

Disruptive Innovation Diffusion

Nicholas C Georgantzas
Fordham University
113 West 60th Street
Suite 617-D
New York, NY 10023
USA
georgantzas@fordham.edu

Nadezhda A Peeva
Deloitte
Two World Financial Center
15th Floor
New York, NY 10128
USA
npeeva@deloitte.com

Howard Weinberg
Deloitte
25 Broadway
14th Floor
New York, NY 10004
USA
hweinberg@deloitte.com

Abstract

An exploratory system dynamics (SD) model presents disruptive innovation diffusion as a replicable process that can spawn business growth for *d, Inc.*, a company that offers an over the air digital subscription TV service. Building on diffusion processes in epidemiology, marketing and sociology, the eight-sector SD model shows customer switching in the high-end, low-end and non-consumption markets the disruptive innovator exploits. As extreme-condition scenarios test its robustness, the model shows performance results for multiple market penetration and defense tactics that disrupter and incumbent firms employ over time. In a relentless hunt for superior performance and a sea of external-change triggers and internal-change levers, *d, Inc.* takes on cable operators who overlook low-end markets to invest in higher-end tiers, their service tailored to more demanding customers. Low-end markets cannot absorb sustaining innovation that exceeds the utility subscribers need or know how to exploit. Those segments are left vulnerable to the advent of disruptive innovators promising less functionality for lower price. The results show that despite high environmental turbulence, market risk and competitive retaliation facing *d, Inc.*, introducing discontinuity and instability systematically into a market driven by incremental competence improvement suggests ample opportunity for sustainable disruptive growth.

Keywords: adoption, broadcast spectrum, cable, customer switching, diffusion, disruptive, growth, innovation, process, system dynamics, technology

Disruptive innovation is a powerful way to create and to sustain business growth (Bower and Christensen 1995, Christensen 1997, Christensen, Johnson and Dann 2002, Christensen and Raynor 2003). The small off-road motorcycles Honda introduced in the 1960s, for example, Apple's first personal computer and Intuit's *QuickBooks* accounting software initially under-performed mainstream offers. But these innovations brought different value propositions to new market contexts that did not need all the performance offered by incumbents. They created massive growth through "creative creation" (Zhang 2001), as opposed to "creative destruction" (Schumpeter 1934). After taking root in a simple, undemanding application, disruptive innovations inexorably get better until they "change the game" (Gharajedaghi 1999), stunningly relegating previously dominant firms to the sidelines.

According to Christensen and Raynor (2003), disruptive innovators employ discontinuity in technological and business innovations as opposed to the sustaining, competency-enhancing innovations that drive incremental improvements to existing technologies and revenue streams, which established industry players enjoy. Christensen (1997) argues that disruption strategies increase the odds of successful growth from six to thirty seven percent. Contrary to popular belief, Christensen and Raynor (2003) do not see innovation as the product of random events. They suggest that disruptive innovation is repeatable, i.e., it can be created and replicated with a sufficient degree of regularity and expectation for

success, given adequate understanding of the circumstances associated with the genesis of disruption and its distinct progression dynamics.

Christensen et al (2002, p. 42) urge managers adept in developing new business processes to design robust, replicable processes for creating and nurturing new growth business areas. In so doing, they advise companies (a) to seek a balance between resources that sustain short-term profit and investments in high-growth opportunities and (b) to use both separate criteria and separate screening processes for judging sustaining and disruptive innovations.

The term ‘disruptive innovation’ refers to innovation that is of highly revolutionary or discontinuous nature, in which customers embrace new paradigms. While the term is becoming widely popular and numerous authors describe many of the multifaceted and interrelated issues of disruptive innovation, this study finds and contributes toward filling a void toward a deep understanding of the disruptive innovation diffusion process which might help companies manage and enable disruptive innovation as a competitive strategy.

Namely the article describes an exploratory system dynamics (SD) model of disruptive innovation diffusion (DID). Its eight-sector model shows customer switching in the high- and low-end and non-consumption markets that disruptive innovators exploit. It presents disruptive innovation as a replicable process that can generate business growth for *d, Inc.*, a company that offers an over the air digital subscription TV service. The model draws on SD adoption-diffusion work, which covers models in economics, epidemiology, marketing and sociology (Homer 1987, Lane and Husemann 2004, Milling 2002, Radzicki and Sterman 1993, Sterman 2000, Ch. 9). Lane and Husemann (2004) show many similarities in the causal structure of adoption-diffusion processes. But at the right level of abstraction, SD researchers often encounter similar causal mechanisms that underlie seemingly highly diverse phenomena (Forrester 1961).

By definition, disruptive innovation diffusion is a dynamic process. As Repenning (2002) points out, any model that purports to explain the evolution of a dynamic process also defines a dynamic system either explicitly or implicitly. A crucial aspect of model building in any domain is that any claim a model makes about the nature and structure of relations among variables in a system must follow as a logical consequence of its assumptions about the system. And attaining logical consistency requires checking if the dynamic system the model defines can generate the real-life performance of the dynamic process the model tries to explain.

But most existing disruptive innovation models are merely textual and diagrammatic in nature. Given a particular disruptive innovation situation, in order to determine if a prescribed disruptive innovation idea can generate superior performance, which only ‘systemic leverage’ endows (Georgantzias and Ritchie-Dunham 2003), managers must mentally solve a complex system of difference or differential equations. Alas, relying on intuition for testing logical consistency in dynamic business processes might contrast sharply with the long-certified human cognitive limits (Morecroft 1985, Paich and Sterman 1993, Sterman 1989); limits that even seasoned researchers who try to understand the dynamic implications of their own models often fail to overcome (Repenning 2002, Sastry 1997).

Aware of these limits, the article makes two contributions. *One* is the culmination of the existing disruptive innovation literature into a generic model of the disruptive innovation diffusion process. Using generic structures from prior SD adoption-diffusion work, the model contains assumptions common to seemingly diverse theories in economics, epidemiology, marketing and sociology. *Two* is the translation of these seemingly diverse components into a computer simulation environment that allows addressing the specific concerns of a real-life client by generating the performance dynamics of the disruptive innovation diffusion process the model explains. Both contributions stem from articulating exactly how elements common to generic adoption-diffusion structures interact through time. Client-driven, the entire SD modeling process aims at helping managers articulate exactly how the structure of circular feedback

relations among variables in the system they manage determines its performance through time (Forrester and Senge 1980).

Multiple new insights emerge from the dynamics the model presented here computes:

1. The literature review shows that contrary to conventional wisdom disruptive innovation diffusion is not the product of random events but a repeatable process. This suggests that some prominent feedback structures might be responsible for the genesis of disruption and its distinct dynamics. Randomness notwithstanding and despite alterations, the generic structures this article's model incorporates from prior SD adoption-diffusion work, namely Bass' (1969) diffusion model (*cf* Lane and Husemann 2004, Sterman, 2000: Ch. 9), prove prominent enough to reproduce distinctly familiar dynamics. Specifically, adoption rate disaggregation patterns persist despite multiple modifications to Bass' original model structure.
2. The results support disruptive innovation proponents who urge disruptive innovators to be hungry for profit over market share.
3. Customer switching entails a reinforcing or positive (+), deviation-amplifying feedback limited only by the number of customers who adopt the goods or services the disrupter (d) and incumbent (i) firms offer. Given a disrupter and an incumbent firm with roughly equally matched capabilities, and depending on the customer lock-in and lock-out rates, sustainable equilibria might emerge, which might prove tough to break off. Under such circumstances, disruptive innovators should not be overly concerned with incumbent firms' retaliation criteria. All disrupters must do is make ready to deal with incumbent retaliation as and when it occurs.
4. It is natural for disruptive innovators to expect good performance under increasingly favorable circumstances. Likewise, incumbent firms might have less to lose when they retaliate if market conditions turn to their favor. But the results here show that a disrupter firm's spectacular performance could easily mask an incumbent firm's performance even when prevailing market conditions turn to the incumbent firm's favor.
5. The earlier disruptive innovators acquire reasonable access to the resources they need to run up market the better off they are. Early up-market runs not only are profitable for disruptive innovators but they also push incumbent firms into retaliation, depriving the latter of their high profit margins prior to retaliation.
6. At least one scenario set shows potential tradeoffs between resource allocation tactics and performance. Even in disruptive innovation situations, it seems difficult to avoid the worse-before-better tradeoffs that sustainable performance solutions frequently entail.
7. Regarding discontinuity, if, for whatever reason, customer switching ends abruptly for either contender, then some extreme-condition scenarios emerge with instability transients in market contraction, which both disrupter and incumbent firms better make ready for.

Following a brief overview of the client's current strategic situation below, the article proceeds with a review of the disruptive innovation literature in the background section. Then the model description precedes the computed scenarios (i.e., simulation results) section, with conclusions for practice and suggestions for further research in the discussion section.

The client: *d, Inc.*

d, Inc. is a new entrant to the cable and direct broadcast satellite (DBS) industry. It has launched an entirely new growth market by making inroads into existing non-consumption and low-end market segments with a unique value proposition. The company offers an over the air digital subscription TV service at affordable prices.

The United States government granted broadcasters digital spectrum in 1996 to enable the conversion to digital broadcasts. *d, Inc.* leases the extra digital broadcast spectrum from regional

broadcasters by using data-casting technology and offers a line-up of local channels and twelve top cable standard definition and high definition channels. Customers purchase a digital antenna/set top box for US\$100 and pay a US\$20 per month subscription fee. *d, Inc.* targets low-end cable and satellite market segments—consumers who are paying for a line-up of channels they don't watch—and non-consumers—people who currently don't subscribe to cable or satellite service. As the company establishes a foothold among low-end market segments and non-consumers, it plans to roll out advanced services such as video-on-demand, digital video recording and high-speed Internet access and to begin targeting premium subscribers.

Currently, *d, Inc.* has operations in three local markets but is planning to expand into 30 more regional markets in the next year. The company has indicated that more than half of its subscribers were previously non-consumers of cable or DBS service. It expects to sign-up about five million subscribers in the next four years.

According to a study commissioned by a competitor with a similar business model, low cost pay TV service is likely to enjoy broad national appeal. The survey covered 1,000 households and found that twenty nine percent of cable and twenty six percent of satellite subscribers would consider a switch to a lower-cost, no-frills service. Twenty percent of non-subscribers also expressed interest in trying this type of service.

The company is a private entity. Its main funding sources are major broadcasters with several broadcast groups owning and controlling the business. The company shares revenues with broadcasters and pays retransmission fees to them.

Background

The innovations continuum ranges from evolutionary to revolutionary (Christensen, 1997; Hill and Jones 1998, Trott 2001, Veryzer, 1998). Evolutionary innovation is critical to sustaining and enhancing shares of mainstream markets (Baden-Fuller and Pitt 1996, Hall and Vredenburg 2003, Hill and Jones 1998). But revolutionary breakthroughs lie at the core of wealth creation (Schumpeter 1934). By definition, revolutionary innovations serve as the basis for future technologies, products, services and industries (Christensen 1997, Christensen and Rosenbloom, 1995, Hamel 2000, Tushman and Anderson 1986). Moreover, disruptive innovations are extremely important to specialized regional economies because they bring radical and fundamental changes to industries (Zhang 2001).

In support of disruptive innovation strategies, Christensen and Raynor point out that the main difference between disruptive innovation and a sustaining strategy is based on the circumstances or context of innovation:

In sustaining circumstances—when the race entails making better products that can be sold for more money to attractive customers—we found that incumbents almost always prevail. In disruptive circumstances—when the challenge is to commercialize a simpler, more convenient product that sells for less money and appeals to a new or unattractive customer set—the entrants are likely to beat the incumbents. This is the phenomenon that so frequently defeats successful companies. It implies, of course, that the best way for upstarts to attack established competitors is to disrupt them (Christensen and Raynor 2003, p. 32).

In order to be successful at launching and growing a disruptive model, a business needs to become aligned with the disruptive context in all its critical aspects: vision, decision making, business processes and cost structure. Once the alignment is in place to translate ambiguity, complexity and uncertainty into information adequacy (Veryzer 1998), growth tends to follow a specific pathway to superior performance (Thomond and Lettice 2002).

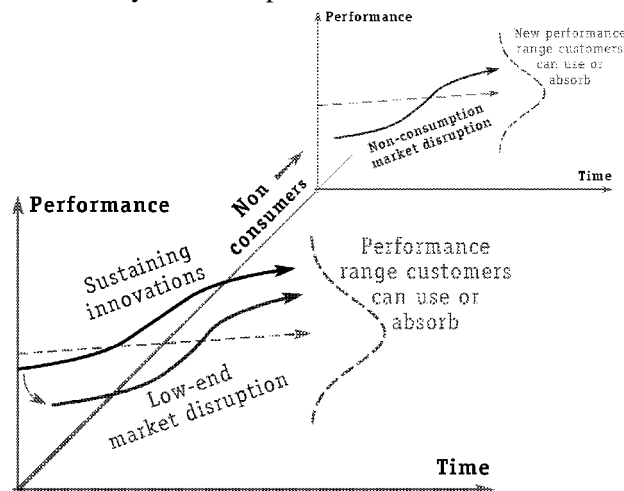
Typically, disrupters start out small and for some time operate on the fringes of existing markets, establishing and growing a foothold under incumbents' radar screen. At the heart of innovations with the

potential to disrupt a mature industry, perhaps even overtake and displace incumbent firms over time, is a technology and a product or service platform that marks a departure from incremental improvement in the form of product extensions and add-ons to existing goods and services (Hall and Vredenburg 2003). Such a technology fills a previously unidentified or unaddressed niche. Its value proposition is closely aligned with the situations customers find themselves in and the needs arising from their peculiar circumstances (Christensen and Raynor 2003, Thomond and Lettice 2002, Ulwick 2002).

Disrupters target market segments currently unable to take advantage of a good or service or fill a specific need for lack of appropriate infrastructure or a specific set of skills or because the price points at which the good or service is available are above what that segment of the population is able to afford. In effect, disrupter firms targeting non-consumption are creating new markets by addressing the needs of existing non-consumers. Each firm also exploits its ability to appeal to incumbent firms' low-end markets, i.e., customers who purchase a good or service with functionality exceeding their needs at a price they are only willing to pay for lack of alternatives. Customers in such low-end market segments cannot absorb sustaining performance improvements that exceed the range of utility those customers need or know how to exploit.

A disrupter firm offers new choices in the form of stripped down functionality at a lower price or 'less for less'. Adapted from Christensen and Raynor (2003, p. 44) and Thomond and Lettice (2002), Fig. 1 shows the low-end and non-consumption markets disrupters exploit. The sustaining innovations of established firms often over-supply customers with excess technological functionality or services that customers do not actually need. The straight broken lines of Fig. 1 show the trajectories of increasing customer requirements for a given good or service. The sustaining innovations solid line on the front panel of Fig. 1 is the increasing performance the good or service offers, which is steeper than the customer requirements broken line. For example, mainframe and mini-computers in the late 1980s offered customers higher levels of performance, features and capability than they could use. This oversupply left a vacuum at the low-end of the market for a 'simpler' product offering: the personal computer (PC).

Figure 1 The low-end (LeM) and non-consumption (NcM) markets disrupter firms exploit (adapted from Christensen and Raynor 2003, p. 44, and Thomond and Lettice 2002)



When introduced, along the solid, low-end disruption line on Fig. 1, PCs offered lower performance to customers and users than mainstream mainframe/mini-computers did. But a niche of consumers valued PCs and, through time, their technological performance improved along the trajectory of the low-end disruption line. At some point, PC performance equaled that demanded by the average mainstream customers of mainframes/mini-computers. So they started to switch, causing a widespread disruption of the established mainframe/mini-computer market and driving many incumbent firms out of business. Depending on the performance ranges customers can use or absorb to get a job done, new goods and

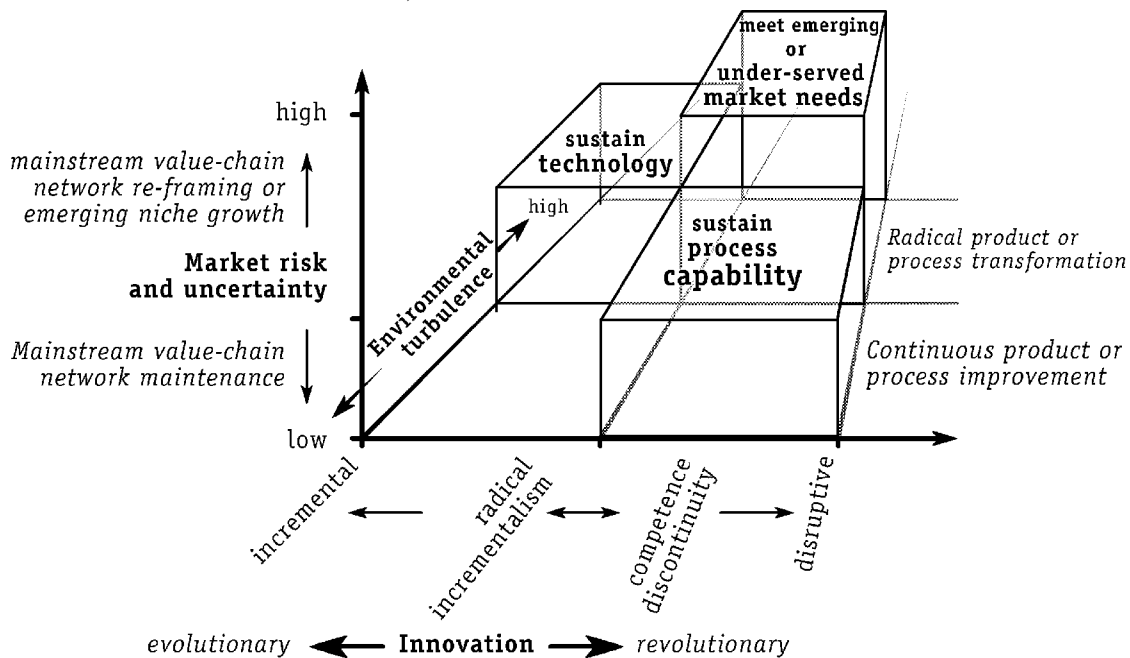
services continually improve, usually faster than the average customer’s requirements, leaving space for new-market disruption waves among non-consumers on the back panel of Fig. 1. Potentially, for example, the fast evolving personal digital assistant (PDA) and Apple’s i-Pod might next disrupt the PC market in the near future.

