note that in the current analysis, we did not limit the parameter values of $P$ and $q$ to the range measured in the empirical marketing literature. The only constraints were $P<1$, $q<1$, and $P<q$ (see Mahajan, Muller, & Srivastava, 1990), in order to maintain the functional form of the adoption curves of the Bass model. Parameter values were tested in increments of 0.01.

For each parameter set, we compared the performance of support-the-strong, support-the-weak, and uniform strategies. Two criteria were defined to summarize the growth performance differences between strategies: The first criterion was the dominance of the penetration curve. A function $f_1(t)$ is said to dominate another function $f_2(t)$, if for *every* $t$, $f_1(t)>f_2(t)$. The second criterion, which is more often used in marketing, and which will be also used during the simulations, was the ratio of the NPV of the growth process, using a 10% discount rate per period, a reasonable yearly rate for many markets.

The second criterion is the NPV ratio. The *NPV Ratio* is the *ratio of the NPV of a given strategy to the uniform strategy*. Hence, if the result of the NPV Ratio for support-the-strong is 0.8 for a certain set of parameters, it means that the monetary value of the growth process of support-the-strong was 80% of that of the uniform strategy with the same parameters. Note that dominance is a stronger criterion than the NPV Ratio, since it requires both functions not to intersect with each other. For each parameter set, the dominance criterion was checked in increments of 0.0025 on the $t$ axis.

### *3.2. Results*

The second criterion is the NPV ratio. The analysis (illustrated in Fig. 1 for a specific case) implies that for every parameter set, $P$, $q$, and initial conditions $x_1^* \neq x_2^*$, the cumulative proportion $X(t)$ of support-the-weak is *higher* than the cumulative proportion $X(t)$ of either uniform or support-the-weak strategies. The cumulative proportion $X(t)$ of uniform strategy is in between the curves of support-the-weak and support-the-strong, and the cumulative proportion

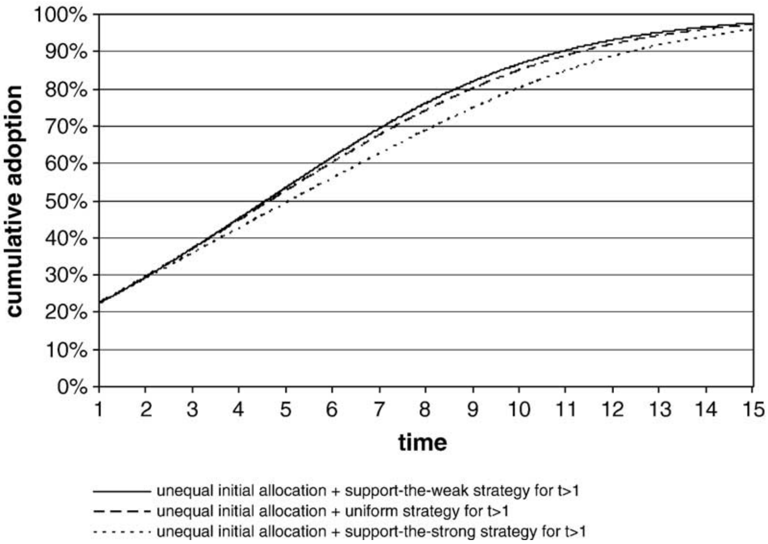


Fig. 1. Cumulative proportion of adopters $X$, as a function of time, for three strategies. Two-region market, with equal region potential. $q=0.35$, $P=0.04$, $x_1*=0.05$, $x_2*=0.4$. NPV Ratio for support-the-weak (vs. uniform)=1.019, NPV Ratio for support-the-strong (vs. uniform)=0.947. Support-the-weak strategy dominates both uniform and support-the-strong.

$X(t)$ of support-the-strong strategy is *lower* than $X(t)$ of either support-the-weak or uniform strategies. In other words, the cumulative adoption curve of support-the-weak strategy *dominate*s that of the uniform strategy, which, in turn, dominates that of support-the-strong, with the same parameters.

Satisfying the strict dominance criterion, the superiority of support-the-weak is also evident using the NPV Ratio. For each parameter set, the NPV Ratio of support-the-weak is larger than 1 (average value of 1.02), and the NPV Ratio of support-the-strong is smaller than 1 (average value of 0.98). Note that the values of the NPV Ratios should not be interpreted as if the performance differences between strategies are not large. As will be demonstrated in the simulations of Section 4, performance differences are much greater when dealing with more than two regions.

**Result 1.** For every initial condition $x_1(t^*)\neq x_2(t^*)$, switching at any time $t^*>0$ to support-the-weak strategy yields a higher cumulative number of adopters at every time point $t$ than either support-the-strong or uniform strategies.

This result, derived from a basic representation of the responsive strategies in the diffusion equations, indicates that unlike common business practice, focusing on the strong regions might not be the preferred strategy for the firm.

### *3.3. The intuition behind the result: the symmetric stationary case*

Result 1 points to the inferior effectiveness of support-the-strong strategy as compared to the uniform and support-the-weak strategies. In order to better understand the cause of this result, we next demonstrate that the greater effectiveness of uniform resource allocation is a consequence of the very nature of diffusion in multi-markets that remains in effect even with simple, stationary allocation. Under the same terminology as before, consider a market composed of $K$ regions. For this analysis, we assume that the regions are of equal size $m$, and that the initial conditions are equal among regions. We further assume that $p_i$ does not change with time. Bass equations for region $i$ have the form:

$$\frac{dx_i(t)}{dt} = p_i(1 - x_i(t)) + qx_i(t)(1 - x_i(t)). \quad (5)$$

**Result 2.** For the stationary case, when starting with equal initial conditions among regions, the *optimal* allocation of a given marketing budget is to distribute the budget equally among the various regions, i.e., given a marketing budget of $p_1+\ldots+p_K=P$, the maximum of the cumulative penetration proportion $x$ for every time $t$ occurs when $p_1=p_2=\ldots=p_K=P/K$.

**Proof.** Let the total cumulative proportion be $X(t)=N(t)/M=(mx_1(t)+mx_2(t)+\ldots mx_K(t))/M=(x_1(t)+x_2(t)+\ldots x_K(t))/K$. We need to show that $X(t,p_1\ldots p_K)\leq X\left(t,\frac{P}{K},\ldots\frac{P}{K}\right)$. □

The proof is based on the concavity *with relation to* $p_i$ of the function $x_i(t, p_i)$, the solution to the Bass equation in a single region. We say that a function $f(p)$ is *concave* if the chord linking any two points on the graph of the function lies beneath the graph, that is for all $\sum_{i=1}^{K} \lambda_i = 1, \quad \lambda_i \geq 0$, we have $\sum_{i=1}^{K} \lambda_i f(p_i) \leq f\left(\sum_{i=1}^{K} \lambda_i p_i\right)$. In particular, this is true for $\lambda_i = 1/K$:

$$\frac{1}{K}\sum_{i=1}^{K} f(p_i) \leq f\left(\frac{1}{K}\sum_{i=1}^{K} p_i\right). \tag{6}$$

Now we take $f(p) = x_i(t, p_i) = x(t, p_i)$, where $x(t, p_i)$ is the solution of the Bass equation in a single region, with equal initial conditions. If $x(t, p_i)$ is concave as a function of $p_i$, it satisfies Eq. (6), which means that:

$$X(t, p_1 \dots p_K) \equiv \frac{1}{K}\sum_{i=1}^{K} x_i(t, p_i) \leq x\left(t, \frac{1}{K}\sum_{i=1}^{K} p_i\right) = x\left(t, \frac{P}{K}\right) = \frac{1}{K}\sum_{i=1}^{K} x_i\left(t, \frac{P}{K}\right) \equiv X\left(t, \frac{P}{K} \cdots \frac{P}{K}\right).$$

The first and last equalities result from the definitions of $X$, the second inequality results from the concavity of $x_i$, the third inequality results from the definition of $P$, and the fourth equality results from averaging the equal terms $x_i\left(t, \frac{P}{K}\right)$, which equals the term itself.

Now what remains is to show that $x(t, p_i)$ is indeed a concave function of $p_i$. For this, we need to prove that $\frac{\partial x_i(t, p_i)}{\partial p}$ is decreasing, i.e., $\frac{\partial^2 x_i(t, p_i)}{\partial p^2}$ is negative. The solution to the Bass equation for a single region with equal initial conditions $x_i(0) = x_0$, is given by:

$$x(t, p) = \frac{\dfrac{x_0 q + p}{1 - x_0} e^{(p+q)t} - p}{q + \dfrac{x_0 q + p}{1 - x_0} e^{(p+q)t}}.$$

Without loss of generality, assume that $q = 1$.

It follows that:

$$\begin{aligned}\frac{\partial^2 x_i(t, p)}{\partial p^2} &= \frac{e^{(p+1)t}(x_0 - 1)((x_0 - 1)(2 + (2 + 4p + 2x_0)t + (p + x_0)(1 + p)t^2))}{(1 - x_0 + (p + x_0)e^{(p+1)t})^3} \\ &\quad + \frac{e^{(p+1)t}(x_0 - 1)\left(e^{(p+1)t}(2(1 - x_0) + t(p + x_0)(2(1 - x_0) + (1 + p)(p + x_0)t))\right)}{(1 - x_0 + (p + x_0)e^{(p+1)t})^3}.\end{aligned}$$

Since $x_0 < 1$, we need to show that the following expression is negative: $2 + (2 + 4p + 2x_0)t + (p + x_0)(1 + p)t^2 - e^{(p+1)t}\left(2 + 2(p + x_0)t + \frac{t^2}{1 - x_0}(1 + p)(p + x_0)^2\right)$. Now use $e^u > 1 + u$ for $u > 0$, with $u = (p+1)t$, which shows that the above is at most the following, which is clearly negative:

$$-t^2(p + x_0)(p + 1)\left[1 + \frac{1}{1 - x_0}(p + x_0)(1 + t(1 + p))\right].$$

Thus, under the conditions of the Bass model with equal initial conditions between regions, optimal penetration is achieved when the marketing budget is equally distributed between regions. When regions differ in their initial penetration rates, the strategy is state dependent, and equal allocation is not necessarily optimal. For example, consider the extreme case of a two-region market, when one region is fully saturated and the other has zero penetration. The optimal allocation in this case is to allocate the entire budget to the region with zero adopters.

Note that unlike the responsive strategies, which, as we demonstrated above, reduce to the uniform strategy when starting with initial penetration rates, the stationary strategies remain distinct even with equal initial conditions between regions. Hence, it is of interest to ask which stationary strategy is preferred. Our result indicates that although one may get the impression that the preferred strategy is focusing the marketing budget on a limited number of regions, the optimal allocation for *every point in time* is actually to distribute the budget equally among regions.

In order to provide some insight into this result, one should go back to the Bass model for a single region. The inflection point $T^*$ of Bass model is given by: $T^* = -(\log(p/q))/(p+q)$. Thus $T^*$ is decreasing and convex with respect to $p$. This means that decreasing $p$ has a *stronger* effect than increasing $p$. The damage to the diffusion process (e.g., increase of $T^*$) caused by decreasing $p$ by one unit, is greater than the contribution to the process when increasing $p$ in one unit. When applying a support-the-strong strategy, the slowdown caused by allocating smaller budgets to the weak regions is more significant than the acceleration caused by the additional budget added to the strong regions.

*3.4. Adding inter-regional influence*

One may argue that the superiority of support-the-weak is not valid in the presence of mutual influence between the regions. A possible claim is that if the diffusion in a region is positively influenced by the diffusion in other regions, focusing on the strong regions will benefit other regions, and thus will create dominance of support-the-strong strategy. In the simulations of Section 4, we will add inter-regional influence to all experiments, but this question can be addressed also in the formal representation. Following Peterson and Mahajan (1978), we can represent the magnitude of the inter-regional influence of another region, $j$, with an additional parameter $\delta_j$. Hence, the equations for both strategies have the form:

$$\text{Support}-\text{the}-\text{strong}:\begin{cases}\frac{dx_1}{dt}=\left(\frac{P\cdot x_1}{x_1+x_2}+q\cdot x_1+\delta_2 x_2\right)(1-x_1)\\ \frac{dx_2}{dt}=\left(\frac{P\cdot x_2}{x_1+x_2}+q\cdot x_2+\delta_1 x_1\right)(1-x_2)\end{cases} \tag{7a}$$

$$\text{Support}-\text{the}-\text{weak}:\begin{cases}\frac{dx_1}{dt}=\left(\frac{P(1-x_1)}{(1-x_1)+(1-x_2)}+q\cdot x_1+\delta_2 x_2\right)(1-x_1)\\ \frac{dx_2}{dt}=\left(\frac{P(1-x_2)}{(1-x_1)+(1-x_2)}+q\cdot x_2+\delta_1 x_1\right)(1-x_2)\end{cases}. \tag{7b}$$

When $\delta_1=\delta_2$, starting from equal initial conditions $x_1^*=x_2^*$ renders both strategies equivalent to the uniform strategy. However, the non-symmetric spillover effect ($\delta_1\neq\delta_2$), or unequal early allocation for any other reason, will lead to regional differences, even when the regions seemed similar to begin with.

In order to test the performance differences between strategies under the initial conditions $x_1^*\neq x_2^*$, we conducted a numerical analysis using the above experimental design. The inter-regional influence parameters $\delta_1$ and $\delta_2$ ranged between $1\times10^{-6}$ and 1, and $\delta_1$, $\delta_2<q$. The results indicate that inter-regional influence, while moderating the differences between strategies, does not change the basic result. For each and every set of parameters, support-the-weak strategy dominates the uniform strategy, and the uniform strategy dominates support-the-strong. In terms of NPV Ratio, for each and every tested parameter set, the value for support-the-weak is greater than 1 (average of 1.012), and the value for support-the-strong is less than 1 (average of 0.99). Note, that although the result holds for all tested ranges of values of $q$, $\delta_1$, and $\delta_2$, the performance differences between strategies decrease as the value of $\delta$ becomes closer to $q$, since high inter-regional influence moderates regional variations, and all strategies become closer to the uniform strategy.