Once a disruptive innovator becomes successful at penetrating non-consumption and low-end tiers, and has been on the market long enough to improve service delivery, strengthen core business processes and achieve a reasonable level of profitability, the business is poised for the next step: an up-market march that entails going after incumbent firms’ higher end segments with enhanced product/service functionality at higher price points. The disrupter must be aware that moving up market to contest an incumbent’s lock-in of lucrative customers might trigger a wave of retaliation. So disrupters must ensure sufficient readiness to address the competitive response prior to embarking on an up-market march.

In competitive dynamics terms, disrupters exploit what Christensen and Raynor (2003, p. 35) call “asymmetric motivation”, namely incumbents’ exclusive focus on investing in sustaining innovations and improved presence in the high-end, more profitable market segments. While established players pay very little attention to new and lower-end markets, disruptive entrants are able to move in under the radar, position themselves to eventually move up-market and begin carving paths into the very markets established players are so busy defending.

Business wise, the critical ingredients to penetrating a disruptive market niche are having the technological and commercial means to align a good or service with circumstances specific to customer needs and the ability to recognize the opportunity in the first place. Innovations that combine commercial and technological discontinuities are most attractive from a disruptive potential perspective. Compact disks and jump drives are good disruptive growth examples. Not only are they technologically capable, but also rank high on Veryzer’s (1998) perceived product (good or service) performance dimension. Despite the high environmental turbulence and market risk and uncertainty (Fig. 2), being in a market that blends commercial and technological competence discontinuity suggests ample opportunity for disruptive growth.

Figure 2 The innovation, environmental turbulence and market risk and uncertainty dimensions associated with disruptive innovation diffusion (adapted from: Hall and Vredenburg 2003, Thomond and Lettice 2002)



Firms that know how to harness technological competence discontinuity to create commercial discontinuities are growing the pie by opening up new market niches. A disrupter's successful venture into uncharted territory with a better value proposition causes a shift in incumbents' perception of established competitive dynamics. Dawning awareness of the nature and magnitude of the disruptive threat does, however, little to relieve the profit motive that keeps traditional players' short-term fortunes wedded to the satisfaction of their most demanding and profitable customers in the higher tiers of the market, even if that opens the door for migration to existing and new competitors in the lower market tiers. Despite beginning to see a shift in the basis of industry competition and grasp the wider implications for long-term growth and perhaps for the very survival of traditional business, established players get caught in a bind.

Hard pressed to maintain short-term profitability by defending their high-end market presence, incumbents begin to compromise long-term growth by allowing disrupters to move into the lower-end tiers. By failing to address the threat in the initial stages of disruption established players undermine their competitive positioning. Furthermore, incumbents face a cost disadvantage compared to disrupters' typically light cost structure. This limits when and how incumbents can respond to the threat. Taking a longer-term view may well suggest retaliating early and with great force. Disrupters are typically ideally positioned to take advantage of the time lag to retaliation by strengthening their market presence and improving the overall value proposition in preparation for an up-market march. A successful up-market march can spell a prolonged period of upset and transformation for entire industries as old ways of doing business and serving customers give way to superior ways of addressing customer needs at a more granular level and lower price.

d, Inc. as disruptive innovator

d, Inc. is a classic disruptive innovator in the cable and DBS industries. It shows those vital signs associated with disruptive innovators as Christensen and Raynor (2003) see them:

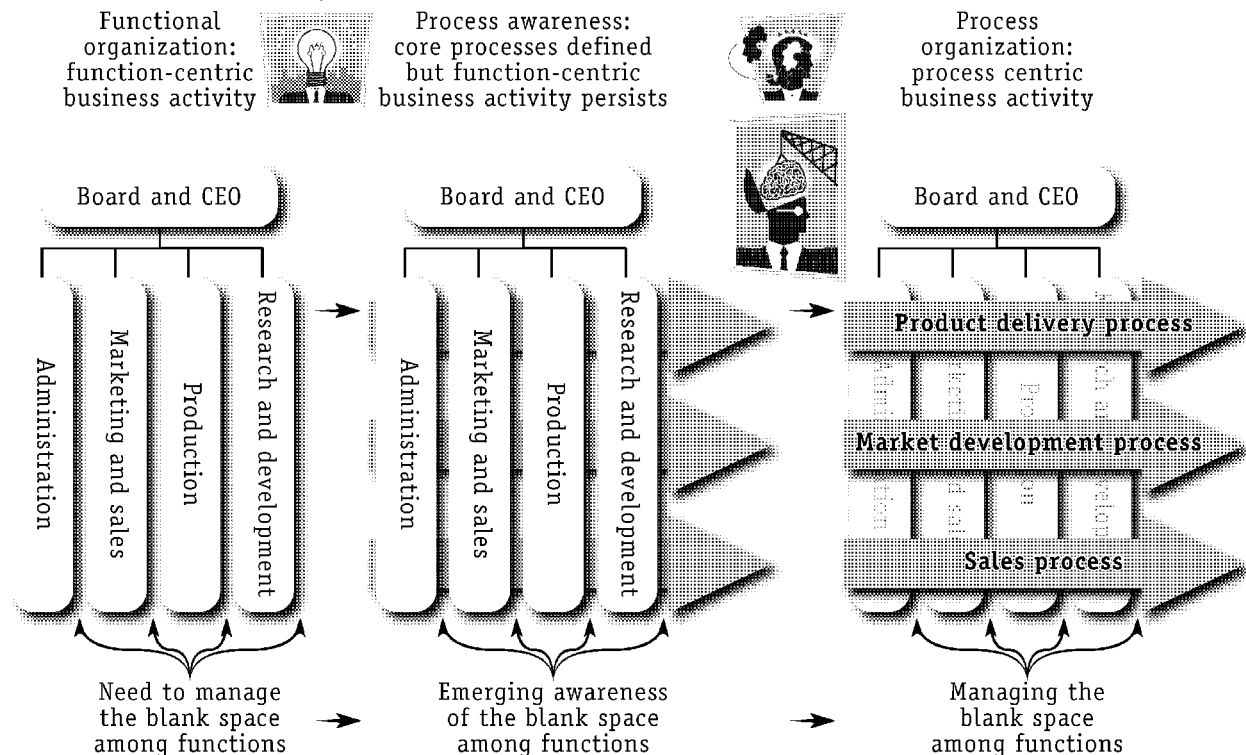
1. **Overshoot by incumbents.** An opportunity for disruption in the cable industry has been opened up by a proliferation in the number of channels and features beyond what consumers are able to utilize. The trend toward continuous sustaining innovation is responsible for creating tiers of subscribers who are over-served and on the lookout for better price for value. Cable operators typically overlook the lower market segments. They devote attention and invest resources into serving the higher-end tiers where profitability drives investment in innovation tailored to addressing the needs of those more demanding customers.
2. **Shift in basis of competition.** *d, Inc.* uses multicasting and data-casting technology to offer digital terrestrial pay-TV enabled by regulatory change, specifically the government mandated conversion to digital broadcasting that opened up the extra digital spectrum *d, Inc.* is leasing from broadcasters. Existing technology combined with resources made available through the impact of regulatory change are creating an entirely new distribution channel for broadcast and cable video programming. The channel allows for over-the-air broadcasting of cable programming at a much lower price using a separately purchased set top box receiver which ensures high quality reception of broadcast signals for the basic package of local channels and twelve top cable channels. The receiver is also scalable to advanced functionality with an eye toward launching features tailored to premium subscribers. *d, Inc.* therefore is investing in building a large and stable foothold among non-consumers and incumbents' lower end segments but not without recognizing and positioning itself to capture emerging pathways to future growth. This new business model enabled by a combination of technological innovation and regulatory trends shifts the basis of competition to price and availability. More affordable pricing allows enticing price-conscious non-consumers and making inroads into incumbents' less profitable segments with a more appropriate overall value proposition. Furthermore, the company expects to have uncontested dominance in areas where infrastructure supporting delivery of traditional cable service does not currently exist. Filling a niche that had previously remained unaddressed permits the

company to establish and to grow a foothold it will leverage as it begins to penetrate the high-end market.

3. **A viable foothold.** The company's goal is to establish a foothold among non-consumers and established players' lower-end subscriber tiers by offering less for less—less but good enough functionality at a lower price. The company expects to capture enough growth over a reasonable period of time while maintaining low visibility to enable it to gain the experience and resources necessary to successfully move up market with improved and enhanced functionality and counter the imminent competitive response.
4. **The up-market march.** Once the company becomes established in the non-consumption and low-end markets, and if successful at developing the operating and financial muscle critical to exploiting new growth avenues, it is likely to go after high-end subscriber tiers by harnessing the appeal of broader channel selection, advanced functionality and improved customer service at more affordable prices.

Figure 3 shows how the SD modeling process is helping *d, Inc.* transition from a functional to a process organization. Georgantzas and Ritchie-Dunham (2003) see organizations as function and process nets (concatenated networks). To them this is clear, but too many researchers, managers and journalists still call for functional improvements as the means to improving performance; only a few emphasize process improvements. Far from well understood is the idea that process improvements can greatly improve organizational performance, and to a much higher level than secondary functional improvements can.

Figure 3 Transition from functional to process organization (adapted from Georgantzas and Ritchie-Dunham 2003)



Superior performance demands process improvements; functions play a supplementary role. A conveyor improves, for example, a transport function, not transportation. Similarly, an automated warehouse (a multimillion-dollar investment) improves a firm's inventory function, not inventory. Improving a process that incorporates transport and inventory eliminates the need for conveyors and automated warehouses altogether.

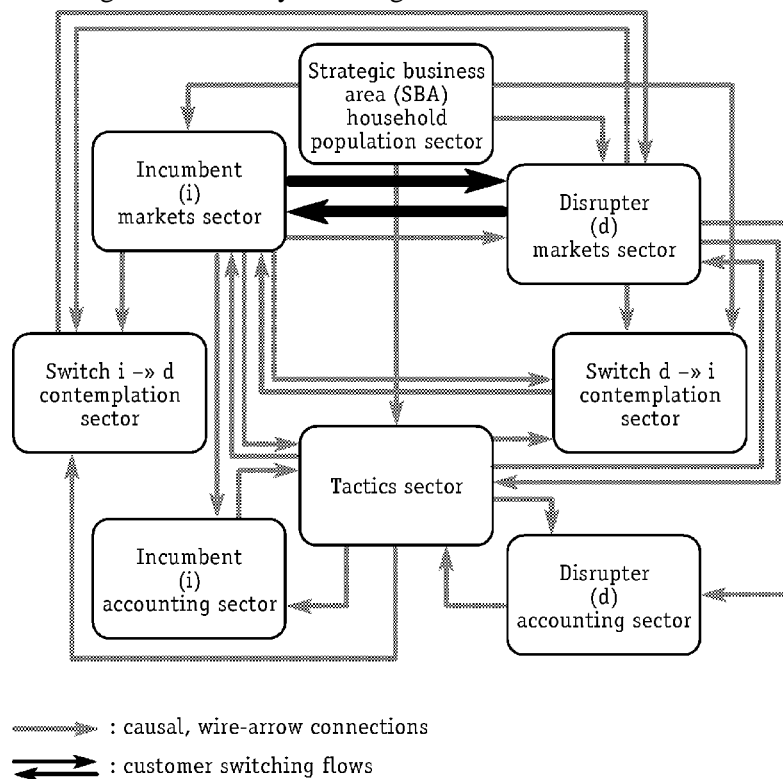
To improve performance, managers and researchers must emphasize process improvements before functional ones. SD modeling helps draw clear distinctions between functions and processes, a fundamental step toward breaking free from old paradigms. It takes creativity, a prerequisite to innovation (Evans 1991), to redesign (reengineer) organizations with coherent and tradeoffs-free corporate-, business- and functional-level strategies (Georgantzis 1995, Zeleny 1994). The enabling stems from decision alternatives that put a firm's strategic planning team on the spot. Having to decide which benefit to promote first among high-quality goods and services, high efficiency, high flexibility and supersonic speed of delivery leads to a good market position, no matter what the strategy level (Georgantzis and Acar 1995).

Model description

Extending disruptive innovation with SD hinges on two bases. *First*, Deming's (2000) *System of Profound Knowledge*, which integrates systems, statistics, knowledge theory and psychology, and begins with building appreciation for a system. *Second*, Deming said: "Until you draw a flow diagram, you do not understand you business" (cf Schultz 1994, p. 21). System dynamics does use stock and flow diagrams to depict relations among variables in a system. A fundamental tenet of SD is that the structure of relations among variables in a system gives rise to its dynamics (Meadows 1989, Sterman 2000, p. 16).

Figure 4 shows a bird's-eye view of the eight-sector SD model of disruptive innovation diffusion. Given *d, Inc.*'s geographical segmentation approach, the model allows looking at a single geographic market or strategic business area (SBA) at a time. Sixty percent of the SBA households or homes are adopters of an incumbent (i) firm's wire cable service. In effect, i has an established strategic business unit (SBU), which dominates the SBA that d penetrates.

Figure 4 The model's eight-sector subsystem diagram



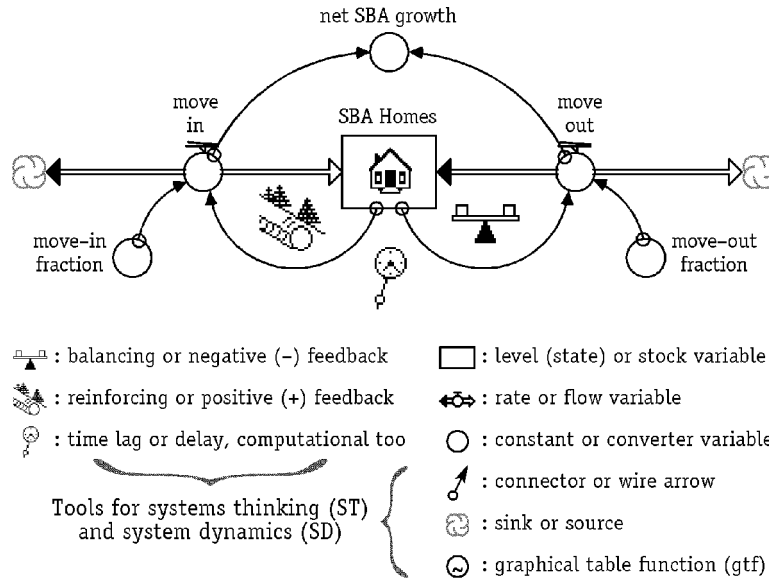
The eight-sector subsystem diagram on Fig. 4 is the result of condensing the original model by using the 'array' option the *iThink® Software* (Richmond et al 2004) offers. *Arrays* provide a powerful

mechanism for managing the visual complexity of a large model's parallel sectors. But beneath the surface, arrays retain the richness of the original disaggregated model.

SBA household population sector

Figure 5 shows the stock and flow diagram of the model's SBA household population sector, a basic population model structure, reproduced from the simulation model built with *iThink*®. Table 1 shows the simulation run specifications of the *iThink*® model.

Figure 5 Strategic business area (SBA) household population sector, with systems thinking (ST) and system dynamics (SD) modeling tools legend



There is a one-to-one association between the model diagram of Fig. 5 and its equations (Table 1). Like the diagram of Fig. 5, the friendly algebra of Table 1 is also actual output from *iThink*®. Building a model entails first diagramming system structure on the glass of a computer screen and then specifying simple algebraic equations and parameter values. The software enforces consistency between model diagrams and equations, while its built-in functions help quantify parameters and variables pertinent to disruptive innovation diffusion.

Table 1 Strategic business area (SBA) household population sector equations

<i>Stock or Level (State) Variable</i>	{·} = comments and/or units	<i>Equation #</i>
SBA Homes(t) = SBA Homes(t - dt) + (move in - move out) * dt		(1)
INIT SBA Homes = 100,000 {homes}		(1.1)
<i>Flows or Rate Variables</i>		
move in = MAX (0, SBA Homes * move-in fraction) {homes/month}		(2)
move out = MAX (0, SBA Homes * move-out fraction) {homes/month}		(3)
<i>Auxiliary Parameters and Converter Variables</i>		
move-in fraction = 0.00167 {1/month}		(4)
move-out fraction = 0.0013 {1/month}		(5)
net SBA growth = move in - move out {homes/month}		(6)
<i>Simulation Run Specifications</i>		
t ∈ [0,120] {months}		
dt = 0.0625		
Integration method = Runge-Kutta 4		

Rectangles represent stocks or level variables that accumulate in SD, such as SBA Homes or households (Fig. 5 and Eq. 1, Table 1). Emanating from cloud-like *sources* and ebbing into cloud-like

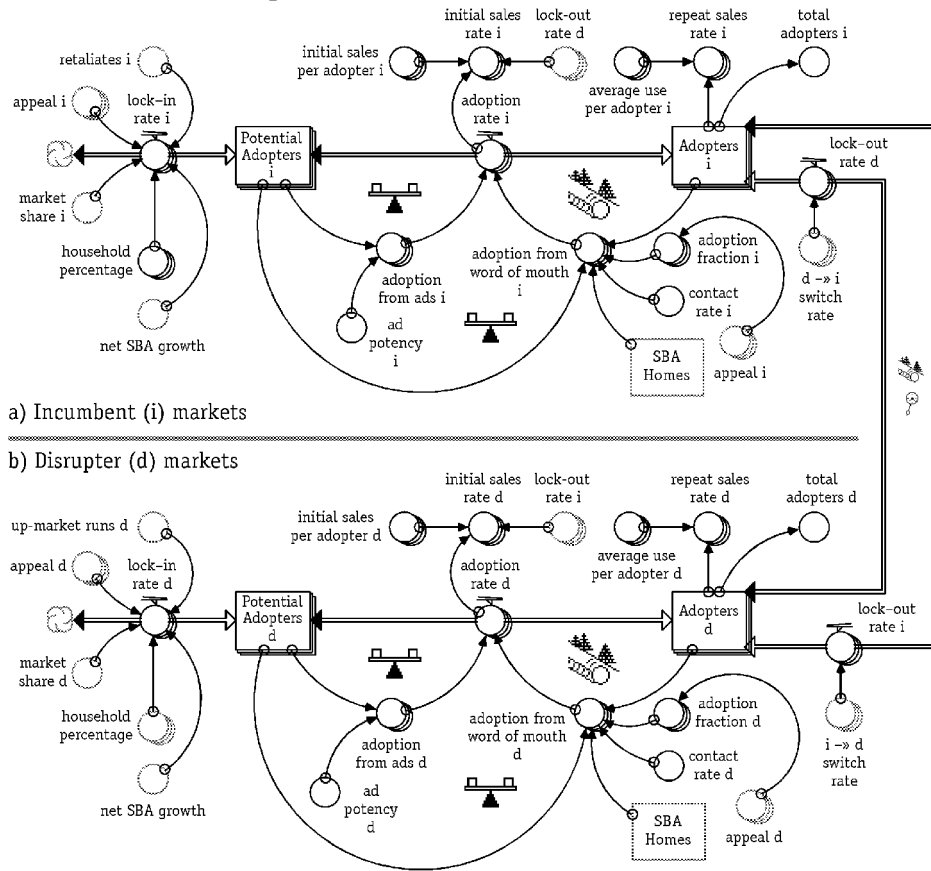
sinks, the double-line, pipe-and-valve-like icons that fill and drain the stocks represent flows or rate variables that cause the stocks to change. The move out outflow of Fig. 5 (Eq. 3), for example, bleeds the SBA Homes stock, initialized (INIT) with 100,000 homes (Eq. 1.1, Table 1). Single-line arrows represent information connectors, while circular icons depict auxiliary converters where constants, behavioral relations or decision points convert information into decisions. The move in inflow (Eq. 2) depends, for example, on the SBA Homes stock multiplied by the move-in fraction (Eq. 4), an exogenous auxiliary constant parameter.