## 4. Exploring responsive strategies using cellular automata

The above analysis fully captures the fundamental nature of the process and the intuition behind it. However, necessitated by the need for analytical solutions, it ignores several aspects that might be of interest in markets for new products. These include mainly market-specific variables such as multiple regions, the response function to advertising, entry barriers, level of innovativeness, and inter-regional influence. In order to take this interrelatedness into account, we will next use stochastic cellular automata, a modeling approach that simulates the dynamics of complex systems, enabling a broader analysis of the multi-market response questions we address.

However, no less important than the need to add region-specific characteristics is the ability to add a stochastic element into the process. Note that the Bass model is deterministic, and thus crucially depends on initial conditions. In practice, even if the regions and initial market conditions are similar, marketing executives will be faced with the problem of marketing resource allocation if growth patterns differ due to stochastic interference or to reasons beyond the firm's control. As word of mouth is an important variable in our setting, small perturbations in the number of adopters early in the process might result in major differences in the diffusion pattern later on during the product life cycle. Thus throughout the entire diffusion process, the stochastic element, which we introduce via stochastic cellular automata, considerably strengthens the case for responsive marketing allocation.

### 4.1. A cellular automata model

*Stochastic cellular automata* is a technique for complex systems modeling that simulates aggregate consequences based on local interactions between individual members of a population. Cellular automata are widely used in a number of disciplines, especially the life sciences, increasingly in the social sciences, and recently in economics and marketing (Goldenberg, Libai, & Muller, 2002; Rosser, 1999).

A cellular automata model describes the market as a matrix of cells, each of which represents an individual consumer who is able to receive information and make decisions during consecutive periods. Fig. 2 illustrates an example of such an environment.

In order to describe a multi-region market, the matrix is divided into sub-matrices, each of which represents a region. For the current study, we used a structure of 25 regions, each containing 25 units. Various region sizes were tested, ranging from 25 to 100 units per region, and the results did not show sensitivity to region size. Since our strategies are defined in term of densities, we normalized the regions to be of equal size.

In the cellular automata environment, time is discrete, and in each period, each cell can accept one of two states: "0," representing a potential customer who has not adopted the innovative product, and "1," representing a customer who adopted the new product. In addition, irreversibility of transition is assumed, so that consumers cannot un-adopt after they have adopted.

In accordance with classical diffusion modeling, the transition of a potential adopter from state "0" to state "1" depends upon two communication factors: *Actions of the firm*, represented by probability $p$, that an individual will be influenced by sales force, advertising, promotions and other marketing efforts, and adopt the innovative product. The parameter $p$ is the individual-level equivalent of the aggregate-level coefficient of innovation, or external influence of the diffusion literature (Mahajan, Muller, & Bass, 1990); *Market dynamics*, represented by probability $q$ that during a given time period, an individual will be affected by an interaction (word-of-mouth, or imitation) with a single other individual from the same region or from another region, who has already adopted the product. The parameter $q$ is the individual-level equivalent of the aggregate-level coefficient of imitation, or internal influence of the diffusion literature (Mahajan, Muller, & Bass, 1990). The model contains two types of communication between consumers: inter-regional and intra-regional.

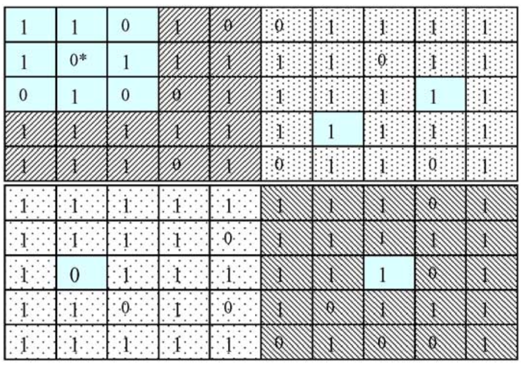

Fig. 2. Cellular automata adoption in a four-region market. The individual in the second row, second column (*) is influenced by all consumers colored in solid color, i.e., the nearest neighbors, and also by consumers from other regions.

1. *Within a region*—Each individual is influenced by his or her nearest neighbors, through parameter $q_s$. The diffusion literature reports a clear correlation between geographic proximity and the strength and speed of word-of-mouth spread, sometimes labeled the "neighborhood effect" (Mahajan & Peterson, 1979).
2. *Between regions*—The individual is influenced by individuals in other regions, which we denote as "relatives," through inter-regional word-of-mouth ties, expressed by $q_w$. These ties are equivalent to the "weak ties" that have been shown to play an important role in the flow of information in a social system (Rogers, 1995; Granovetter, 1983).[2] Note, that the marketing literature reports an additional mechanism for inter-regional influence, which is termed spillover, or *lead–lag effect*. It assumes that the mere existence of adopters in other regions has a positive influence on the diffusion in a region (Takada & Jain, 1991), even without active word-of-mouth interactions. Performing all of our simulations with spillover did not show any sensitivity to its value, therefore the inter-regional influence is modeled through word-of-mouth ties alone.

If in period $t$, an individual is connected to $s(t)$ adopters belonging to his or her region, and to $w(t)$ adopters from other regions, then the probability of adoption of that individual is shown by the following:

$$\mathrm{prob}(t) = 1 - (1-p)(1-q_s)^{s(t)}(1-q_w)^{w(t)}. \tag{8}$$

A step-by-step outline of a cellular automata simulation will look as follows: in period 0, none of the consumers have yet adopted the product, so all cells have a value of 0. In each successive period $n$, the probabilities for each consumer are computed using Eq. (8). A random number $U$ is drawn from a uniform distribution in the range [0,1]. If $U < \mathrm{prob}(t)$, then the consumer moves from non-adopter to adopter (receiv-

[2] Because of the two-dimensional nature of the matrix, the number of intra-regional ties per cell was set at eight. Similarly the number of inter-regional ties was set at eight as well. Preliminary checks revealed that the results are not sensitive to this number.

ing the value of 1). Otherwise, the consumer remains a non-adopter. This process is repeated until a certain percentage (e.g., 95%) of the total market turns into adopters. In our simulations, each market was examined for 30 periods. Note, that since the communication parameters $p$, $q_s$, and $q_w$ represent probabilities, their absolute value range determines the magnitude of a "period", which is of less interest to us. Our interest is in the *relative* values of the parameters analyzed.

### 4.2. Responsive marketing strategies

Following the formal analysis, we deal with three types of strategies: support-the-strong, support-the-weak, and uniform (which will serve as a benchmark stationary strategy). The relationship between the coefficient ($p_i$) and the marketing expenditure for the region ($P_i$) is given via the equation $p_i = \alpha + \beta \cdot f(P_i)$. In each period, the regional budget $P_i$ is calculated according to the relevant strategy. The allocation is expressed in the model through the value of $p_i$ using Eq. (8). The marketing budget was taken to be $M \cdot p$, where $M$ is the total market potential, the function $f$ was taken to be linear, $f(P) = P$ (in Section 5.5 we deal with non-linear response functions). For the basic experiment, $\alpha$ was set to 0, $\beta$ to 1. The influence of $\alpha$ and $\beta$ is specifically investigated in Section 5.4. The allocation of marketing budget is done per region. That is, each region receives a marketing budget that is divided uniformly among its individuals. When there is no option for implementing the strategy (for example, nobody has adopted yet in support-the-strong), uniform allocation is performed.

In the formal analysis, we used two criteria to describe performance differences between strategies: dominance and NPV Ratio. The dominance criterion is not applicable to the stochastic environment of the cellular automata, since random fluctuations can cause temporary dominance changes between strategies. Therefore, only the NPV Ratio was used. To minimize random effects due to the particular realization of the stochastic simulation, we ran the program 10 times for each set of parameters and averaged the result over the 10 runs.

Besides randomness and more complex market structures, the flexibility of the cellular automata enables us to investigate a more realistic version of support-the-strong strategy. Clearly a "pure" support-the-strong strategy, described in the formal analysis, is sub-optimal, since after a certain point, the dominant influence is that of communication among consumers, and thus the contribution of marketing efforts to such a region is negligible. A more realistic strategy would be to allocate the budget of the region in proportion to the number of adopters until the region reaches a certain proportion of adoption (termed here "breakpoint" and denoted by parameter $b$), and then stop regional marketing efforts altogether. For example, $b = 0.4$ indicates that in support-the-strong strategy, the budget is proportional to the percentage of adopters only until the region achieves 40% adoption, and then the region receives no budgets. If the adoption in all the regions in the market exceeded the breakpoint, uniform allocation is performed. We use $b$ as a parameter to compare various levels of "strength" of support-the-strong; a breakpoint value of 1 is equivalent to the "pure" strategy discussed in the formal analysis. The lower $b$ is, the closer the strategy resembles uniform strategy, since the market sooner reaches the state where all regions are above the breakpoint and hence receive equal allocation. When testing the effect of support-the-strong strategy on performance, we used the entire range of values for $b$ from zero to 1.

As Fig. 4 illustrates, the best performance for support-the-strong is achieved when $b = 0$, that is, when support-the-strong is equivalent to the uniform strategy. In order not to create an artificial bias in the results due to inordinately small values of $b$ (in which support-the-strong is applied for a short time) or inordinately large values of $b$ (which, as explained above, are clearly inferior in performance), an intermediate range of values was chosen for all other simulations.

Since we are interested in testing the effect of advertising budgets on the process, we chose the breakpoint parameter $b$ as the point from which the contribution of advertising and other firm-induced influences falls below that of word of mouth. Although both advertising and word of mouth influence consumers right from the start, the relative contribution of advertising decreases with the growth in the number of adopters (Mahajan, Muller, & Srivastava, 1990).

Rogers (1995) suggests that as soon as when about 16% of the market potential adopts, the role of advertising in affecting adoption becomes negligible. We examined a broader range for that point in time, from about the point suggested by Rogers up to the period of the maximum number of new adopters (which is close to when about half the market potential adopts according to the Bass model, see Mahajan, Muller, & Srivastava, 1990).

The range of the other parameters was chosen based on the diffusion literature. Parameters $p$ and $q$ were determined according to Sultan, Farley, and Lehmann (1990), and Goldenberg, Libai, and Muller (2001), after

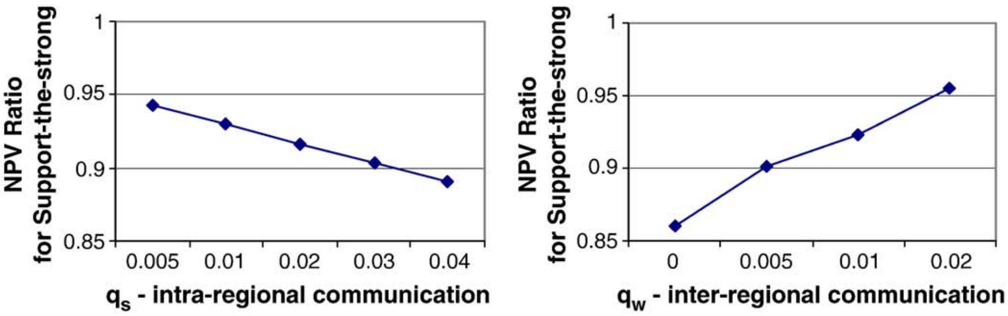


Fig. 3. NPV Ratio for support-the-strong strategy vs. uniform strategy as a function of the inter-regional and the intra-regional communication parameters. Performance level of support-the-strong strategy decreases with the increase of the intraregional communication parameter $q_s$, and increases with the increase of the inter-regional influence parameter $q_w$ (averaged over the entire range of values of $p$ and $b$, respectively).

the adaptation to individual levels (see Goldenberg et al., 2002, 2001 for further discussions on the parameter range for an individual-level cellular automata growth model). All combinations of the parameters were considered in a full factorial design experiment. Parameter ranges were set as follows:

1. $p$—advertising (marketing efforts) influence parameter 0.005–0.04 (0.005,0.01,0.02,0.03,0.04)
2. $q_s$—parameter for communication within region 0.005–0.04 (0.005,0.01,0.02,0.03,0.04)
3. $q_w$—parameter for communication between regions — 0.0–0.02 (intervals of 0.05)
4. $b$—breakpoint of support-the-strong strategy— 20–60% (intervals of 10%)

In the next section, we show that even under the above general conditions with stochastic elements, the result that support-the-strong is inefficient still holds. We then show the conditions under which these results break, which include high entry costs and variations in innovativeness between regions.

## 5. Results: the strong should not get stronger, unless...

### 5.1. The strong should not get stronger

Averaging for the entire set of parameters given in the previous section, the NPV Ratio of support-the-strong vs. uniform was 0.91 (with $\sigma=0.1$), while the average NPV Ratio of support-the-weak vs. uniform was 1.008 ($\sigma=0.01$).[3] Thus, a firm could gain an average of 10% or more NPV by employing a uniform (or support-the-weak) strategy instead of the common business practice of support-the-strong. The uniform and support-the-weak strategies show near-equal performance. This result firmly holds for all values of $q_s$ and $q_w$. The influence of $q_s$ and $q_w$ runs in opposite directions, as illustrated in Fig. 3. As $q_s$ increases, the point at which the main influence is that of word of mouth is reached earlier; therefore allocating high advertising budgets to regions is less efficient and as a result, the performance of support-the-strong decreases. Obviously, performance differences between strategies decrease with the increase in $q_w$, since high inter-regional influence moderates regional variations, and all strategies become closer to the uniform strategy.

Note that the above NPV Ratio for support-the-strong is averaged over various values of parameter $b$. Recall that $b$ indicates the breakpoint value for the support-the-strong strategy, i.e., $b$ measures the point at which the firm stops supporting that particular region. The higher the breakpoint value, the closer the strategy resembles the pure support-the-strong of the formal analysis. Fig. 4 illustrates the NPV Ratio for support-the-strong (vs. uniform) as a function of the breakpoint, averaging over all the values of $p$, $q_s$, and $q_w$.