SD knowledge ecology begins by differentiating stocks from flows and how stocks and other variables and parameters determine the flows. Identifying the integration points facilitates understating one source of dynamic behavior in the system. The stock and flow diagrams on Fig. 5 through Fig. 9 show accumulations and flows essential in generating the performance dynamics of a disruptive innovation diffusion process. These diagrams also tell, with the help of the equations on Tables 1 through 8, what drives the flows in the system. In the context of systems thinking (ST), stock and flow diagrams like the one on Fig. 5 help accelerate what Richmond (1993) calls *operational thinking*.

Markets sectors

Operationally speaking, SBA Homes and net SBA growth (Fig. 5 and Eqs 1 and 6, Table 1) affect both the disrupter (d) and the incumbent (i) markets sectors on Fig. 6 and Tables 2 and 3. The almost identical north and south panels of Fig. 6 show the somewhat modified but well-known model structures used in epidemiology (Murray 1993) and marketing (Bass 1969).

Figure 6 Incumbent (i) and disrupter (d) markets sectors



Their contagion-based formulation captures the spreading of information about the services the two competitors (d and i) offer through repeated contacts between household members from homes that adopt the service either from the incumbent (Adopters $i[m]$, Fig. 6a and Eq. 8, Table 2) or from the disrupter

(Adopters $d[m]$, Fig. 6b and Eq. 27, Table 3) and those who do not. The latter take the role of potential adopters for either i (Potential Adopters $i[m]$, Fig. 6a and Eq. 8, Table 2) or d (Potential Adopters $d[m]$, Fig. 6b and Eq. 28, Table 3).

Table 2 Incumbent (i) markets sector equations

<i>Stock or Level (State) Variables</i>	<i>({·} = comments and/or units)</i>	<i>Equation #</i>
Adopters $i[m](t) = \text{Adopters } i[m](t - dt) + (\text{adoption rate } i[m] + \text{lock-out rate } d[m] - \text{lock-out rate } i[m]) * dt$	$\{m = \text{HeM, LeM, NcM: high- and low-end and non-consumption markets}\}$	(7)
INIT Adopters $i[\text{HeM}] = \text{SBA Homes} * \text{household percentage}[\text{HeM}]$	$\{\text{homes}\}$	(7.1)
INIT Adopters $i[\text{LeM}] = \text{SBA Homes} * \text{household percentage}[\text{LeM}]$	$\{\text{homes}\}$	(7.2)
INIT Adopters $i[\text{NcM}] = 0$	$\{\text{homes}\}$	(7.3)
Potential Adopters $i[m](t) = \text{Potential Adopters } i[m](t - dt) + (\text{lock-in rate } i[m] - \text{adoption rate } i[m]) * dt$	$\{\text{markets } m = \text{HeM, LeM and NcM}\}$	(8)
INIT Potential Adopters $i[\text{HeM}] = \text{MAX}(0, \text{household percentage}[\text{HeM}] * \text{net SBA growth} * (\text{appeal } i[\text{HeM}] + \text{market share } i))$	$\{\text{homes}\}$	(8.1)
INIT Potential Adopters $i[\text{LeM}] = \text{MAX}(0, \text{household percentage}[\text{LeM}] * \text{net SBA growth} * (\text{appeal } i[\text{LeM}] + \text{market share } i))$	$\{\text{homes}\}$	(8.2)
INIT Potential Adopters $i[\text{NcM}] = 0$	$\{\text{homes}\}$	(8.3)
<i>Flows or Rate Variables</i>		
adoption rate $i[m] = \text{MAX}(0, \text{adoption from ads } i[m] + \text{adoption from word of mouth } i[m])$	$\{\text{homes/month}\}$	(9)
lock-in rate $i[\text{HeM}] = \text{MAX}(0, \text{household percentage}[\text{HeM}] * \text{net SBA growth} * (\text{appeal } i[\text{HeM}] + \text{market share } i))$	$\{\text{homes/month}\}$	(10)
lock-in rate $i[\text{LeM}] = \text{MAX}(0, \text{household percentage}[\text{LeM}] * \text{net SBA growth} * (\text{appeal } i[\text{LeM}] + \text{market share } i))$	$\{\text{homes/month}\}$	(11)
lock-in rate $i[\text{NcM}] = \text{IF}(\text{retaliates } i[\text{NcM}] = 1) \text{ THEN } (\text{MAX}(0, \text{household percentage}[\text{NcM}] * \text{net SBA growth} * (\text{appeal } i[\text{NcM}] + \text{market share } i * \text{household percentage}[\text{NcM}])) \text{ ELSE } (0)$	$\{\text{homes/month}\}$	(12)
lock-out rate $d[m] = \text{MAX}(0, d \rightarrow i \text{ switch rate}[m])$	$\{\text{homes/month}\}$	(13)
lock-out rate $i[m]$	$\{\text{Disrupter (d) markets sector, Table 3, Eq. 33}\}$	
<i>Auxiliary Parameters and Converter Variables</i>		
ad potency $i = 0.011$	$\{1/\text{month}\}$	(14)
adoption fraction $i[m] = \text{appeal } i[m]$	$\{\text{unitless}\}$	(15)
adoption from ads $i[m] = \text{Potential Adopters } i[m] * \text{ad potency } i[m]$	$\{\text{homes/month}\}$	(16)
adoption from word of mouth $i[m] = \text{Adopters } i[m] * \text{Potential Adopters } i[m] * \text{adoption fraction } i[m] * \text{contact rate } i[m] / \text{SBA Homes}$	$\{\text{homes/month}\}$	(17)
average use per adopter $i[m] = 1$	$\{\text{units/home/month}\}$	(18)
contact rate $i = 8$	$\{1/\text{month}\}$	(19)
household percentage $[\text{HeM}] = 0.3$	$\{\text{unitless}\}$	(20)
household percentage $[\text{LeM}] = 0.3$	$\{\text{unitless}\}$	(21)
household percentage $[\text{NcM}] = 0.4$	$\{\text{unitless}\}$	(22)
initial sales per adopter $i[m] = 1$	$\{\text{units/home}\}$	(23)
initial sales rate $i[m] = (\text{adoption rate } i[m] + \text{lock-out rate } d[m]) * \text{initial sales per adopter } i[m]$	$\{\text{units/month}\}$	(24)
repeat sales rate $i[m] = \text{Adopters } i[m] * \text{average use per adopter } i[m]$	$\{\text{units/month}\}$	(25)
total adopters $i = \text{ARRAYSUM}(\text{Adopters } i[*])$	$\{\text{homes}\}$	(26)

The above four, one-dimensional arrayed stocks are arrayed along the markets $[m]$ dimension, which stands for the high- (HeM) and low-end (LeM) and non-consumption (NcM) markets of the SBA where the disrupter and the incumbent firms compete. Through its already established SBU, the monopolist incumbent serves 60 percent of the SBA Homes. Thirty percent of these (Eq. 20, Table 2) comprise the high-end market (HeM) and 30 percent (Eq. 21) the low-end market (LeM). The balance (Eq. 22) or 40 percent of the SBA Homes define the non-consumption market (NcM), readily available for the disrupter firm to penetrate. NcM is the market segment the incumbent firm ignores, with constituents who cannot take advantage of the service i offers because of price or lack of infrastructure.

The initial (INIT) values of the four, one-dimensional arrayed stocks of Fig. 6 reflect these assumptions in Eqs 7.1-7.3 and 8.1-8.3 (Table 2) and Eqs 27.1 and 28.1-28.3 (Table 3).

Table 3 Disrupter (d) market sector equations

<i>Stock or Level (State) Variables</i>	<i>({·} = comments and/or units)</i>	<i>Equation #</i>
Adopters $d[m](t) = \text{Adopters } d[m](t - dt) + (\text{adoption rate } d[m] + \text{lock-out rate } i[m] - \text{lock-out rate } d[m]) * dt$	{m = HeM, LeM, NcM: high- and low-end and non-consumption markets}	(27)
INIT Adopters $d[m] = 0$	{homes}	(27.1)
Potential Adopters $d[m](t) = \text{Potential Adopters } d[m](t - dt) + (\text{lock-in rate } d[m] - \text{adoption rate } d[m]) * dt$	{m = HeM, LeM, NcM: high- and low-end and non-consumption markets}	(28)
INIT Potential Adopters $d[\text{HeM}] = 0$	{homes}	(28.1)
INIT Potential Adopters $d[\text{LeM}] = 0$	{homes}	(28.2)
INIT Potential Adopters $d[\text{NcM}] = \text{SBA Homes} * \text{household percentage}[\text{NcM}] - \text{Adopters } d[\text{NcM}]$	{homes}	(28.3)
<i>Flows or Rate Variables</i>		
adoption rate $d[m] = \text{MAX}(0, \text{adoption from ads } d[m] + \text{adoption from word of mouth } d[m])$	{homes/month}	(29)
lock-in rate $d[\text{HeM}] = \text{IF}(\text{up-market runs } d = 1) \text{ THEN } (\text{MAX}(0, \text{household percentage}[\text{HeM}] * \text{net SBA growth} * (\text{appeal } d[\text{HeM}] + \text{market share } d * \text{household percentage}[\text{HeM}])) \text{ ELSE } (0)$	{homes/month}	(30)
lock-in rate $d[\text{LeM}] = \text{MAX}(0, \text{household percentage}[\text{LeM}] * \text{net SBA growth} * (\text{appeal } d[\text{LeM}] + \text{market share } d)) + (0 * \text{up-market runs } d)$	{homes/month}	(31)
lock-in rate $d[\text{NcM}] = \text{MAX}(0, \text{household percentage}[\text{NcM}] * \text{net SBA growth} * (\text{appeal } d[\text{NcM}] + \text{market share } d)) + (0 * \text{up-market runs } d)$	{homes/month}	(32)
lock-out rate $d[m]$	{Incumbent (i) markets sector, Table 2, Eq. 13}	
lock-out rate $i[m] = \text{MIN}(\text{Adopters } i[m], i \rightarrow d \text{ switch rate}[m])$	{homes/month}	(33)
<i>Auxiliary Parameters and Converter Variables</i>		
ad potency $d = 0.011$	{1/month}	(34)
adoption fraction $d[m] = \text{appeal } d[m]$	{unitless}	(35)
adoption from ads $d[m] = \text{Potential Adopters } d[m] * \text{ad potency } d[m]$	{homes/month}	(36)
adoption from word of mouth $d[m] = \text{Adopters } d[m] * \text{Potential Adopters } d[m] * \text{adoption fraction } d[m] * \text{contact rate } d[m] / \text{SBA Homes}$	{homes/month}	(37)
average use per adopter $d[m] = 1$	{units/home/month}	(38)
contact rate $d = 8$	{1/month}	(39)
initial sales per adopter $d[m] = 1$	{units/home}	(40)
initial sales rate $d[m] = (\text{adoption rate } d[m] + \text{lock-out rate } i[m]) * \text{initial sales per adopter } d[m]$	{units/month}	(41)
repeat sales rate $d[m] = \text{Adopters } d[m] * \text{average use per adopter } d[m]$	{units/month}	(42)
total adopters $d = \text{ARRAYSUM}(\text{Adopters } d[*])$	{homes}	(43)

Lane and Husemann (2004) show that isomorphic adoption-diffusion model structures similar to the ones on Fig. 6 appear in multiple disciplines such as economics, epidemiology, marketing, sociology and SD itself. In so doing, they also draw four lessons from Bass' (1969) diffusion model (*sa* Sterman 2000, Ch. 9), which apply here:

- adoption from ads on Fig. 6 and in Eqs 16 (Table 2) and 36 (Table 3) remove the start-up problem of the logistic or Verhulst growth model,
- the adoption from ads balancing (–) feedback generates the initial adopters required to activate the adoption from word of mouth reinforcing (+) feedback on Fig. 6 and in Eqs 17 (Table 2) and 37 (Table 3),
- which reinforcing (+) feedback becomes in turn crucial for generating initial sales both for the incumbent through the adoption rate i (Fig. 6a and Eq. 9, Table 2) and the disrupter through the adoption rate d (Fig. 6b and Eq. 29, Table 3), and

d) a situation equivalent to ‘herd immunity’ can suppress the word of mouth reinforcing (+) feedback, which ads alone will find very tough and prohibitively expensive to substitute for.

The logistic or Verhulst growth model, after François Verhulst who first published it in 1838 (*cf* Richardson 1991), could also help replicate the exponential sales growth that disrupter firms often experience and thereby come to anticipate. But sales growth is a real quantity that cannot grow forever. Every system that initially grows exponentially, whether it is food supply for moose, the number of people susceptible to infection, or the potential market for a good or service, eventually approaches the carrying capacity of its environment. As an autopoietic system approaches its limits to growth, it goes through a non-linear transition from a region where positive (+) feedback dominates to a negative (–) feedback dominated regime (Richardson 1995). S-shaped growth often results: a smooth transition from exponential growth to equilibrium, instigated by both the logistic growth and the Bass (1969) diffusion models (see the computed scenarios section below).

A modification to the Bass diffusion model with repeat sales from adopters, but not necessarily of a lesson status, which helps accommodate customer switching (Garcia Mariñoso 2001, Klemperer 1987, Nilssen 1992, Oliva, Sterman and Giese 2003) in disruptive innovation diffusion situations, entails establishing both the customer lock-in rate i for the incumbent (Fig. 6a and Eqs 10-12, Table 2) and the customer lock-in rate d for the disrupter (Fig. 6b and Eqs 30-32, Table 3). Both rates for all six sub-markets (three for d and three for i , respectively) depend on the net SBA growth rate and on the respective contender’s appeal and market share. But the high-end market (HeM) is inaccessible to d unless the disrupter firm runs up market (Fig. 6b and Eq. 30, Table 3). Similarly, the non-consumption market (NcM) is inaccessible to i unless the incumbent firm retaliates (Fig. 6a and Eq. 12).

The structure of Eq. 12 gives d a comparative advantage in recruiting new customers in NcM. Similarly, Eq. 30 gives i an advantage in recruiting new customers in HeM. Together, these two equations guard against the total number of new customers from net SBA growth exceeding net SBA growth.

Another modification to Bass’ diffusion model with repeat sales, which might deserve a lesson status perhaps, helps accommodate customer switching in disruptive innovation diffusion situations. That is:

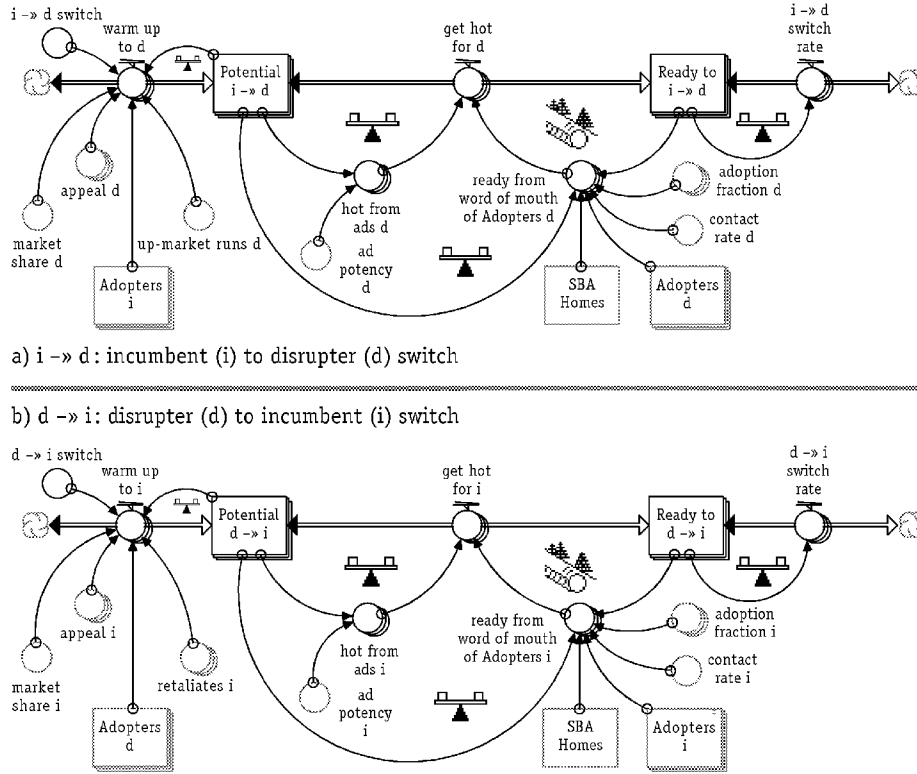
e) once the disrupter firm has penetrated the low-end (LeM) and non-consumption (NcM) markets, an additional reinforcing (+) feedback becomes in turn crucial for generating initial sales for both the incumbent firm (i) through the lock-out rate d (Fig. 6a and Eq. 13, Table 2) and the disrupter firm (d) through the lock-out rate i (Fig. 6b and Eq. 33, Table 3), that of customer switching.

Switch contemplation sectors

The $i \rightarrow d$ switch rate (Fig. 7a and Eq. 47, Table 4) determines the lock-out rate i on Fig. 6b; similarly, the $d \rightarrow i$ switch rate (Fig. 7b and Eq. 55, Table 5) the lock-out rate d on Fig. 6a. But households do not switch automatically. If they consist of meaning-seeking creatures, they go through a switch contemplation period before they are ready to switch (Eqs 45 on Table 4 and 54 on Table 5).

The warm-up rates, which turn adopters into potential switchers (Fig. 7 and Eqs 44 on Table 4 and 53 on Table 5), depend on the respective adopters, appeal and market share of each contender firm as well as on whether the disrupter (d) runs up market (Eq. 48, Table 4) and the incumbent (i) retaliates (Eq. 57, Table 4). But the warm-up rates merely turn service users into potential switchers. Following Bass’ diffusion structure, potential switchers must first get hot for the respective service provider they end up switching to before they are ready to make the switch. The same ad potency and contact rate of each contender that converts potential adopters into adopters also makes potential switchers hot and Ready either to $i \rightarrow d$ or to $d \rightarrow i$ switch.

Figure 7 Incumbent to disrupter (i → d) and disrupter to incumbent (d → i) switch contemplation sectors



a) i → d : incumbent (i) to disrupter (d) switch

b) d → i : disrupter (d) to incumbent (i) switch

Table 4 Switch i → d contemplation sector equations

Stock or Level (State) Variables	({·} = comments and/or units)	Equation #
Potential i → d[m](t) = Potential i → d[m](t - dt) + (warm up to d[m] - get hot for d[m]) * dt		(44)
INIT Potential i → d[HeM] = 0 {homes}		(44.1)
INIT Potential i → d[LeM] = MAX (0, Adopters i[LeM] * appeal d[LeM]) {homes}		(44.2)
INIT Potential i → d[NcM] = MAX (0, Adopters i[NcM] * appeal d[NcM]) {homes}		(44.3)
Ready to i → d[m](t) = Ready to i → d[m](t - dt) + (get hot for d[m] - i → d switch rate[m]) * dt		(45)
INIT Ready to i → d[m] = 0 {homes}		(45.1)
Flows or Rate Variables		
get hot for d[m] = MAX (0, hot from ads d[m] + ready from word of mouth of Adopters d[m])		(46)
{homes/month}		
i → d switch rate[m] = MAX (0, Ready to i → d[m])		(47)
warm up to d[HeM] = IF ((up-market runs d = 1) AND ((Adopters i[HeM] * (appeal d[HeM] + market share d) ≤ (Adopters i[HeM] - Potential i → d[HeM]))) THEN (MAX (0, Adopters i[HeM] * (appeal d[HeM] + market share d))) ELSE (0) {homes/month}		(48)
warm up to d[LeM] = IF ((Adopters i[LeM] * (appeal d[LeM] + market share d) ≤ (Adopters i[LeM] - Potential i → d[LeM])) THEN (MAX (0, Adopters i[LeM] * (appeal d[LeM] + market share d))) ELSE (0) {homes/month}		(49)
warm up to d[NcM] = IF ((Adopters i[NcM] * (appeal d[NcM] + market share d) ≤ (Adopters i[NcM] - Potential i → d[NcM])) THEN (MAX (0, Adopters i[NcM] * (appeal d[NcM] + market share d))) ELSE (0) {homes/month}		(50)
Converter Variables		
hot from ads d[m] = MAX (0, Potential i → d[m] * ad potency d[m])		(51)
ready from word of mouth of Adopters d[m] = MAX (0, (Ready to i → d[m] + Adopters d[m]) * Potential i → d[m] * adoption fraction d[m] * contact rate d / SBA Homes)		(52)
{homes/month}		

Table 5 Switch $d \rightarrow i$ contemplation sector equations

<i>Stock or Level (State) Variables</i>	({·} = comments and/or units)	<i>Equation #</i>
Potential $d \rightarrow i[m](t) = \text{Potential } d \rightarrow i[m](t - dt) + (\text{warm up to } i[m] - \text{get hot for } i[m]) * dt$		(53)
INIT Potential $d \rightarrow i[m] = 0$ {homes}		(53.1)
Ready to $d \rightarrow i[m](t) = \text{Ready to } d \rightarrow i[m](t - dt) + (\text{get hot for } i[m] - d \rightarrow i \text{ switch rate}[m]) * dt$		(54)
INIT Ready to $d \rightarrow i[m] = 0$ {homes}		(54.1)
<i>Flows or Rate Variables</i>		
$d \rightarrow i \text{ switch rate}[m] = \text{MAX}(0, \text{Ready to } d \rightarrow i[m])$ {homes/month}		(55)
get hot for $i[m] = \text{MAX}(0, \text{hot from ads } i[m] + \text{ready from word of mouth of Adopters } i[m])$		(56)
warm up to $i[\text{HeM}] = \text{IF}((\text{Adopters } d[\text{HeM}] * (\text{appeal } i[\text{HeM}] + \text{market share } i)) \leq (\text{Adopters } d[\text{HeM}] - \text{Potential } d \rightarrow i[\text{HeM}])) \text{ THEN } (\text{MAX}(0, \text{Adopters } d[\text{HeM}] * (\text{appeal } i[\text{HeM}] + \text{market share } i))) \text{ ELSE } (0)$ {homes/month}		(57)
warm up to $i[\text{LeM}] = \text{IF}((\text{Adopters } d[\text{LeM}] * (\text{appeal } i[\text{LeM}] + \text{market share } i)) \leq (\text{Adopters } d[\text{LeM}] - \text{Potential } d \rightarrow i[\text{LeM}])) \text{ THEN } (\text{MAX}(0, \text{Adopters } d[\text{LeM}] * (\text{appeal } i[\text{LeM}] + \text{market share } i))) \text{ ELSE } (0)$ {homes/month}		(58)
warm up to $i[\text{NcM}] = \text{IF}((\text{retaliates } i[\text{NcM}] = 1) \text{ AND } ((\text{Adopters } d[\text{NcM}] * (\text{appeal } i[\text{NcM}] + \text{market share } i)) \leq (\text{Adopters } d[\text{NcM}] - \text{Potential } d \rightarrow i[\text{NcM}]))) \text{ THEN } (\text{MAX}(0, \text{Adopters } d[\text{NcM}] * (\text{appeal } i[\text{NcM}] + \text{market share } i))) \text{ ELSE } (0)$ {homes/month}		(59)
<i>Converter Variables</i>		
hot from ads $i[m] = \text{MAX}(0, \text{Potential } d \rightarrow i[m] * \text{ad potency } i[m])$ {homes/month}		(60)
ready from word of mouth of Adopters $i[m] = \text{MAX}(0, (\text{Ready to } d \rightarrow i[m] + \text{Adopters } i[m]) * \text{Potential } d \rightarrow i[m] * \text{adoption fraction } i[m] * \text{contact rate } i / \text{SBA Homes})$ {homes/month}		(61)

Accordingly, Bass' diffusion structures on Fig. 6 (and Tables 2 and 3) and Fig. 7 (and Tables 4 and 5) are practically identical. But there is a difference. As they get hot contemplating a switch, potential switchers listen not only to those who are ready to switch but also, and most importantly perhaps, to those who have already adopted the service to which households contemplate switching to. So the Adopters d stock on Fig. 7a enters the ready from word of mouth of Adopters d converter (Eq. 52, Table 4). Symmetrically, the Adopters i stock on Fig. 7b enters the ready from word of mouth of Adopters i rate (Eq. 61, Table 5).

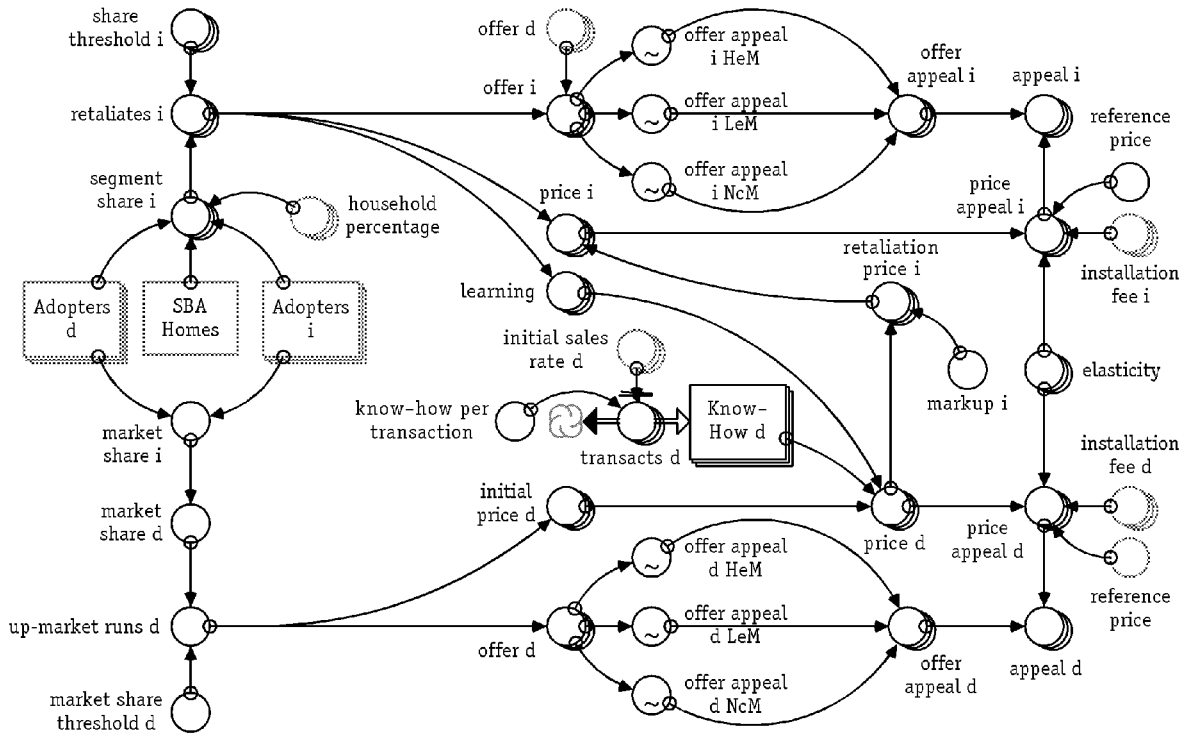
Tactics sector

To enable bidirectional customer switching, the warm-up rates depend not only on adopter perceptions and actions, but also on contender competitive tactics (Fig. 8 and Table 6). Together, the disrupter firm's market share d (Eq. 77) and market share threshold d (Eq. 79) determine if d runs up market or not (Eq. 104, Table 6). Likewise, the incumbent firm's segment share i (Eqs 100-102) and share threshold i (Eq. 103) determine if i retaliates or not (Eqs 95-97). Regarding the latter decision (to retaliate or not), clarity rules in the high- (HeM) and low-end (LeM) markets (Eqs 95 and 96, respectively): i retaliates in each market once its market share drops below its internally established share threshold i criteria.

But i has no market share in the non-consumption market (NcM), at least not initially. So the criterion for its 'retaliation' depends on how well its contender, the disrupter firm does there. As long as $d, Inc.$'s market share performance in NcM stays below i 's share threshold, i stays put. Once d 's NcM market share exceeds i 's mark, however, then i sees a missed opportunity in the non-consumption market and *retaliates* immediately (Eq. 97).

When the incumbent firm retaliates, it does so by altering both its offer i (Fig. 8 and Eqs 85-87) and its price i (Eqs 91-93, Table 6) for each respective market. So does the disrupter firm (Eqs 82-84 and Eq. 90, respectively) when it runs up market. Explicitly, Eq. 90 shows the tactics sector single stock: Know-How d (Fig. 8 and Eq. 62, Table 6). The other three stocks that Fig. 8 shows, Adopters d , Adopters i and SBA Homes, are 'ghosted' here from their respective sectors. All SD software tools provide this *ghosting* option for model elements to avoid clutter.

Figure 8 Incumbent (i) and disrupter (d) tactics sector



Three additional stocks that Fig. 8 does not show hide in Eq. 90 (Table 6). Namely in *iThink*®'s SMTH3 built-in function, which performs a third-order exponential smooth of the disrupter firm's noesis, using an exponential averaging time of three months for the smooth. SMTH3 does this by setting up a cascade of three first-order exponential smoothed stocks, each with an averaging time of one month ($= 3/3$, Eq. 90). SMTH3 returns the value of the final smooth in the three-stock cascade. So, although the disrupter firm's price i is not explicitly treated as a stock, its friendly algebra structure contains not just one but three stocks.

No explicit learning takes place in the tactics sector for the incumbent (i) firm, since i has been in this strategic business area for some time before the disrupter (d) firm attempts to penetrate NcM and, subsequently, to run up market to HeM and LeM. Yet the 20 percent retaliation markup i of Eq. 98, which acts as i 's umbrella pricing mechanism, has i ready, willing and able to also share cost savings with its customers as soon as $d, Inc.$ does.

According to Sterman (2000, p. 337-8), when competitive rivalry rises, new product prices drop through time as organizational learning and scale and scope economies lower production and transaction cost. Learning or experience curves, like those of $d, Inc.$ in HeM and LeM (Eqs 75 and 76, Table 6), represent the way firms learn to produce and to transact at lower cost through time. Cost usually declines as cumulative know-how or noesis grows with goods production and service delivery, a benefit that d shares with its customers when i retaliates in HeM and LeM (Eqs 75-76). Cumulative production often determines cumulative noesis in manufacturing. In services, however, cumulative transactions might be a more logical noesis determinant than cumulative production (Eqs 62-63).

Each contender's overall appeal to potential adopters and switchers depends both on its offer appeal (Eq. 80), determined by three identical graphical table functions (Eq. 81), one for each market per contender, and on each contender's price appeal (Eqs 88 and 89, respectively). Price appeal in turn depends on price elasticity of demand in each respective market (Eq. 67), each contender's initial installation fee (in US\$ per unit) and the potential customer's reference price (Eq. 94), i.e., buying power of the US\$ dollar.