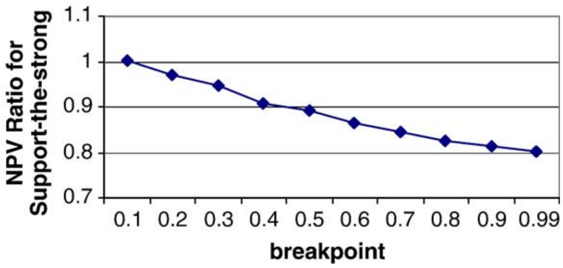


Fig. 4. Breakpoint effects on NPV Ratio for support-the-strong vs. uniform strategy. Performance level decreases as the strategy is more focused on the strong regions (a high breakpoint implies funds to be allocated to the strong regions for longer time periods).

[3] Differences in both cases are significant ($p$-value<0.01). However, readers may want to be cautious in applying statistical significance to such simulations, where the number of observations can be very high.

It is evident that focusing on strong regions has a negative effect on performance level. For high breakpoint values (i.e., intensive support of the strong regions), the average performance of support-the-strong decreases to 80% of the uniform (and support-the-weak) strategy.

**Result 3.** With advertising parameters being equal across regions, support-the-strong strategy shows a lower NPV than both the support-the-weak and uniform strategies. Using support-the-weak and uniform marketing strategies can significantly increase the growth of new product diffusion and profits.

While Result 3 generalizes the formal analysis derived in Section 3, it clearly contradicts conventional business intuition. Focusing marketing efforts to enhance penetration in the strong regions is *less* effective than either supporting the weak regions *or* simply distributing the marketing budget equally. Moreover, Fig. 4 demonstrates that as support-the-strong becomes focused on the strong regions, its performance becomes weaker.

### 5.2. The power of seeding

Looking at the diffusion pattern for the three strategies (illustrated in Fig. 5 for a specific parameter set) provides insight into the mechanism behind the results. Support-the-strong creates a sequential entry, where regions are filled one after another. When the first consumers start to adopt, marketing efforts are allocated to their respective regions. These regions fill more quickly, due both to intensive marketing efforts and to communication between consumers, while the other regions depend only on inter-regional connectivity.

When the initial regions reach the breakpoint, the marketing efforts shift to other regions. That note unlike the entry process described in the literature, the entry order is *not* predetermined by the firm, but is rather a *result* of the adoption dynamics.

Support-the-weak and uniform strategies create a simultaneous entry pattern, since in the beginning, all regions contain many non-adopters, and hence receive some marketing budget. As a result, multiple small seeds of adopters start to develop in the market.

Our basic result states that under our assumptions so far, the power of this seeding is greater than the power of focus. Since the size of the market is large relative to that of a single region, the average expected number of adopters, emerged from the random seeds created by the dispersed marketing, is larger than the expected number of adopters in the small number of regions that received intensive marketing.

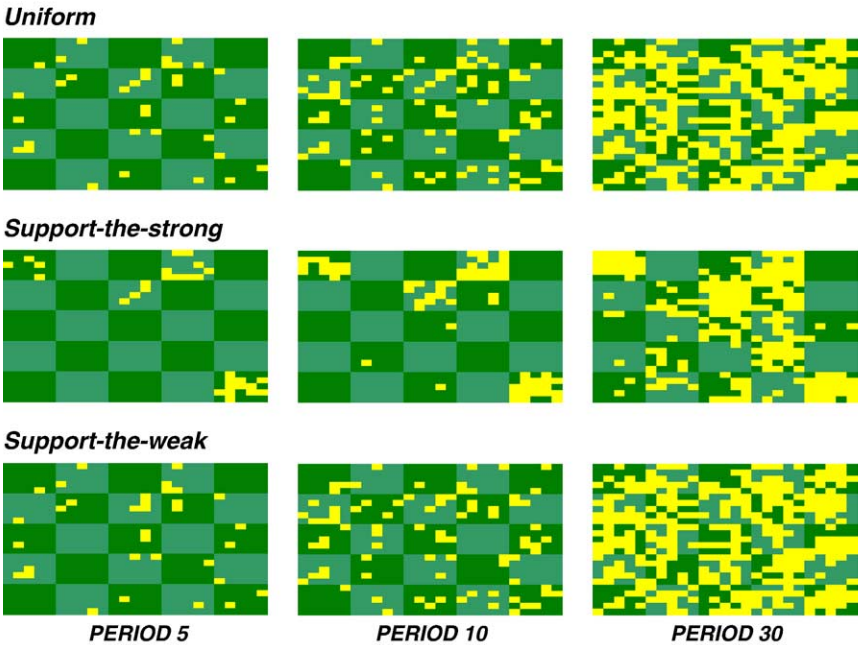


Fig. 5. Diffusion patterns for periods 5, 10, and 30 for the three strategies. Darker rectangles represent the regions. Activated cells are colored lighter. Support-the-strong creates sequential entry, and adopters are concentrated in a limited number of regions, while uniform and support-the-weak generate dispersed diffusion ($p$=0.01, $q_s$=0.01, $q_w$=0.005, breakpoint=70%, $\alpha$=0, $\beta$=1).

## 5.3. Effect of entry cost on strategy

One may suggest that the existing business practice of focusing marketing efforts is a consequence of the fact that in real markets, dispersion of marketing efforts requires financial and managerial efforts. Geographical distance, regulation barriers, and sales infrastructure setup in a new country all require a substantial investment (Dekimpe, Parker, & Sarvary, 2000).

The multinational diffusion literature has discussed the effect of entry costs on entry strategy for pre-entry decisions. Kalish et al. (1995) claimed that high fixed entry cost into the foreign market can render "waterfall" entry strategy more efficient than "sprinkler". Ayal and Zif (1979) also mention high operation costs in the foreign market as a consideration for choosing a focused marketing strategy. In this section we extend the discussion to investigate the influence of entry costs on the performance of responsive strategies.

Entry cost was inserted into the model through an additional parameter in the NPV calculations. The parameter, denoted by $C$, is the proportion of adopters in the region needed to cover the fixed entry cost, i.e., $C=0.1$ in a region of 25 units means that the firm needs 2.5 adopters to cover the entry cost. Although in reality $C$ might be region-specific, we assume that $C$ is identical for all regions, since we are not interested in the order of entry, but rather in assessing the effectiveness of each of the marketing strategies.

Using an identical $C$ is also consistent with business practice, since $C$ depends more on the type of industry and less on specific regional variables. This formulation covers both cases of one-time entry costs and fixed periodic operation costs. Recall that the net present value of an annuity $C$ is $C/d$, where $d$ is the discount rate. Hence, the initial *one-time entry cost C* is equivalent to *fixed periodic operation cost* of $d{*}C$. A full factorial experiment was re-run, with all the parameters listed in the previous section, plus the parameter $C$, in the range of 5–25% (increments of 5%).

The simulation results presented in Fig. 6 indicate that for low values of $C$ ($C<0.065$, averaging over all parameter values), the dispersed strategies (support-the-weak and uniform) are superior; yet as $C$ increases, the results change, and support-the-strong improves its standing. No meaningful differences were found between uniform and support-the-weak. This result implies that entry or operation costs in a region are moderators to the power of seeding, since in such cases, having multiple adopters' seeds decreases the profitability of the firm.

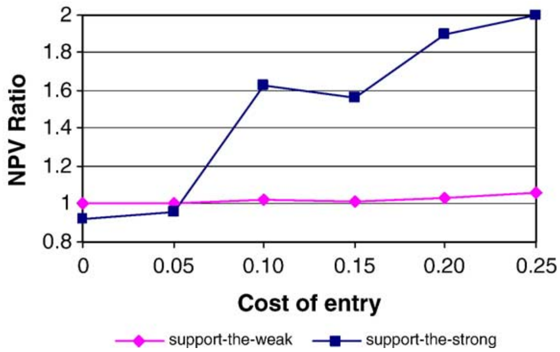


Fig. 6. NPV ratio and entry cost (expressed as a fraction of region potential). For low entry costs, the uniform and support-the-weak strategies are superior, but as the entry cost increases, the performance of support-the-strong improves.

**Result 4.** As entry costs to regions, or periodic fixed regional operation costs, increase, the NPV of support-the-strong strategy exceeds both support-the-weak or uniform strategies. That is, entry costs to a region above a certain level can render support-the-strong strategy superior.

## 5.4. Effect of regional innovativeness on strategy

It is well known that countries differ in their levels of innovativeness. Significant differences in takeoff values between countries were measured even in the heavily communicated, unified Europe (Tellis, Stremersch, & Yin, 2002). The empirical research speculated that the firm might want to focus its initial marketing efforts in the innovative countries (ibid.), and if the firms assume uniform distribution of innovators, they might want to disperse their marketing efforts (Ganesh, 1998). In this section we investigate whether differences in the level of innovativeness between regions are a consideration in determining marketing strategy.

In the diffusion literature, the level of innovativeness is measured through the value of $p$, the coefficient of innovation. According to Eq. (2), the relationship between $p$ and marketing expenditures $P$ (for a linear function $f$) is given by $p=\alpha+\beta P$. Therefore, variations among regions in the value of $p$ can be expressed in either $\alpha$ or in $\beta$. The parameter $\alpha$ represents the region's intrinsic innovativeness, while $\beta$ represents the region's responsiveness to marketing efforts.

Consistent with the conventional division of adopter categories (Mahajan, Muller, & Srivastava, 1990), in each run we randomly chose four regions (16% of 25 regions) to represent the innovators. These regions received higher values of either $\alpha$ or $\beta$, depending upon the experiment. Note that the assumption here is that the firm does *not* know which regions are innovative, rather it simply responds to the activity in the market, and allocates resources based on the number of adopters/nonadopters. This is often the situation when marketing innovative technological organizational products, particularly when the product creates a new category, and market reactions are difficult to forecast.

### 5.4.1. The effect of intrinsic innovativeness

Without loss of generality, let the intrinsic innovativeness of all regions be zero ($\alpha=0$), except the innovative regions, whose intrinsic innovativeness is positive. The parameter $\beta$ of the relationship between $p$ and marketing expenditures $P(p=\alpha+\beta P)$ was set to 1, and the values of $P$ and $\alpha$ were chosen to be in the range of $p$, where initially $\alpha$ is in the same order of magnitude as $P$ in order to balance between the intrinsic innovativeness and the strategy.

A full factorial experiment was conducted, with the range of the parameters as in Section 4, where we vary $\alpha$ instead of varying parameter $p$ in the same range. Results closely matched those of Section 5.1: the uniform and support-the-weak strategies were superior to support-the-strong. Averaging over the entire range of parameters, the average NPV Ratio for support-the-strong is 0.93 ($\sigma=0.1$), while the average NPV Ratio for support-the-weak is 1.01 ($\sigma=0.01$).

**Result 5.** Even where there are large differences in intrinsic innovativeness ($\alpha$), support-the-weak and uniform strategies result in higher NPV than support-the-strong strategy.

### 5.4.2. The effect of responsiveness to marketing efforts

Using the same paradigm as the previous experiment, we tested the effect of differences in $\beta$ on marketing strategy. The innovative regions had $\beta=1$, while the non-innovative regions received an identical value in the range of 0.01–1, using intervals of 0.01 (since in this section $p=\beta \cdot P$, only the ratio of $\beta$ to $P$ is of importance). The parameter $\alpha$ was set to zero, since it was already shown that $\alpha$ does not create differentiation between strategies. A full factorial experiment was conducted.

As shown in Fig. 7, for all parameter values, the performance of support-the-strong improves as the ratio between the values of $\beta$ of the innovative to non-innovative regions increases. Support-the-weak slightly exceeds uniform as the differences in $\beta$ increase. Only when the responsiveness of the innovators is eight times (or more) the responsiveness of the non-innovators does support-the-strong strategy become superior.

**Result 6.** The NPV of support-the-strong strategy becomes higher as the ratio between the responsiveness of the innovative to non-innovative markets increases. The responsiveness of the innovators has to be considerably stronger than that of the non-innovators for support-the-strong strategy to exceed the others in effectiveness.

Result 6 confirms the supposition of the empirical studies (Tellis et al., 2002; Ganesh, 1998) that the firm might want to focus its initial marketing efforts in the innovative countries, and if the firm assumes uniform distribution of innovators, it might want to disperse its marketing efforts. However, our results add to these findings by drawing a distinction between the two sources of innovativeness: differences in *intrinsic innovativeness* are not enough to render support-the-strong superior, since they have the same effects with all strategies. Only considerable differences in *responsiveness* to marketing efforts render support-the-strong strategy superior.

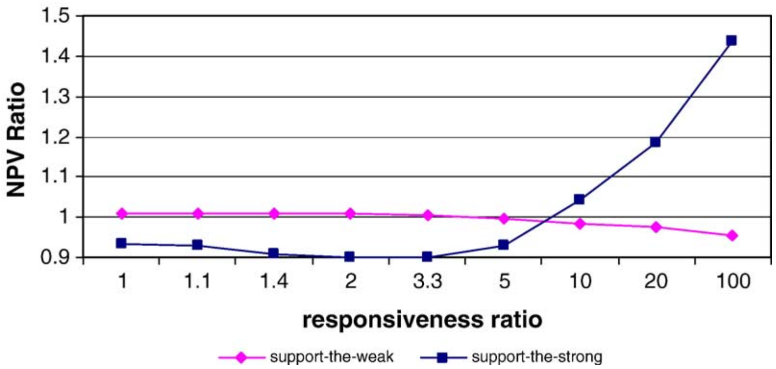


Fig. 7. NPV Ratio for the two strategies as a function of the ratio of the responsiveness of innovative to non-innovative regions (averaged over all parameter values). Support-the-strong strategy improves its performance as the inequality in $\beta$'s increases. Support-the-weak strategy slightly worsens. They intersect when the responsiveness of the innovators is eight times the responsiveness of the non-innovators.

The development of random adopter seeds is inhibited in regions with low responsiveness and accelerated in the highly responsive regions. Therefore, a strategy that focuses on the strong regions will perform better. This also explains why the performance of support-the-weak worsens with the increase in differences: the weak regions are by nature the non-responsive regions. When the firm allocates its marketing resources to the weak regions, it practically wastes its efforts in non-responsive regions, rendering overall effectiveness less than that of the uniform strategy.