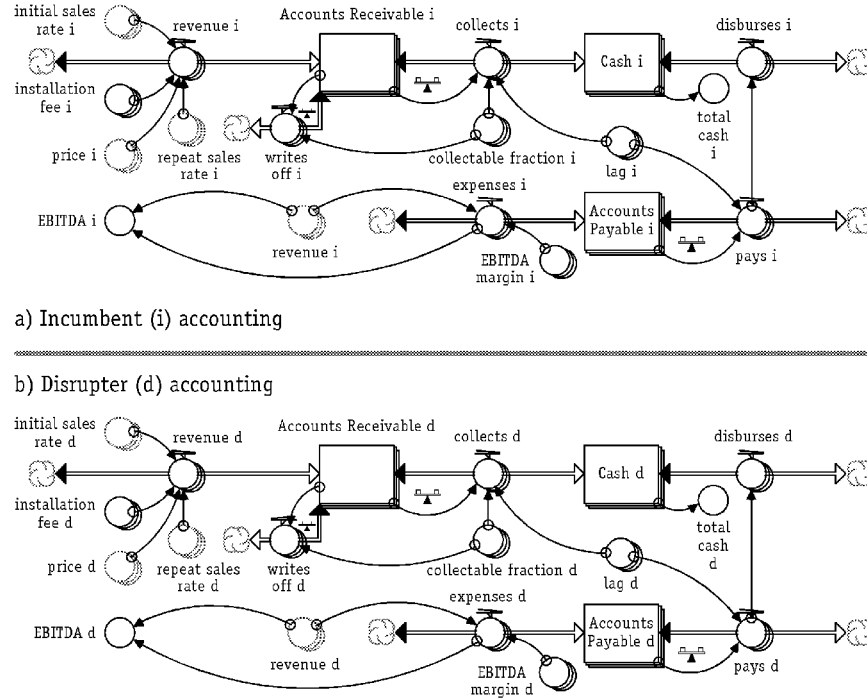
Table 6 Tactics sector equations

<i>Stock or Level (State) Variable</i>	(\cdot) = comments and/or units	<i>Equation #</i>
Know-How $d[m](t) = \text{Know-How } d[m](t - dt) + (\text{transacts } d[m]) * dt$		(62)
INIT Know-How $d[m] = \text{Adopters } d[m] + 1$ {noesis; the cumulative number of transactions with adopter homes the disrupter (d) transacts might be a logical determinant of its collective noesis}		(62.1)
<i>Flow or Rate Variable</i>		
transacts $d[m] = \text{MAX}(0, \text{initial sales rate } d[m] * \text{know-how per transaction})$ {noesis/month}		(63)
<i>Auxiliary Parameters and Converter Variables</i>		
appeal $c[\text{HeM}] = 0.7 * \text{offer appeal } c[\text{HeM}] + 0.3 * \text{price appeal } d[\text{HeM}]$ {c = d, i; unitless}		(64)
appeal $c[\text{LeM}] = 0.3 * \text{offer appeal } c[\text{LeM}] + 0.7 * \text{price appeal } c[\text{LeM}]$ {c = d, i; unitless}		(65)
appeal $c[\text{NcM}] = 0.1 * \text{offer appeal } c[\text{NcM}] + 0.9 * \text{price appeal } c[\text{NcM}]$ {c = d, i; unitless}		(66)
elasticity[HeM, LeM, NcM] = -0.88, -0.94, 1 {unitless}		(67)
initial price $d[\text{HeM}] = \text{IF}(\text{up-market runs } d = 1) \text{ THEN } (90) \text{ ELSE } (0)$ {US\$/unit}		(68)
initial price $d[\text{LeM}] = \text{IF}(\text{up-market runs } d = 1) \text{ THEN } (50) \text{ ELSE } (20)$ {US\$/unit}		(69)
initial price $d[\text{NcM}] = \text{IF}(\text{up-market runs } d = 1) \text{ THEN } (20) \text{ ELSE } (20)$ {US\$/unit}		(70)
initial price $i[\text{HeM}] = \text{IF}(\text{retaliates } i[\text{HeM}] = 1) \text{ THEN } (\text{retaliation price } i[\text{HeM}]) \text{ ELSE } (150)$ {US\$/unit}		(71)
initial price $i[\text{LeM}] = \text{IF}(\text{retaliates } i[\text{LeM}] = 1) \text{ THEN } (\text{retaliation price } i[\text{LeM}]) \text{ ELSE } (75)$ {US\$/unit}		(72)
initial price $i[\text{NcM}] = \text{IF}(\text{retaliates } i[\text{NcM}] = 1) \text{ THEN } (\text{retaliation price } i[\text{NcM}]) \text{ ELSE } (0)$ {US\$/unit}		(73)
know-how per transaction = 1 {noesis/unit}		(74)
learning $c[\text{HeM and LeM}] = \text{LOGN}(0.9) / \text{LOGN}(2)$ {competitors c = d, i; unitless}		(75)
learning $c[\text{NcM}] = 0$ {very doubtful that prices can drop in NcM; competitors c = d, i; unitless}		(76)
market share $d = \text{MAX}(0, 1 - \text{market share } i)$ {unitless}		(77)
market share $i = \text{MAX}(0, \text{ARRAYSUM}(\text{Adopters } i[*]) / (\text{ARRAYSUM}(\text{Adopters } i[*]) + \text{ARRAYSUM}(\text{Adopters } d[*])))$ {unitless}		(78)
market share threshold $d = 0.08$ {unitless}		(79)
offer appeal $c[m] = \text{NORMAL}(\text{offer appeal } c \ m, \text{offer appeal } c \ m / 3)$ {c = d, i and m = HeM, LeM, NcM; unitless}		(80)
offer appeal $c \ m = \text{GRAPH}(\text{offer } c[m])$ {competitors c = d, i and market m = HeM, LeM, NcM; unitless}		(81)
(0, 0), (0.5, 0.001), (1, 0.004), (1.5, 0.012), (2, 0.027), (2.5, 0.05), (3, 0.073), (3.5, 0.088), (4, 0.096), (4.5, 0.099), (5, 0.1)		
offer $d[\text{HeM}] = \text{IF}(\text{up-market runs } d = 1) \text{ THEN } (5) \text{ ELSE } (0)$ {unitless}		(82)
offer $d[\text{LeM}] = \text{IF}(\text{up-market runs } d = 1) \text{ THEN } (4) \text{ ELSE } (1)$ {unitless}		(83)
offer $d[\text{NcM}] = \text{IF}(\text{up-market runs } d = 1) \text{ THEN } (1) \text{ ELSE } (1)$ {unitless}		(84)
offer $i[\text{HeM}] = \text{IF}(\text{retaliates } i[\text{HeM}] = 1) \text{ THEN } (\text{offer } d[\text{HeM}] + 2) \text{ ELSE } (5)$ {unitless}		(85)
offer $i[\text{LeM}] = \text{IF}(\text{retaliates } i[\text{LeM}] = 1) \text{ THEN } (\text{offer } d[\text{LeM}] + 1) \text{ ELSE } (4)$ {unitless}		(86)
offer $i[\text{NcM}] = \text{IF}(\text{retaliates } i[\text{NcM}] = 1) \text{ THEN } (\text{offer } d[\text{NcM}] + 1) \text{ ELSE } (0)$ {unitless}		(87)
price appeal $d[m] = \text{NORMAL}(((\text{price } d[m] + \text{installation fee } d[m]) / \text{reference price}) ^ \text{elasticity}[m]), ((\text{price } d[m] + \text{installation fee } d[m]) / \text{reference price}) ^ \text{elasticity}[m] / 3)$ {unitless}		(88)
price appeal $i[m] = \text{NORMAL}(((\text{price } i[m] + \text{installation fee } i[m]) / \text{reference price}) ^ \text{elasticity}[m]), ((\text{price } i[m] + \text{installation fee } i[m]) / \text{reference price}) ^ \text{elasticity}[m] / 3)$ {unitless}		(89)
price $d[m] = \text{initial price } d[m] * \text{SMTH3}((\text{Know-How } d[m] / (\text{INIT}(\text{Know-How } d[m]))) ^ \text{learning}[m], 3)$ {US\$/unit}		(90)
price $i[\text{HeM}] = \text{IF}(\text{retaliates } i[\text{HeM}] = 1) \text{ THEN } (\text{retaliation price } i[\text{HeM}]) \text{ ELSE } (150)$ {US\$/unit}		(91)
price $i[\text{LeM}] = \text{IF}(\text{retaliates } i[\text{LeM}] = 1) \text{ THEN } (\text{retaliation price } i[\text{LeM}]) \text{ ELSE } (75)$ {US\$/unit}		(92)
price $i[\text{NcM}] = \text{IF}(\text{retaliates } i[\text{NcM}] = 1) \text{ THEN } (\text{retaliation price } i[\text{NcM}]) \text{ ELSE } (0)$ {US\$/unit}		(93)
reference price = 1 {US\$/unit}		(94)
retaliates $i[\text{HeM}] = \text{IF}(\text{segment share } i[\text{HeM}] < \text{share threshold } i[\text{HeM}]) \text{ THEN } (1) \text{ ELSE } (0)$ {unitless}		(95)
retaliates $i[\text{LeM}] = \text{IF}(\text{segment share } i[\text{LeM}] < \text{share threshold } i[\text{LeM}]) \text{ THEN } (1) \text{ ELSE } (0)$ {unitless}		(96)
retaliates $i[\text{NcM}] = \text{IF}(\text{segment share } i[\text{NcM}] < \text{share threshold } i[\text{NcM}]) \text{ THEN } (0) \text{ ELSE } (1)$ {unitless}		(97)
retaliation markup $i[m] = 0.2$ {unitless}		(98)
retaliation price $i[m] = \text{price } d[m] * (1 + \text{retaliation markup } i[m])$ {US\$/unit}		(99)
segment share $i[\text{HeM}] = \text{MAX}(0, \text{Adopters } i[\text{HeM}] / (\text{Adopters } d[\text{HeM}] + \text{Adopters } i[\text{HeM}]))$ {unitless}		(100)
segment share $i[\text{LeM}] = \text{MAX}(0, \text{Adopters } i[\text{LeM}] / (\text{Adopters } d[\text{LeM}] + \text{Adopters } i[\text{LeM}]))$ {unitless}		(101)
segment share $i[\text{NcM}] = \text{MAX}(0, \text{Adopters } d[\text{NcM}] / (\text{SBA Homes} * \text{household percentage}[\text{NcM}]))$ {unitless}		(102)
share threshold $i[\text{HeM, LeM, NcM}] = [0.95, 0.85, 0.15]$ {unitless}		(103)
up-market runs $d = \text{IF}(\text{market share } d < \text{market share threshold } d) \text{ THEN } (0) \text{ ELSE } (1)$ {unitless}		(104)

Financial accounting sectors

The initial installation fees, which enter Eqs 88 and 89, respectively, again are ghosted, this time from their respective accounting sectors (Fig. 9 and Eqs 117 and 132, Tables 7 and 8, respectively).

Figure 9 Incumbent (i) and disrupter (d) accounting sectors



a) Incumbent (i) accounting

b) Disrupter (d) accounting

Table 7 Incumbent (i) accounting sector equations

<i>Stock or Level (State) Variables</i>	{·} = comments and/or units	<i>Equation #</i>
Accounts Payable $i[m](t) = \text{Accounts Payable } i[m](t - dt) + (\text{expenses } i[m] - \text{pays } i[m]) * dt$		(105)
INIT Accounts Payable $i[m] = \text{expenses } i[m] * \text{lag } i[m]$	{US\$}	(105.1)
Accounts Receivable $i[m](t) = \text{Accounts Receivable } i[m](t - dt) + (\text{revenue } i[m] - \text{collects } i[m] - \text{writes off } i[m]) * dt$		(106)
INIT Accounts Receivable $i[m] = \text{revenue } i[m] * \text{collectable fraction } i[m] * \text{lag } i[m]$	{US\$}	(106.1)
Cash $i[m](t) = \text{Cash } i[m](t - dt) + (\text{collects } i[m] - \text{disburses } i[m]) * dt$		(107)
INIT Cash $i[m] = 8,000,000$	{Total initial cash $i = 24,000,000$; US\$}	(107.1)
<i>Flows or Rate Variables</i>		
$\text{collects } i[m] = \text{MAX}(0, \text{collectable fraction } i[m] * \text{Accounts Receivable } i[m] / \text{lag } i[m])$		(108)
	{US\$/month}	
$\text{disburses } i[m] = \text{MAX}(0, \text{pays } i[m])$		(109)
	{US\$/month}	
$\text{expenses } i[m] = \text{MAX}(0, (1 - \text{margin } i[m]) * \text{revenue } i[m])$		(110)
	{US\$/month}	
$\text{pays } i[m] = \text{MAX}(0, \text{Accounts Payable } i[m] / \text{lag } i[m])$		(111)
	{US\$/month}	
$\text{revenue } i[m] = \text{MAX}(0, \text{initial sales rate } i[m] * \text{installation fee } i[m] + \text{price } i[m] * \text{repeat sales rate } i[m])$		(112)
	{US\$/month}	
$\text{writes off } i[m] = \text{MAX}(0, (1 - \text{collectable fraction } i[m]) * \text{Accounts Receivable } i[m])$		(113)
	{US\$/month}	
<i>Auxiliary Parameters and Converter Variables</i>		
$\text{collectable fraction } i[m] = 0.98$		(114)
	{unitless}	
$\text{EBITDA } i = \text{ARRAYSUM}(\text{revenue } i[*]) - \text{ARRAYSUM}(\text{expenses } i[*])$		(115)
	{US\$/month}	
$\text{EBITDA margin } i[m] = 0.3$		(116)
	{unitless}	
$\text{installation fee } i[m] = 130$		(117)
	{US\$/unit}	
$\text{lag } i[m] = 2$		(118)
	{months}	
$\text{total cash } i = \text{ARRAYSUM}(\text{Cash } i[*])$		(119)
	{US\$}	

Table 8 Disrupter (d) accounting sector equations

<i>Stock or Level (State) Variables</i>	<i>({·} = comments and/or units)</i>	<i>Equation #</i>
Accounts Payable $d[m](t) = \text{Accounts Payable } d[m](t - dt) + (\text{expenses } d[m] - \text{pays } d[m]) * dt$		(120)
INIT Accounts Payable $d[m] = \text{expenses } d[m] * \text{lag } d[m]$	{US\$}	(120.1)
Accounts Receivable $d[m](t) = \text{Accounts Receivable } d[m](t - dt) + (\text{revenue } d[m] - \text{collects } d[m] - \text{writes off } d[m]) * dt$		(121)
INIT Accounts Receivable $d[m] = \text{revenue } d[m] * \text{collectable fraction } d[m] * \text{lag } d[m]$	{US\$}	(121.1)
Cash $d[m](t) = \text{Cash } d[m](t - dt) + (\text{collects } d[m] - \text{disburses } d[m]) * dt$		(122)
INIT Cash $d[m] = 8,000,000 / 3$	{Total initial cash $d = 8,000,000$; US\$}	(122.1)
<i>Flows or Rate Variables</i>		
collects $d[m] = \text{MAX}(0, \text{collectable fraction } d[m] * \text{Accounts Receivable } d[m] / \text{lag } d[m])$		(123)
	{US\$/month}	
disburses $d[m] = \text{MAX}(0, \text{pays } d[m])$	{US\$/month}	(124)
expenses $d[m] = \text{MAX}(0, (1 - \text{margin } d[m]) * \text{revenue } d[m])$	{US\$/month}	(125)
pays $d[m] = \text{MAX}(0, \text{Accounts Payable } d[m] / \text{lag } d[m])$	{US\$/month}	(126)
revenue $d[m] = \text{MAX}(0, \text{initial sales rate } d[m] * (\text{installation fee } d[m] + \text{price } d[m]) + \text{price } d[m] * \text{repeat sales rate } d[m])$	{US\$/month}	(127)
writes off $d[m] = \text{MAX}(0, (1 - \text{collectable fraction } d[m]) * \text{Accounts Receivable } d[m])$		(128)
	{US\$/month}	
<i>Auxiliary Parameters or Converter Variables</i>		
collectable fraction $d[m] = 0.98$	{unitless}	(129)
EBITDA $d = \text{ARRAYSUM}(\text{revenue } d[*]) - \text{ARRAYSUM}(\text{expenses } d[*])$	{US\$/month}	(130)
EBITDA margin $d[m] = 0.2$	{unitless}	(131)
installation fee $d[m] = 120$	{US\$/unit}	(132)
lag $d[m] = 2$	{months}	(133)
total cash $d = \text{ARRAYSUM}(\text{Cash } d[*])$	{US\$}	(134)

Some people see accounting as the ultimate form of social control. The three balancing or negative (–) feedback loops that populate each sector on Fig. 9 support that view. Each stock here (Eqs 105-107, Table 7 and Eqs 120-122, Table 8) comes from the accountant’s balance sheet. Conversely, the flows or rates (Eqs 108-113, Table 7 and Eqs 123-128, Table 8) go on the accountant’s income or profit and loss (P&L) statement. In short, these last two sectors provide financial performance metrics for each contender. One metric shown on the graphs of the results or computed scenarios section below is EBITDA (earnings before interest, taxes, depreciation and amortization) for the incumbent firm *i* (Eq. 115, Table 7) and for the disrupter firm *d* (Eq. 130, Table 8), respectively. A second metric reported is total cash for *i* (Eq. 119, Table 7) and for *d* (Eq. 134, Table 8), respectively.

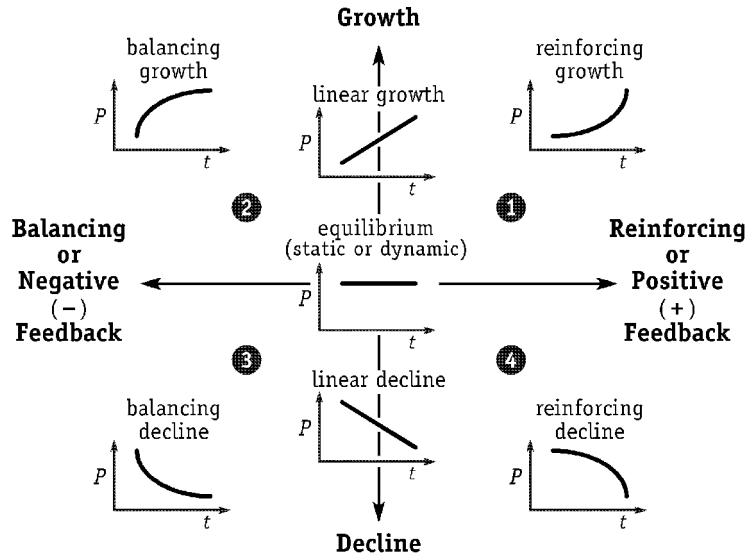
Computed scenarios

Not just model analysis but the entire, client-concern driven SD modeling process aims at helping managers articulate exactly how the structure of circular feedback relations among variables in a system they manage determines its performance through time (Forrester and Senge 1980). To the endless hunt for superior performance that, again, only *systemic leverage* endows, SD brings its basic tenet: the structure of feedback relations in a system gives rise to its dynamics (Meadows 1989, Sterman 2000, p. 16).

Ideally, to articulate exactly how structure drives performance, the scenarios computed with this article’s model, and every exploratory SD model for that matter, should run through Mojtahedzadeh’s (1996) pathway participation metric (PPM) implemented in his *Digest*® software (Mojtahedzadeh, Andersen and Richardson 2004). Linked to eigenvalue (Forrester 1983) and loop dominance (Richardson 1995) research, Mojtahedzadeh’s (1996) PPM is most promising in formally linking performance to system structure. Mojtahedzadeh *et al* (2004) give an extensive overview but, briefly, PPM sees a model’s individual causal links or paths among variables as the basic building blocks of structure. The metric can identify dominant loops, but does not start with them as its basic building blocks. Using a

recursive heuristic approach, PPM detects compact structures of chief causal paths and loops that contribute the most to the performance of a selected variable through time.

Figure 10 Archetypal performance (P) patterns through time (t), i.e., *dynamics* (adapted from Mojtahedzadeh *et al* 2004; *sa* Sterman 2000, Ch. 4)



But *Digest*® is still experimental and cannot yet handle all the *iThink*® built-in functions and random components that this article’s model contains. A practical alternative is to analyze the computed scenarios using the archetypal performance (P) dynamics of Fig. 10. Doing so is, however, a necessary but insufficient condition for insight. The canon? Insightful articulations that link performance to system structure demand integrating insight from dynamic, operational and feedback loop thinking (Mojtahedzadeh *et al* 2004, Richmond 1993).