### 5.5. The effect of non-linear market-response functions

Eq. (2) relates the coefficient ($p_i$) to the marketing expenditure for the region ($P_i$) via the equation $p_i=\alpha+\beta\cdot f(P_i)$, where $f$ is the market response function to advertising. The analysis so far dealt with a linear response function, $f(P_i)=P_i$. Dispersed strategies (e.g., support-the-weak and uniform) distribute the marketing budget across regions, and therefore operate in average low regional budgets. In focused strategies, such as support-the-strong, the average regional budget of those regions that receive budgets is high. A non-linear response function, which assigns differing weights to high and low regional budgets, might, in theory, affect the relative performance of the strategies, or even change the basic result. In this section we investigate the effect of two additional types of response functions commonly found in the marketing literature: logarithmic and S-shaped.

The logarithmic response function $f(P_i)=\log(1+P_i)$, used for example in Horsky and Simon (1983), shows diminishing returns to scale. Since it is less effective in high budgets, we expect that the superiority of dispersed strategies, which operate in the low budgets, will be enhanced. The full factorial experiment of Section 5.1 was re-run with the logarithmic response function. Averaging over all values of $p$, $q_s$, $q_w$, and $b$, the average NPV Ratio of support-the-strong vs. uniform is 0.90 (compared to 0.91 for the linear response), while the average NPV Ratio of support-the-weak vs. uniform is 1.008, the same as the linear response.

The S-shaped response function (Sasieni, 1989; Mahajan & Muller, 1986) usually implies a minimum level for effective return on marketing efforts, an increasing return in low budgets, and a diminishing return in high budgets. It is well known that if the firm faces an S-shaped advertising response function, it linearizes the convex part of the response function by pulsing (or ideally chattering) between high and zero levels of advertising (Sasieni, 1989; Mahajan & Muller, 1986). This result was extended to the competitive case in that the two firms alternate their high and zero levels of advertising (Villas Boas, 1993), and there is reason to believe that a similar extension could be derived for the multi-market case, but such an extension is beyond the scope of this paper.

The effect of the S-shaped response curve on the performance of the strategies depends on the distribution of budgets along the curve. Consider the extreme case, in which the response function is a step function, where all low budgets have zero response, and high budgets have a positive response. In such a case, it is evident that support-the-strong is the preferred strategy. The low regional budgets in support-the-weak and uniform strategies will yield a zero return. Empirical evidence suggests that in such conditions, concentration of marketing efforts is required (Lodish, Curtis, Ness, & Simpson, 1988).

However, assuming that the firms do not pulse, then the scenario where the lower budgets yield zero return is less likely to happen in reality, since we can assume that the firm will operate only in budgets where it has at least a minimal return. Under this assumption, we expect that the higher responsiveness (i.e., higher derivative) in the low budgets and the lower responsiveness in the high budgets will help the small adopter seeds to develop, and therefore increase the efficiency of working in low budgets and enhance the performance of the dispersed strategies. While it is true that the *absolute* return is lower relative to the linear response case, as was shown in the previous sections, it is not the absolute value of the response which influences the effectiveness of the strategies, but rather the *level of responsiveness* which helps in developing, or inhibiting, the initial adopter seeds.

The full factorial experiment from Section 5.1 was re-run with the S-shaped response function $f(P_i)=\exp(b_0-b_1/P_i)$ (Vakratsas, Feinberg, Bass, & Kalyanaram, 2004; Hanssens, Parsons, & Schultz, 2002, p. 106; Sasieni, 1989; Mahajan & Muller, 1986). The parameter $b_0$ determines the value of the asymptote, and the inflection point ($\max(f'(P_i)$, i.e., $f'(P_i)=0$) happens when $P_i=b_1/2$. Note that since we want the budgets to be distributed from both sides of the inflection point, and since the range of budgets $P_i$ varies between the runs and depends on the parameter $p$, conducting a meaningful simulation requires computing dynamically $b_0$ and $b_1$ for each run. Therefore, each value of $p$, $b_0$, and $b_1$ were computed in order to:

1. Intersect with the linear function at a single point, that is, never having a greater-than-one return (as

used in Feinberg, 2001; Sasieni, 1989; Mahajan & Muller, 1986). This leads to the condition $b_0 = \ln(b_1) + 1$.
2. Span the entire range of budgets while reaching non-zero return even in low budgets. In order to satisfy this requirement, we chose the inflection point to be at $P_i = p$, meaning that $b_1 = 2p$. With such an inflection point, the function spans the relevant range of budgets, with low budgets in its convex part, and high budgets in its concave part, and in addition, even the low budgets do not have zero return.

These two conditions determine unique values for $b_0$ and $b_1$. The results support the hypothesis that the average NPV Ratio of support-the-strong vs. uniform was 0.85 (compared to 0.91 for the linear response), while the average NPV Ratio of support-the-weak vs. uniform is 1.014 and shows no significant difference from the linear response. That is, assuming that the regional budgets are above the takeoff, an S-shaped curve worsens the relative performance of support-the-strong.

**Result 7.** With advertising parameters being equal across regions (and assuming that the S-shape was chosen to span the entire range of budgets), support-the-strong strategy shows lower NPV than both the support-the-weak and uniform strategies, for linear, logarithmic, and S-shaped response functions.

Fig. 8 illustrates the NPV Ratio for support-the-strong strategy vs. the breakpoint, for linear, logarithmic and S-shaped response curves. We see that for every breakpoint value $b$, the performance of support-the-strong under a logarithmic response function is slightly lower than its performance under a linear response curve, and that the performance under the S-shaped response curve enhances the performance differences between strategies. That is, our basic result holds even for logarithmic and S-shaped response functions.

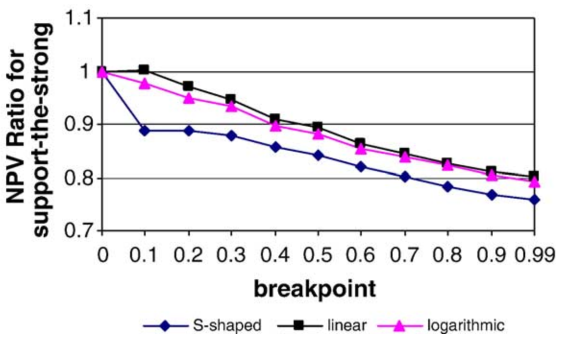


Fig. 8. NPV Ratio for support-the-strong as a function of the breakpoint for linear, logarithmic, and S-shaped response curves. Performance level decreases as strategy is more focused on the strong regions for linear, logarithmic, and S-shaped response curves (averaged over the entire range of values of $p$, $q_s$, $q_w$).

## 6. Discussion

The aim of this study is to explore the performance of responsive budgeting strategies during the introduction of a new product into multi-market, and to investigate the dependence of performance on various market variables. We focused on three classes of strategies used by practitioners: support-the-strong, support-the-weak, and uniform strategy (which serves as a benchmark stationary strategy). We found that in a market where entry costs to regions are low, and differences in responsiveness to marketing efforts are not extreme, strategies that disperse marketing efforts (such as uniform or support-the-weak strategies) perform better, in terms of the net present value of number of adopters.