In lieu of performance reproduction tests

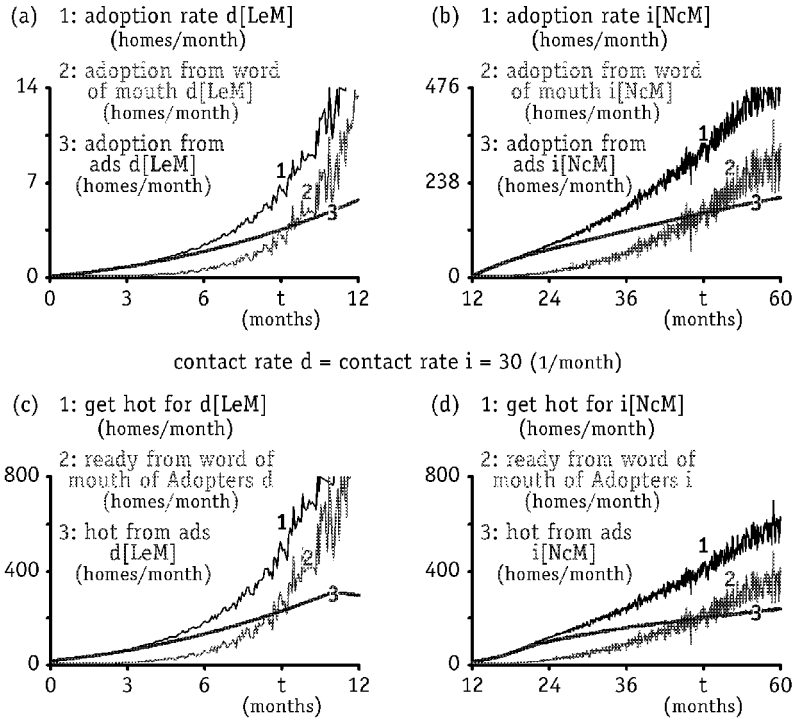
Being a fairly new venture, *d, Inc.* could not provide enough real-life data to run against the model’s base-case scenarios. It is possible, however, to compare model dynamics with the adoption rate disaggregation that Lane and Husemann (2004) and Sterman (2000, Ch. 9) see in Bass’ (1969) diffusion model. Making it so entails letting the move-in fraction = 0.0167 per month in Eq. 4 (Table 1) for a fast-growth SBA scenario, with the contact rate = 30 per month for both competitors to match Sterman’s base-run parameter choices. The results are on Fig. 11.

Randomness notwithstanding (Hayes 2001, Sterman 2000, p. 127), under a fast-growth SBA scenario, both the adoption and the contemplation (get hot for) rate disaggregations reproduce the dynamics one would expect from Bass’ diffusion model. Overall, each aggregate adoption rate on Fig. 11 seems to come mostly from word-of-mouth adoption, with ads-driven sales being much smaller in comparison. This confirms, per the archetypal dynamics on the *first* quadrant of Fig. 10, the most critical role the reinforcing (+) feedback plays in the model sectors that contain Bass’ diffusion model on Fig. 6 and 7. But looking closely at the left panel of Fig. 11, *d* gets neither sales nor contemplation in LeM from word of mouth for the first three months.

Similarly, on the right panel of Fig. 11, *i* gets neither sales nor contemplation in NcM attributed to word of mouth for the first six months after the incumbent (*i*) firm penetrates, around $t = 12$ months, what used to be its non-consumption market. Both firms need initial sales from ads (line #3 on Fig. 11) to catalyze imitative sales from word of mouth. But once they do, *d* in LeM around $t = 9$ months and *i* in NcM around $t = 48$ months, respectively, then the reinforcing (+) feedback loops of Fig. 6 and 7 drive

word-of-mouth adoption, while the balancing (–) loops on the same stock and flow diagrams sequester service adoption from ads.

Figure 11 Adoption and contemplation (get hot for) rate disaggregation in a fast-growth strategic business area (SBA), i.e., move-in fraction = 0.0167 per month, for the disrupter (d) in the low-end market (LeM) and the incumbent (i) in the non-consumption market (NcM), with contact rate = 30 per month for both competitors



SBA growth effects on performance

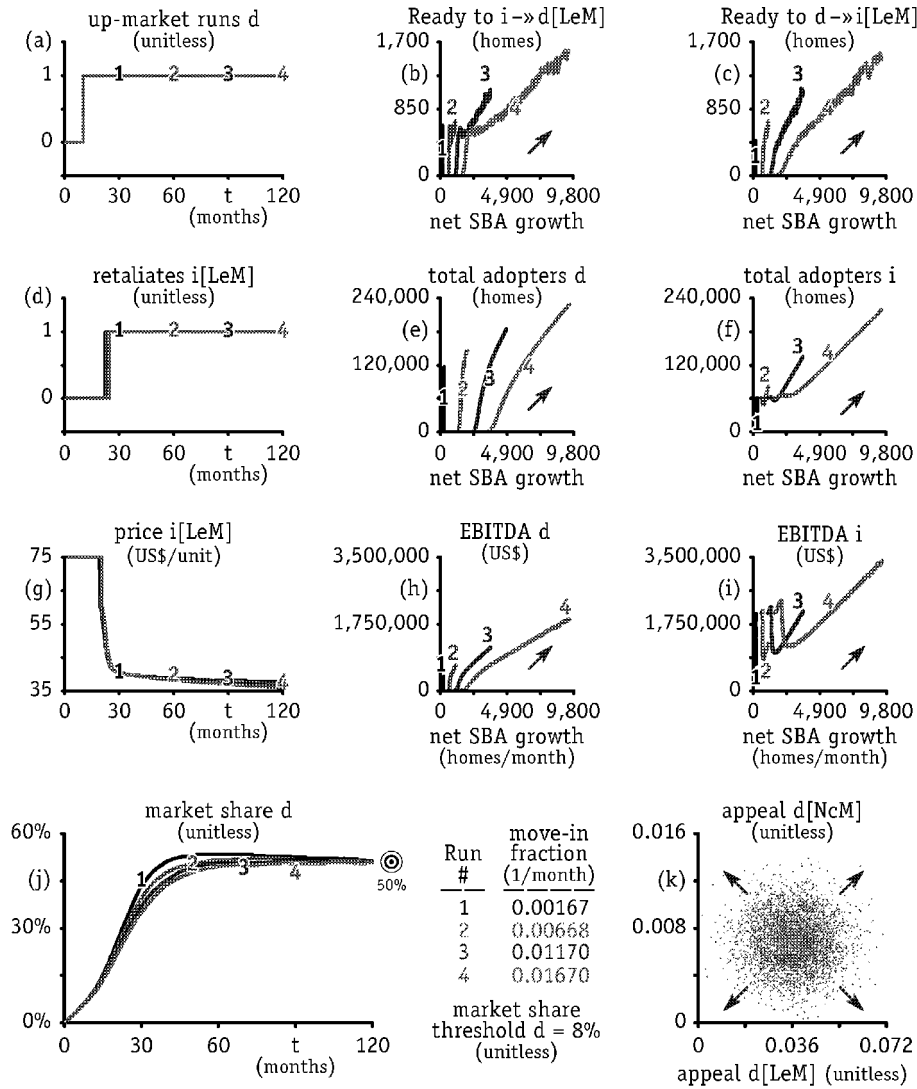
To gain a more granular insight on the SBA growth effects on performance requires increasing the exogenous move-in fraction parameter (Eq. 4, Table 1) gradually. The top three time-series graphs on the left panel of Fig. 12 (a, d and g) show the progression of events as they unfold through time under four consecutive simulation runs or SBA growth scenarios. Under each scenario, the disrupter (d) firm runs up market consistently around $t = 9$ months (Fig. 12a), when its combined (LeM and NcM) market share reaches its fixed market share threshold $d = 8$ percent. In response, the incumbent firm (i) retaliates in the low-end market between months 19 and 21 (Fig. 12d), once it sees its respective segment share $i[\text{LeM}]$ drop below its fixed share threshold $i[\text{LeM}] = 85$ percent mark (Eq. 96, Table 6).

The top three phase plots on the middle panel of Fig. 12 (b, e and h) show how the incumbent (i) firm's adopters might become ready to switch from i to d, causing d's total adopters and EBITDA to increase as each of these four scenarios play. Similarly, the top three phase plots on the right panel of Fig. 12 (c, f and i) show how, in response to the same four SBA growth scenarios and i's retaliation, the disrupter (d) firm's adopters might in turn get ready to switch back from d to i, with potential implications for i's total adopters and EBITDA.

Looking at the phase plots on Fig. 12e and f, the higher the net SBA growth is, the more adopters each firm recruits. Following the time arrow on these graphs, however, d's total adopters increase consistently, first at an increasing rate and then at a declining one, while i's total adopters first decline as some of them switch to d, Inc.'s service and then increase again, following the SBA net growth rate. The two contenders' EBITDA rates perform analogously. EBITDA d increases consistently (Fig. 12h), while

i's does so only after an initial big dip (Fig. 12i). The drop in total adopters causes the EBITDA i dips, combined with i's retaliation, which entails substantial price cuts (Eqs 91 and 92, Table 6).

Figure 12 Strategic business area (SBA) household population growth effects on the disrupter (d) and incumbent (i) overall performance, but with emphasis on the low-end market (LeM)



EBITDA = earnings before interest, taxes, depreciation and amortization

Back to the time domain. In the long run, as the concentric circles show on the right of Fig 12j, the disrupter firm's market share d reaches a stable equilibrium at 50 percent. Until it gets there, however, the higher the net SBA growth is, the worse off d, Inc. might be performing in market share terms. Even if caused just by computational time lags and delays in determining the unitless market share ratio, this result backs Christensen and Raynor (2003), who urge disruptive innovators to be profit (EBITDA) but not market-share hungry.

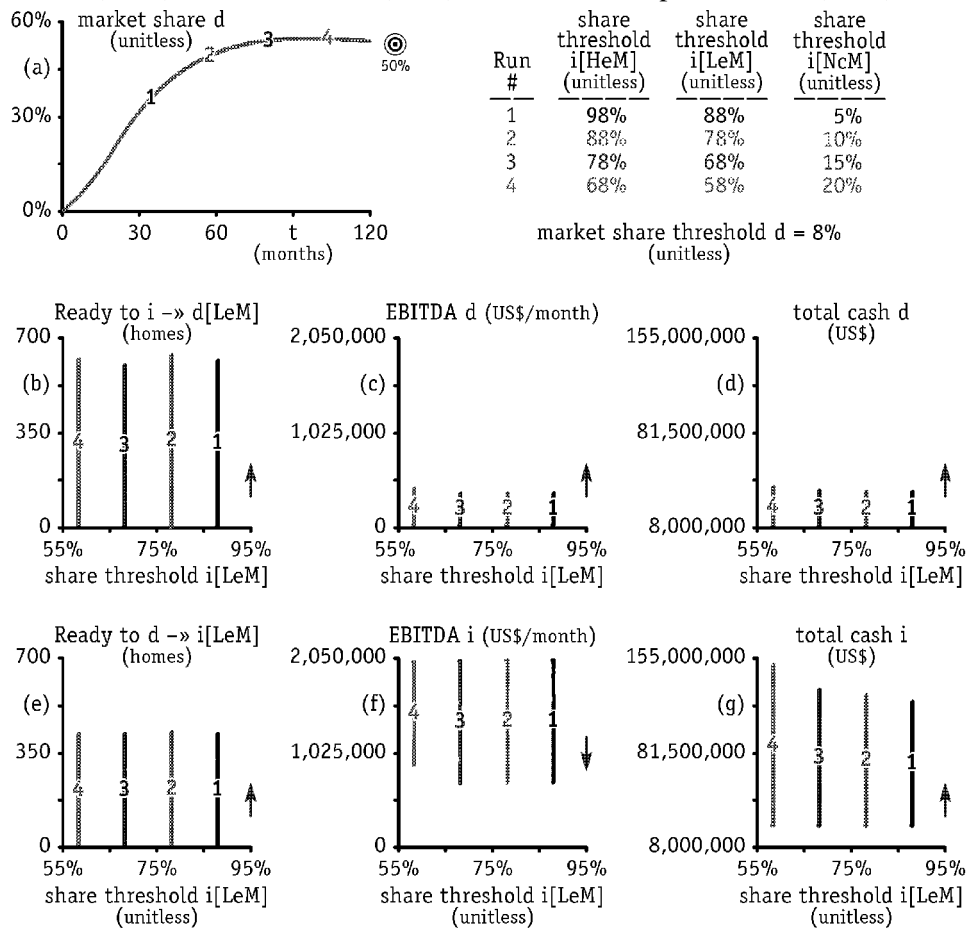
In lieu of formal model analysis

Under the first, base-run scenario on Fig. 12j, and with respect to the archetypal dynamics on Fig. 10, between t = 0 and t = 22 months market share d follows a reinforcing growth pattern similar to the one on the first quadrant of Fig. 10. During this period, the set of reinforcing or (+) feedback loops on Fig. 6 and 7 are most prominent in causing its behavior. At t = 22 months, market share d reaches its first inflection

point around 28 percent. Then, between $t = 23$ and $t = 70$ months, market share d follows a *balancing growth* pattern similar to the one on the *second* quadrant of Fig. 10. During this period, strengthened by the incumbent firm's retaliation, the balancing or (-) feedback loops on Fig. 6 and 7 become the most prominent causal paths in creating its behavior. By $t = 70$ months, market share d has reached its second inflection point around 53 percent.

Between $t = 71$ and $t = 120$ months, with i 's retaliation pressure still on, market share d alternates a couple of times between a *reinforcing decline* pattern, similar to the one on the *fourth* quadrant of Fig. 10, and a *balancing decline* pattern, similar to the one on the *third* quadrant of Fig. 10. Obviously, market share d also passes through a couple of inflection points during this period. But while in a reinforcing decline mode, the reinforcing or (+) feedback loops of Fig. 6 and 7 are most prominent in determining the behavior of market share d . While following a balancing decline pattern, the pattern in which market share d finishes the simulation, the balancing or (-) feedback loops on Fig. 6 and 7 are most prominent in causing its behavior. By $t = 120$ months, and while in a balancing decline mode, market share d has reached its long-term equilibrium of 50 percent, which it sustains even when the model's time horizon doubles from 120 to 240 months or from 10 to 20 years.

Figure 13 Performance responses to the incumbent's retaliation share thresholds i in the high-end market (HeM), low-end market (LeM) and non-consumption market (NcM)



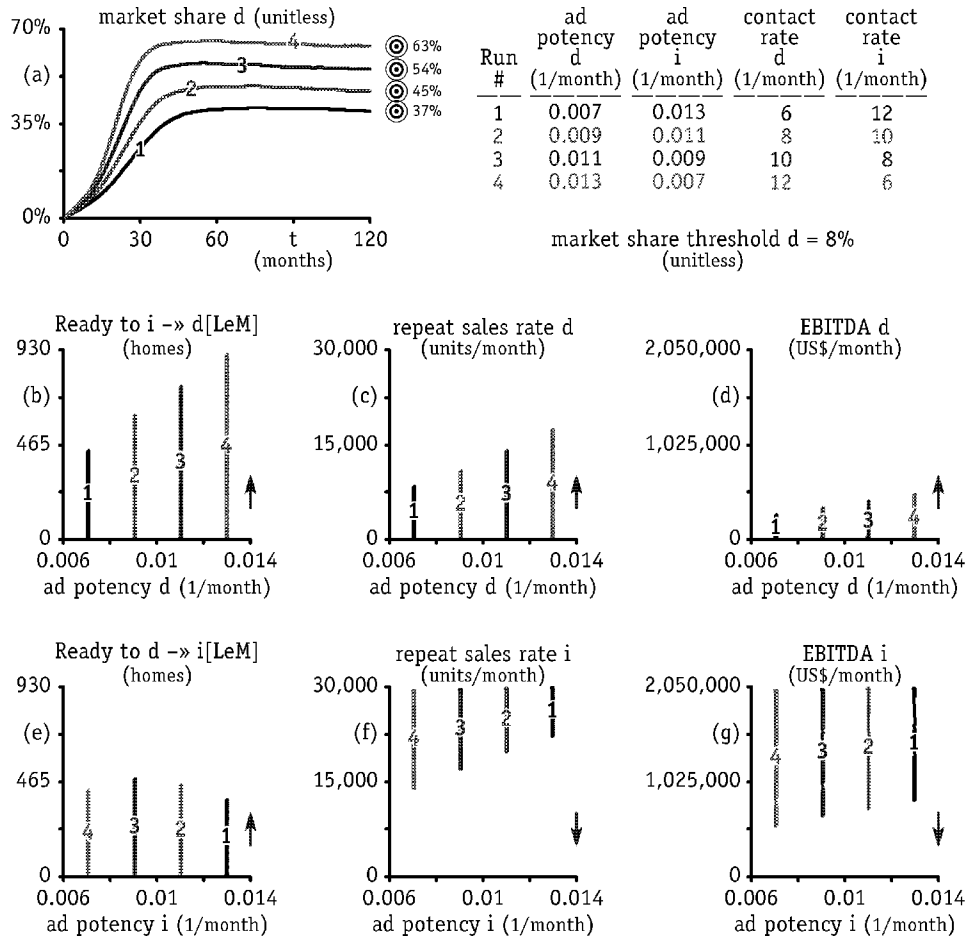
Last but not least, the phase plot on Fig. 12k helps check for possible autocorrelation in *iThink*'s non-replicable pseudo-random number generation procedures. The graph shows a random sample of $n = 7,680$ observations from d , *Inc.*'s appeal in the low-end (LeM) and non-consumption (NcM) markets. The observations appear to be i.i.d. (independent and identically distributed), drawn from a bivariate normal distribution, without any apparent or glaringly significant bias present.

Performance responses to incumbent retaliation

With its up-market run pending, both explicitly and unambiguously has *d, Inc.* expressed its concerns about the incumbent (*i*) firm’s possible retaliation tactics. While holding the disrupter’s up-market run market share threshold *d* constant at 8 percent, under the four scenarios of Fig. 13, the incumbent’s retaliation share threshold *i* gradually decreases from 98 to 68 percent in HeM and from 88 down to 58 percent in LeM, respectively, while it gradually increases from five to 20 percent in what used to be *i*’s non-consumption market (NcM).

Without any strong evidence to the contrary, the simulation results of Fig. 13 show that changing the share threshold *i* has no major effects on the disrupter firm’s performance. The market share *d* changes on Fig. 13a are rather imperceptible. Similarly, other than slight increases in EBITDA *d* (Fig. 13c) and total cash *d* (Fig. 13d), no major effects seem apparent under computed scenario or run #4. Conversely, under the same scenario, the combination of a low retaliation share threshold *i* in HeM and LeM, respectively, and a high share threshold *i* in NcM seems to benefit *i* comparatively more (Fig. 13e, f and g) than it does *d*. So, disruptive innovators should not be overly concerned with incumbent firms’ retaliation thresholds. All *d, Inc.* must do is make ready to deal with incumbent’s retaliation as and when the latter occurs.

Figure 14 Performance responses to increasingly favorable conditions for the disrupter (*d*) in terms of ad potency and contact rates, with the incumbent (*i*) retaliation share thresholds *i* in the high-end market (HeM), low-end market (LeM) and non-consumption market (NcM) fixed at 95, 85 and 15 percent, respectively



Performance under increasingly favorable scenarios

Again even, the number of scenarios on Fig. 14 guards against the cognitive human pitfall of misperceiving scenarios in the middle as the most likely ones to play. Increasingly favorable scenarios allow at once exploring *d, Inc.*'s potential performance under the current model's extremely conservative parameters as well as testing the model itself for robustness. The multitude of exogenous parameters in Bass' diffusion model facilitates such two-fold tests. *Ceteris paribus*, moving from the first to the fourth scenario or simulation run on Fig. 14, the disrupter (*d*) firm's ad potency *d* and contact rate *r* change from low to high while, conversely, the incumbent (*i*) firm's ad potency *i* and contact rate *i* change from high to low.

These increasingly favorable conditions cause *d*'s market share to improve dramatically from a low 37 to a whopping 63 percent on Fig. 14a. The market share equilibria on the right of Fig. 14a are stable even when the model's time horizon increases from 10 to 20 years or from 120 to 240 months. As those familiar with Bass' diffusion dynamics might have expected, the higher the ad potency *d* is, the higher the Ready to *i* → *d* switch households stock is in the low-end market, and the higher its repeat sales and EBITDA *d* rates are. Likewise, the higher *i*'s ad potency is, the less its repeat sales and EBITDA *i* rates drop, but the Ready to *d* → *i* switch households stock in LeM presents an anomaly, artificially masked by the increasingly favorable conditions that the scenarios of Fig. 14 create for the disrupter firm. So, both *d, Inc.* and the model this article presents perform very well under increasingly favorable conditions. But the incumbent firm might also have less to lose if conditions turn to its favor unless, of course, *d*'s spectacular performance somehow continues to mask *i*'s performance.

To run or not to run up market?

Of course, the real question is: how can a disruptive innovator create its own favorable market conditions or, alternatively, enable increasingly favorable scenarios to play? According to the performance results on Fig. 15, the answer is to start the up-market run as soon as possible or as early as the disrupter firm's resources permit it. Again *ceteris paribus*, with *i*'s share thresholds held constant at 95, 85 and 15 percent in HeM, LeM and NcM, respectively, market share threshold *d* drops from 49 percent under scenario #1 to 4 percent under scenario #4.

So, even without the up-market run, *d, Inc.* might do quite well in market share terms, attaining 45 percent of the combined LeM and NcM markets by the end of 10 years (scenario #1, Fig. 15a). But *d* can do much better than that if it runs up market, capturing 50 percent of the total SBA market, HeM now included (scenarios #2 - #4, Fig. 15a). But what about EBITDA?

The gray area on Fig. 15b shows the total loss *d* might incur in EBITDA *d* without the up-market run, compared to running up market early, i.e., when its combined LeM and NcM market share exceeds the 4 percent mark. Similarly, the gray area on Fig. 15c shows the total gain *i* might enjoy in EBITDA *i* without *d*'s up-market run, compared to *d*'s running up market early.

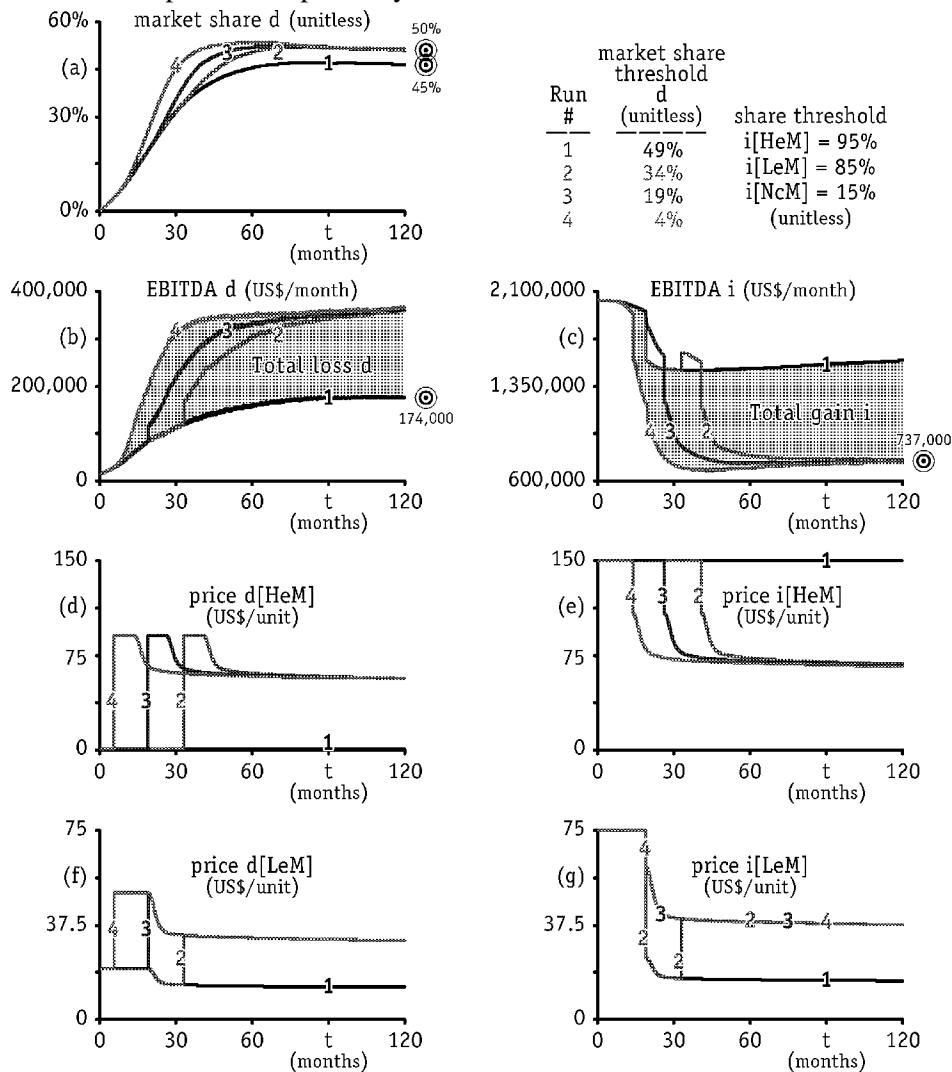
Most importantly perhaps, when *d* does *not* run up market, its own EBITDA *d* might level off at about US\$174,000 per month (run #1, Fig. 15b), while the incumbent firm's EBITDA *i* could continue growing along with net SBA growth (run #1, Fig. 15c). Conversely, when *d* runs up market, its own EBITDA *d* could continue to grow along with net SBA growth (runs #2-#4, Fig. 15b), while forcing the incumbent firm's EBITDA *i* to level off at about US\$737,000 per month (runs #2-#4, Fig. 15c). Figures 15d through 15g show the two contenders' respective prices in HeM and LeM, which in part explain EBITDA performance differences.

Creating own favorable conditions

Christensen et al (2002, p. 42) urge managers to seek a balance between resources that sustain short-term profit and investments in high-growth opportunities. Similarly, Christensen and Raynor (2003) highlight how central the resource allocation process is as a shaper of disruptive innovation strategies. And even the federal government tries to regulate some aspects of the resource allocation process in broadcast and

video programming. Figure 16 shows what might happen if *d, Inc.* attempts to strengthen its market share foothold among non-consumers and established cable service subscribers.

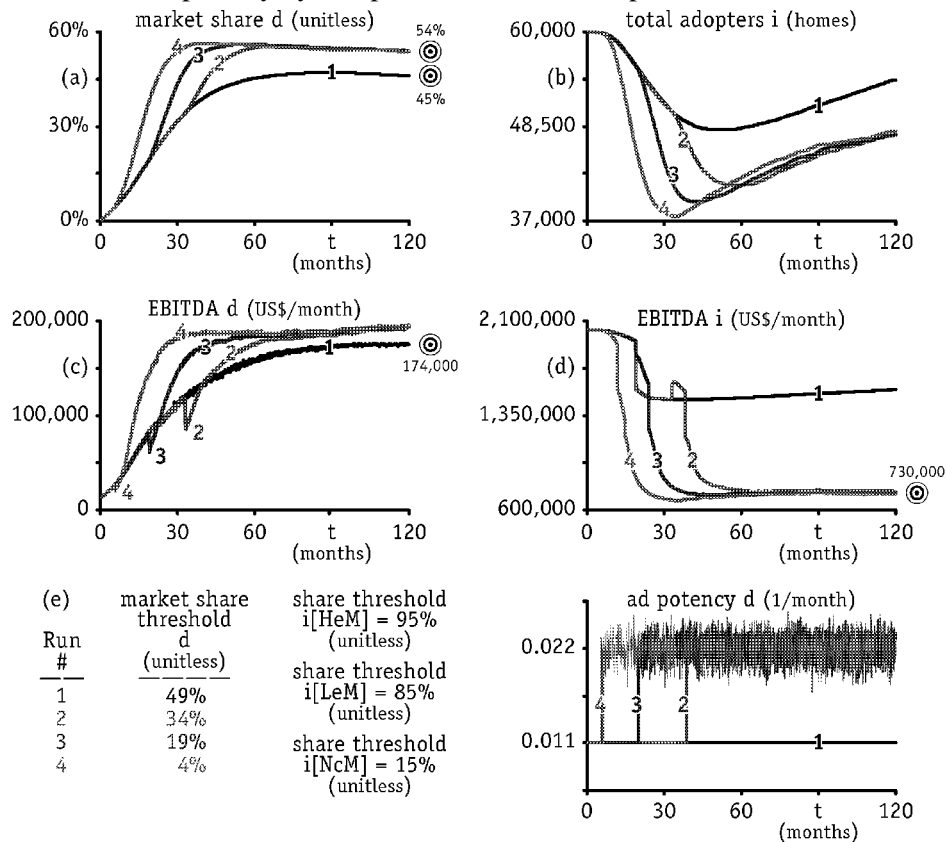
Figure 15 Performance and price responses to the disrupter (*d*) market share threshold *d* for its up-market run in the high-end market (HeM) and low-end market (LeM), with the incumbent (*i*) retaliation share thresholds *i* in the HeM, LeM and non-consumption market (NcM) fixed at 95, 85 and 15 percent, respectively



Specifically, Fig. 16e shows the scenarios under which, when the disrupter (*d*) firm runs up market, it allocates 10 percent of its sales revenue *d* to doubling its ad potency *d*. The tradeoff is clear: under three different market share threshold *d* percentages, trading off 10 percent of revenue consistently buys *d* nine percentage point of market share (Fig. 16a). And the higher market share *d* translates into more total adopters *d* but less total adopters *i* for the incumbent (*i*) firm (Fig. 16b).

In response to the abrupt change in *d*'s resource allocation policy, its EBITDA *d* drops immediately, but recovers quickly and continues to rise as the disrupter firm recruits more adopters (runs #2-#4, Fig. 16c). Again, EBITDA *d* might level off when *d* does *not* run up market (run #1, Fig. 16c), letting EBITDA *i* to continue growing at the net SBA growth rate (run #1, Fig. 16d). Yet, combined with *d*'s aggressive strengthening of its market share foothold among non-consumers and established cable service subscribers, its up-market run might now further suppress the incumbent firm's EBITDA *i*, forcing it to level off at a rate lower than before (runs #2-#4, Fig. 15c).

Figure 16 Performance responses to the disrupter (d) market share threshold d for its up-market run in the high-end (HeM) and low-end (LeM) markets, with a 10 percent revenue d allocation that increases its ad potency by 100 percent when d runs up market



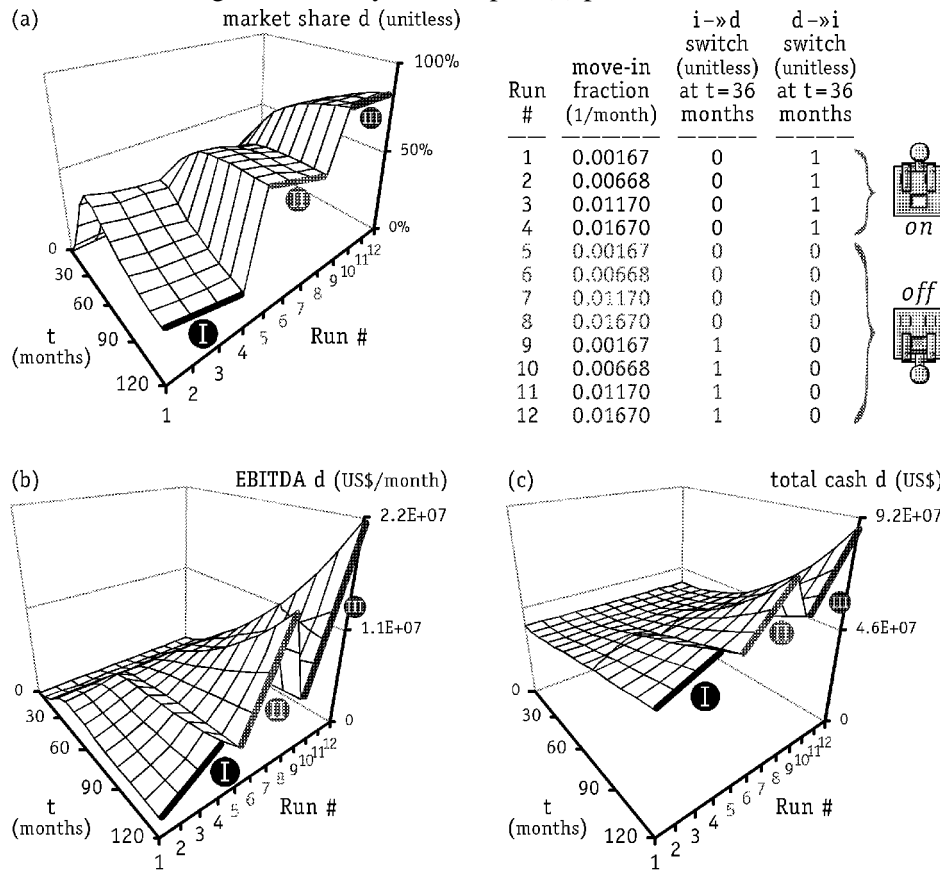
The added variance in the disrupter firm's ad potency d (Fig. 16e) does not seem to affect either contender's performance much. But it is a useful reminder to all concerned that all parameters in Bass' diffusion model components are merely averages that can vary randomly in a specific firm's situation, be it a disrupter (d) or an incumbent (i) one.

Combined effects of SBA growth and customer switching discontinuity on performance

A drastic change in customer preferences or taste might prevent changes in the disrupter firm's internal policy levers from altering its performance in a predetermined fashion. The 12 scenarios computed on Fig. 17 show how a set of external-change triggers might fire concurrently to affect d , $Inc.$'s performance together. Three distinct performance regions might emerge, for example, if, while the SBA grows at rates commensurate with its exogenous move-in fraction parameter (legend, Fig. 17), customer switching were to end abruptly after three years ($t = 36$ months), either from the incumbent (i) to the disrupter (d) firm ($i \rightarrow d$) or from d to i ($d \rightarrow i$) or both.

The region I performance results work against the disrupter and in favor of the incumbent firm. Namely d 's performance becomes compromised in terms of all three, now shown in 3D, performance metrics on Fig. 17: (a) market share d , (b) EBITDA d and (c) total cash d . Region II on Fig. 17a again shows the rather stable equilibrium of 50 percent market share d , which has been showing up persistently under a sea of external-change trigger and internal-change lever scenarios. This performance region (II) results from continued SBA growth combined with customer switching that ends abruptly at $t = 36$ months both from i to d and from d to i .

Figure 17 Combined effects of strategic business area (SBA) household population growth and customer switching discontinuity on disrupter (d) performance



The four scenarios (runs #5–#8) that yield the region II performance levels are equally likely to play with the rest of the scenarios on Fig. 17. They are not any more likely to play than the rest are just because region II happens to be the middle. But it is region III that would be the best news for *d, Inc.*, at least for its market share *d* performance, if scenarios #9 through #12 were to play. A drastic change in customer preferences or taste for the technological innovation behind the over the air digital subscription TV service that *d, Inc.* offers might stop the $d \rightarrow i$ customer switching and speed up the $i \rightarrow d$ one, making the last four scenarios play.