We investigated the conditions required to change this pattern and to favor support-the-strong strategy. First, the higher the entry costs into a region, or the fixed periodic operation costs in a region, the better support-the-strong strategy performs. Our simulations indicate that as soon as entry costs increase beyond about 5% of the region's profit potential, support-the-strong strategy becomes preferred. This effect is substantial and can lead to performance that, with high level of entry costs, can be as twice as good as that of the dispersed strategies.

Second, empirical research indicates that regions vary in their levels of innovativeness. These differences can be expressed in both intrinsic innovativeness and in responsiveness to marketing efforts. The differences in intrinsic innovativeness between regions have no effect on the basic result. However, when the innovative regions vary significantly from other regions in their response to marketing efforts, support-the-strong strategy might be preferred.

The validity of the results for stationary and responsive strategies, as well as other simulations we conducted with hybrid strategies, indicates that the issue is not the specific strategy, but rather the tension between focus vs. dispersion. In a low level of market constraints such as responsiveness to advertising and entry costs, and assuming that the size of the market is large relative to the size of a region, the average expected number of adopters emerging from the random seeds created by the dispersed marketing efforts, is greater than that in the small number of regions that received intensive marketing. Therefore, dispersed random seeding overrides intensive, targeted efforts.

However, some market conditions might yield effects in opposite directions: Regarding costs of entry into a new region, the firm pays a penalty for each new market it enters. Thus, dispersed strategies, which operate simultaneously on multiple regions, involve higher costs, and strategies such as support-the-strong, in which regions fill one after the other, become more profitable. With respect to innovativeness, the differences in intrinsic innovativeness between regions have the same effect in all strategies, and therefore do not change the basic result. However, when the innovative regions vary significantly from other regions in their responses to marketing efforts, the random seeds of adopters created in the non-innovative regions due to the dispersed strategies, are depressed because of the intrinsic low responsiveness of these regions. Therefore, a strategy that does not "waste" efforts on nonresponsive regions is the more effective one.

### 6.1. Entry or fixed periodic costs in real markets

Our results suggest that a firm's choice of strategy depends greatly on the magnitude of entry and periodic operation costs that the introduction of the innovative product to a new region requires from the firm. As soon as these costs rise beyond a certain level (about 5% in our simulations), support-the-strong yields a higher net present value of adopters. It is therefore useful to inquire about the distribution of these costs in real markets. These data are typically part of the internal budgeting process of firms, and in many cases are not included in the financial reports.

In a series of depth interviews with executives of global technological firms from various industries, which we conducted in order to understand the managerial background of this study, we asked the executives to provide estimates and examples for entry, or periodic operation costs of products, when entering a new region. Although we do not aim to provide a tight statistical analysis, their evaluations and anecdotal examples imply that costs vary within a large range of values, and depend mainly on four variables:

*Existence of current global infrastructures*—In multi-product companies, which already have marketing infrastructures in various regions, the additional costs of adding a product to the existing portfolio of the region are low. For example, an executive from a *Fortune 500* firm in the digital printing industry reported that launching a new product in a region such as Asia Pacific costs on average about \$200,000, which equals the gross profit from 4 to 5 systems, which are about 1% of the region's potential. However, the CEO of a single-product start-up in the call center industry said that their entry into the United Kingdom required creating marketing and support facilities, which incurred costs of almost \$700,000 that equal the gross profits from about 15% of the potential adopters in the region. A global provider of mobile telecommunication services stated that in one of the Mediterranean countries it took two years (and 12% of the market potential) to return the initial investment.

*Use of distributors*—Companies that use distributors to handle their sales and marketing, and provide customer training and first-tier support, might tend to have lower entry costs, even when they do not have established infrastructures in the new region. For example, the VP Marketing of a single-product *Nasdaq 100* company engaged in Internet security indicated that since the firm relies heavily on its distributor infrastructures, its entry costs to a new region are estimated at 2–3% of the region's profit potential.

*Type of product*—Products that have to be physically produced, stored, or shipped, seem to be more costly to launch. The introduction of a virtual product such as software or Internet services might be cheaper. The chair of a \$500 million company that develops large-scale billing hardware–software systems for telecom providers evaluated the additional costs resulting from the introduction of a new product as an average of 10% of the potential of adopters in a region such as the United States. A US-based firm engaged in scientific programs, whose customers load the software from the Internet, reported entry costs equal to 1–2% of potential adopters.

*Gross margins*—Launching profitable products is not necessarily more costly than introducing products with lower gross profit margins. Therefore, the time for return of investment in products with high profit margins (such as software) might be shorter.

Note that our sample is not representative, and is biased toward global, larger firms in the high-tech business-to-business industry. We do not recommend generalizing the above examples to other firms and industries. However, it is seen that even in our small sample, there are costs above and below the transition point that we found in our simulations.

### 6.2. Limitations and further research

A few issues should be considered when examining the results of this study. Our basic approach is built on the original Bass formulation. Price and competition, which affect budgeting decisions in real markets, are not modeled. The effect of advertising is expressed only through parameter $p$, although communication between consumers can be also affected by advertising. In addition, some of the results rely on numerical analysis and not on closed-form analytical solutions. Further research can extend the model regarding these points.

In addition, future research can explore the influence of additional market constraints such as complex market connectivity, negative word of mouth, dynamic total marketing budget, and the like. Better understanding and empirical measurements of $\alpha$ and $\beta$, i.e., intrinsic innovativeness vs. responsiveness, are also required. In addition, other, hybrid strategies could be further investigated in order to find the appropriate strategy under each combination of market constraints.

## 7. Conclusions

What answer can this study suggest for the dilemma of the marketing digital printing executive we discussed in the Introduction? Clearly there is no simple answer, as the proper strategy is contingent on case-related factors. However, we can direct the executive to the factors to look for, and their possible effects. We can also warn against misjudging market-related signals that may lead to focusing on certain regions when this is not optimal. For example, managers may interpret an initial adoption pattern as a sign of the market potential of the various regions. In such cases, of course, our assumptions are not valid, and it may be worthwhile to focus on the regions with the highest market potentials. Yet what this study does point to is the possible cost of a misjudgment in such a case: If some regions adopt earlier as the result of a stochastic process, or because of a difference in innovativeness, misjudging these phenomena to be indications of market potential and focusing on these regions can be a costly strategy.

The main goal in this paper is to explore the mechanisms that influence the relative performance of responsive budgeting decisions, and in particular, to direct attention to the interplay between seeding and its inhibiting forces. Managers should aim to evaluate the relative power of seeding versus the inhibiting forces in their industry, and consider the total effect when determining resource allocation strategy. In many industries, market structure might be more suitable for focusing: entry costs are high, and countries vary in their responsiveness to marketing efforts. However, for globally established firms in high-tech industries, the influence of seeding plays a significant role. Such firms already have established global marketing infrastructures, and thus the additional entry costs for each new product are proportionately less. Their target markets are relatively homogenous, highly communicated, and exposed to marketing efforts. Such a firm, which can correctly evaluate the conditions in the various regions in which it operates, and as a result efficiently manages to disperse its marketing efforts, will gain a business advantage.

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