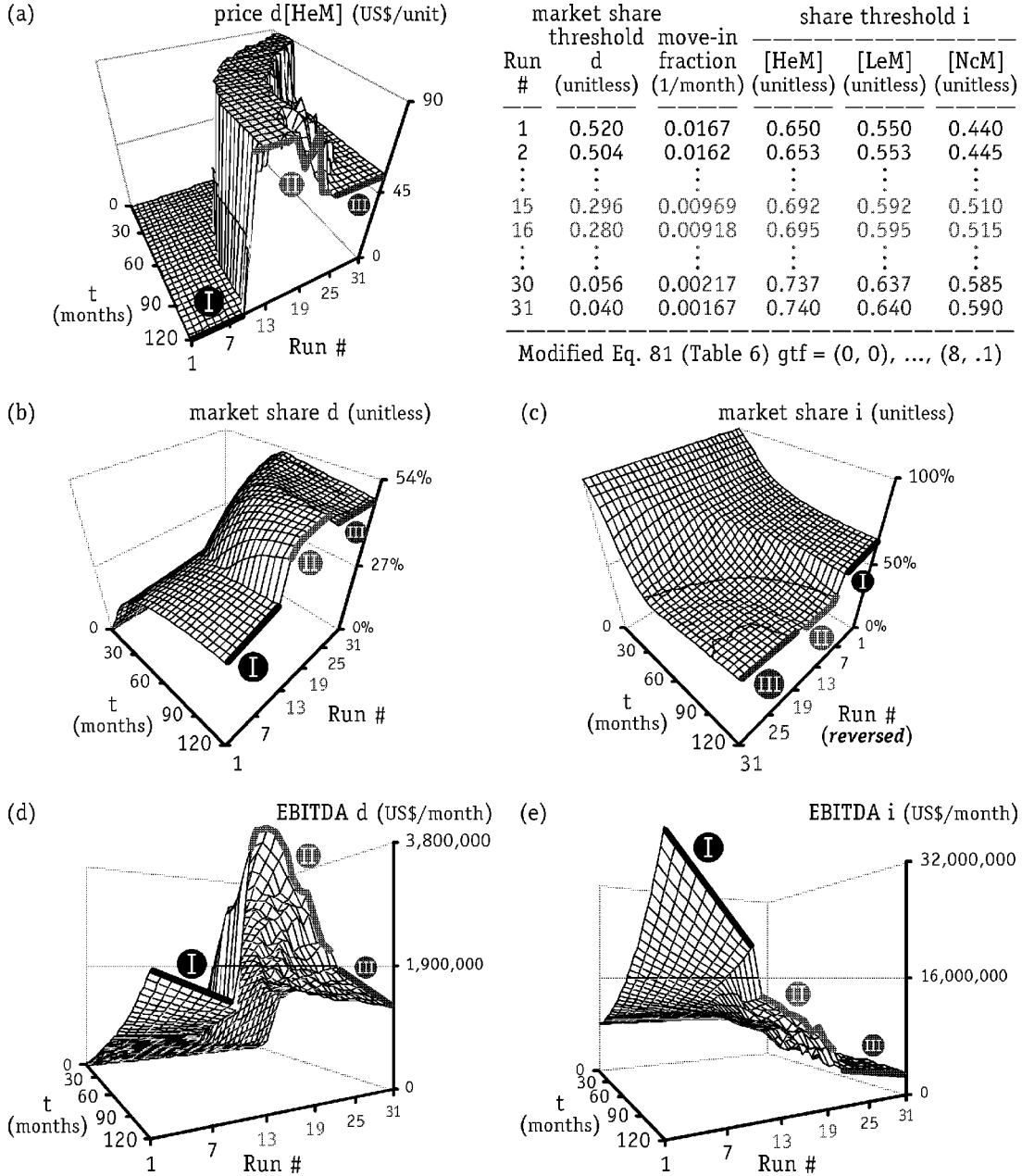
Combined effects of SBA decline and adverse share thresholds on performance

But what if instead of net SBA growth and abrupt customer switching discontinuities net SBA growth were to decrease, forcing the disrupter (*d*) firm to drop its up-market run market share threshold *d* and, conversely, the incumbent (*i*) firm to increase its retaliation share threshold *i*? With a minor adjustment to the six graphical table functions (*gtfs*) of Eq. 81 on Table 6, Fig. 18 shows the combined effects of gradually decreasing the up-market run market share threshold *d* and SBA move-in fraction, and increasing the retaliation share threshold *i* on performance.

The vertical climb of price $d[\text{HeM}]$ from zero to US\$90 per unit on Fig. 18a shows *d*'s up-market march. Following this sharp discontinuity is a brief period of retaliation-free up-market penetration, during which *d* maintains its newly set price constant in the high-end market. As net SBA growth declines because of the gradually decreasing move-in fraction parameter, *d*'s up-market march causes market share *d* performance to move from region I to region II on Fig. 18b. The sharp discontinuity also makes market share *i* jump to a new level. So, *d*'s up-market march pushes *i*'s market share performance into a new basin of attraction lower than before, from region I to region II on Fig. 18c (reversing the run # dimension

helps make the new basin of attraction visible). *d. Inc.* also enjoys a sharp increase in profit (EBITDA *d*), which shoots up vertically from region I to region II on Fig. 18d, while *i*'s profit (EBITDA *i*) drops even lower than before, from its previous declining region I trend to region II on Fig. 18e.

Figure 18 Combined effects of market share threshold *d* decline, SBA decline and retaliation share threshold *i* growth on *d*'s and *i*'s performance, with Eq. 81 on Table 6 modified



But *d*'s retaliation-free up-market penetration cannot last forever. The three retaliation share threshold *i* parameters gradually increase along with the also gradually but declining SBA move-in fraction (top right, Fig. 18). The incumbent (*i*) firm retaliates in each market as soon as its segment share *i* drops below its share threshold *i* on the top left of Fig. 8 (Eqs 95–102, Table 6). So, using its umbrella-pricing scheme, *i* retaliates by dropping its prices to 20 percent above *d*'s prices. In response, *d* begins passing on learning-curve savings to its customers, causing *i* to start discounting as well. The price wars that ensue cause the right half of region II to show instability transients just before price *d*[HeM] settles in

its new equilibrium of region III on Fig. 18a. Even if somewhat tamed, the same instability transients also show up in the two contenders' market share performance (Fig. 18b and Fig. 18c, respectively), and again become prominent on the right half of region II on the EBITDA *d* and EBITDA *i* response surfaces (lower panel, Fig. 18).

Discussion

An exploratory SD model has presented disruptive innovation diffusion as a replicable process that can create and sustain successful business growth for *d, Inc.* - an over the air digital subscription TV service. Drawing upon diffusion theories from economics, epidemiology, marketing and sociology, the eight-sector SD model incorporates customer switching (Garcia Mariñoso 2001, Klemperer 1987, Nilssen 1992, Oliva *et al* 2003) in the high- (HeM) and low-end (LeM) and non-consumption (NcM) markets, which disruptive innovators typically exploit. Following a brief overview of the client firm's current strategic situation, the article briefly reviewed the disruptive innovation literature. Then the model description preceded the computed scenarios (i.e., simulation results) section, with multiple conclusions and insights for practice and suggestions for further research.

Overall, system dynamics is well suited for disruptive innovation diffusion modeling and policy design because the process entails multiple chains of stocks and flows, with extended time horizons. And the decision rules governing the flows create multiple feedback loops among stakeholder groups' actions, including those of competitive tactics. Extreme condition scenarios test model robustness and shows performance results while the two contenders, *d* and *i*, execute multiple tactics of market penetration and defense through time. In a relentless hunt for superior performance and a sea of external-change triggers and internal-change levers, *d, Inc.* takes on *i*, a cable operator firm that overlooks non-consumption and low-end markets and devotes its attention and invests in higher-end tiers, with innovations tailored to address the needs of demanding customers. But low-end segments cannot absorb sustaining performance improvements that exceed the range of utility they need or know how to exploit. The results show that despite the high environmental turbulence and market risk and uncertainty that *d, Inc.* faces, being in a market that blends commercial and technological competence discontinuity suggests ample opportunity for sustainable disruptive growth.

Suggestions for further research

It is impossible to show all the results the current model can generate in a single article. Some parameters are left unexplored, such as elasticity (Eq. 67, Table 6). But one interesting variant to the model presented here might entail adding outflows to drain potential customers who become disinterested from the potential adopter and switcher stocks in both the markets and the switch contemplation sectors, respectively. But that would mean making a modification to Bass' diffusion model even more radical than the structural changes the current model contains.

Another possibly useful extension to the model's tactics sector (Fig. 8) might entail adding more up-market run and retaliation thresholds for both the disrupter (*d*) and the incumbent (*i*) firms. But in addition to using the current model's financial accounting metrics, such as profit (EBITDA) and total cash, to make it so, one might integrate entirely new sectors pertaining to the technology investment and R&D (research and development) processes.

Extending the model along these lines might require linking Bass' diffusion model to the resource-based view of the firm (Foss, 1997). Warren's (1997) resource dynamics models give some valuable clues concerning such linkages.

Implications for practice

The results show how *d, Inc.*'s disruptive innovation diffusion might be an inevitable consequence of its stock and flow structure. But most academics and practitioners persistently see demand forecast

inaccuracy as the most prominent cause of low performance in customer-supplier value chains and markets. Indeed, forecasting has become quite sophisticated in carrying out extrapolations of past trends. Graphically extrapolating a curve, however, does not render the future more predictable in business or other economico-socio-political environments. In their comprehensive treatment of Delphi, for example, Linstone & Turoff (1975) find most forecasting techniques unsatisfactory both in substance and method. Ackoff (1981) concurs and describes three conditions under which:

perfectly accurate forecasts could be obtained. First, if a system and its environment did not and could not change, and we knew its state at any one moment of time, then, of course, we would know its state at any other moment of time, including the future. Clearly, these conditions do not exist, but even if they did, preparation would not be possible because it requires change. Second, perfectly accurate forecasts would be possible if a system and its environment were, or were part of, a deterministic system. If the future of a system that could be so predicted were determined, it would not be subject to change. Preparation presupposes choice but determinism presupposes a lack of it. Third, we would be able to predict the future perfectly if we were omnipotent (Ackoff 1981: 59-60).

Even the popular Delphi, which entails revising prior probabilities about the future as tangible evidence of changes in business becomes available, is more of a consensus-building rather than a forecasting technique. And Hax and Majluf (1984) warn managers against bounding strategic situations by making a pseudoscience out of the art of consensus building.

Similarly, Farmer (1973) emphasizes the shortcomings of forecasting changes in the business environment. After examining forecasts published in *Fortune* from 1933 to 1950, Farmer concludes that even the most radical forecasts were too conservative when compared with actual business trends.

Such flaws have prodded major firms to dissolve archetypal economic and econometric forecasting departments, Citibank, Compaq, Dell, GE, even IBM, included. While the cost of forecasting skyrocketed, its precision and reliability either stagnated or declined. The ever-decreasing sample size of the corporate market is amply responsible. It is easy to predict the behavior of statistically large mass markets through time, but with rapidly narrowing market niches, small groups and individual customers, prediction becomes hard. Forecasters can predict what ten thousand people will do, but not what one person might do (Zeleny 1997).

“Markets do not buy anything, individuals do” warns Tom Peters. What matters most is what individual households do, not what they say they will or would do on assorted polls or consumer market surveys. Household members of each strategic business area *d, Inc.* penetrates have complete freedom to do as they please and to say as they please. They do not have to do what they say or say what they do. They can change their minds, preferences and reasoning as many times as they want and do not have to explain it. They do not have to be transitive or consistent in their preferences. Disruptive innovators that rely on forecasting face a nasty dilemma. In the short run, they can forecast but cannot act. In the long run, they can act but cannot forecast.

Bound by their disruptive innovation diffusion processes, resources and core competencies, in the short term, managers might feel as if they are sitting on their hands. They cannot act. The long term unties their hands. Now they can act. They have the time they need to change their processes, resources and core competencies... but in what direction? Long-term forecasts are always wrong!

SD models do not forecast what *will* happen by extrapolating historical trends, but generate forward-looking performance scenarios, computed from system structure, about what *might* happen through time. The stock and flow diagram of a system captures its fundamental feedback loops and allows for parameter changes or alterations in the structure of causal relations to reflect shifts in conditions external and internal to the system in question. A coherent modeling method, SD provides both flexibility and speed in accommodating internal and external change and in capturing the impact of change in structure-driven multi-path performance scenarios. SD is *not* a crystal ball. But given a reasonable and

adjustable set of assumptions, the SD modeling process vastly improves managers' ability to anticipate performance as a behavior pattern through time.

SD often reveals counterintuitive aspects of performance through time that may provide critical insight with respect to strategic planning, but which remain hidden under approaches less sensitive to system dynamics. This article's model, for example, reveals an inverse relationship between SBA growth and market share *d*, i.e., higher net SBA growth (the result of a higher move-in fraction) leads to lower market share for *d*, *Inc.* (Fig. 12j). Both before and more so after *i* retaliates, *d* is at a disadvantage relative to *i* with respect to the percentage of net SBA growth *d* can capture. Market share for *i* exceeds market share for *d*, at least initially. Furthermore, *i*'s appeal improves substantially following retaliation. Both market share and each contender's appeal are vital inputs in determining lock-in rates for *i* and *d*. A larger share of net SBA growth goes into Potential Adopters *i* and then the reinforcing word-of-mouth feedback takes over to amplify the effect by adding to Adopters *i* at a faster rate relative to the adoption rate *d*.

Reinforcing feedback amplification tends to be less pronounced for lower move-in fraction values, i.e., lower net SBA growth, which explains why at such rates *d* stands on a more equal footing with *i* and even slightly exceeds *i*'s market share under the lowest growth scenario (run #1, Fig. 12j). Market share performance for *d* through time in run #1 can be explained by taking into account not only a weaker amplification effect associated with less benefit accruing to *i* but also by the fact that lower net SBA growth means *i*'s retaliation thresholds will take longer to reach, i.e., *d* is free from the balancing feedback impact of retaliation for a slightly longer time compared to runs #2–#4 (sa Fig. 12d). Despite this counterintuitive finding, linking lower net household growth to higher market share for *d*, the model also reveals that a higher market share time path is also less profitable. Higher net SBA growth in runs #2–#4 results in lower market share for *d* as *i* captured most of the growth due to the amplification effect. However, runs #2–#4 also imply faster adopter growth in real terms within higher-margin segments generating higher EBITDA for both *d* and *i*. This finding supports the argument Christensen and Raynor (2003) make in favor of pursuing profitability over market share growth in order to maintain momentum as a disruptive innovation enterprise moves up market.

Another unexpected finding reveals that, as long as the chosen SBA is growing, the timing of *i*'s retaliation has a little effect if any on *d*'s market share performance through time (Fig. 13a). Four simulation runs exploring sensitivity to variation in segment share thresholds show no change in the pattern of market share growth regardless of the pace of *d*'s market penetration. Market share for *d* follows an identical trajectory and reaches the 50 percent equilibrium by month 90 in each of the four runs. The implications for *d*'s growth strategy cannot be overstated. A major concern in the development of an effective growth strategy has to do with identifying an ideal pace of growth in view of the impact of competitive retaliation and *d*'s ability to respond appropriately. The model shows that regardless of the pace of growth within the range covered by simulation runs #1–#4, *d*'s market share performance remains stable. Looking at financial performance, in terms of EBITDA *i* and total cash *i*, as retaliation threshold *i* varies, reveals that despite the stability in market share *d*, *i* would be motivated to wait before retaliating until *d* has achieved significant market penetration (run #4, Fig. 13f and g). Lower retaliation thresholds might lessen the decline in *i*'s EBITDA per month and increase its total cash. On the other hand, concerns around triggering retaliation, as the model demonstrates, might be exaggerated and should not lead *d* into a mode of deliberate growth control.

Attempting to understand the triggers and impact of competitive retaliation carries implications for timing *d*'s up-market march. Simulation runs for four different market share threshold values reveal that *d* can expand its market penetration and profitability by going up-market as soon as resources, infrastructure and capabilities are in place. Setting the up-market march threshold in terms of total market share too high results in *d* falling short of reaching its own threshold and missing the opportunity to move up market (run #1, Fig. 15). Despite remaining locked out of the high-end market (HeM), this scenario affords healthy market share *d* growth toward the 45 percent equilibrium on Fig. 15a. But market penetration does improve under each consecutive run as the up-market run threshold drops. The results

show that market penetration from achievable market share thresholds in runs #2–#4 coalesce into a 50 percent equilibrium by month 90—a result equivalent to simulation runs of varied move-in fraction and retaliation thresholds. Despite the long-term difference of only 5 percent between the two market share equilibria, the profitability potential is much greater. The amount of EBITDA per month *d* might forgo if it fails to go up market renders the very thought of not doing so unattractive. On the other hand, the EBITDA *d* results under scenario #4 might encourage *d* to embark on an up-market march as early as possible. Moving up market early enables *d* to capture the benefits of establishing a strong presence in higher-margin subscriber segments without sacrificing volume-driven growth.

Instead of getting fixated on avoiding or delaying *i*'s retaliation, *d, Inc.* might do better by taking steps toward improving its ad effectiveness. The results show that *d*'s market share and financial performance exhibit heightened sensitivity to more favorable ad potency in combination with a growing contact rate (Fig. 14a, c and d). There is little *d* could do to change subscribers' contact rate, an exogenous parameter beyond *d*'s control. But to the extent market share gains are determined by higher ad potency, greater investments in sales and marketing could go a long way toward strengthening *d*'s market presence. An early up-market march combined with a 10 percent of revenue reinvestment in improving ad potency (Fig. 16e) leads to improved market share (Fig. 16a), but at the expense of profitability, such that market share gains are more than offset by the drop in EBITDA *d* (Fig. 16c). In comparing Fig. 15b and Fig. 16c, results imply that investments in sales and marketing are necessary but must be balanced against *d*'s profit objectives.

The results on Fig. 18 show that the system may be seen as exhibiting tendencies toward bifurcation, i.e., gradual parameter changes cause the system to predictably fall out of one equilibrium state only to stabilize into a new dynamic equilibrium which it then maintains for some time. Although in our case the shifts to new dynamic equilibrium states are structurally determined by upmarket march thresholds and retaliation triggers, we may speculate that the complex adaptive system of cable industry competitive dynamics would be prone to bifurcation. One might even conclude that disruption stimulates evolution by pushing mature industries out of a rigid, ordered state that compromises adaptability.

Ordered systems are less sensitive to changing conditions and are therefore slower to react and adapt. We can speculate that disruptive innovation exploits and begins to fill newly opened niches within a system which is moving up a local fitness peak or basin of attraction toward continual optimization driven by sustaining innovation. Optimization is the opposite of radical innovation. A system that evolves in the direction of optimization might well find itself unable to move out of certain areas of its fitness landscape, which severely limits its growth and evolutionary potential. Disruptive innovation may be seen as serving to disturb equilibrium and push the system off the fitness peak it's climbing and into a search for new basins of attraction (Pascale *et al* 2000). By creating such discontinuities, disruptive innovation can push an industry beyond ordered states into a phase transition space where it might move to new fitness peaks and evolve toward greater complexity at a faster rate. Such a "poised system" would have maximum evolutionary potential (Kauffman 1995).

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