

Co-evolution of demand and supply under competition

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Co-Evolution of Demand and Supply under Competition

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In this paper, we derive strategies to enforce dominance in a business-to-consumer market with heterogeneous, competing products, while the market segmentation evolves through interaction of demand and supply. By using evolutionary economic notions, we extend operations management studies on manufacturing facing demand diffusion. We arrive at a synthesis of a Forrester delay manufacturing model and a technology substitution-diffusion model and show that the actual operationalization of product attractiveness, reflecting what consumers deem important, as well as the responsiveness of production capacity scaling greatly determine the market dynamics and asymptotic outcome.

We obtain analytic results on absolute dominance in case of the constant inherent attractiveness of products, say technical performance, and numerical results on instability and quasi-stability in case of more encompassing definitions of attractiveness involving price and service level.

We conclude, in general, that in establishing market dominance, firms should focus on timely entry to capture first-buyers, high responsiveness and predatory pricing. Scale advantages and resilience through responsiveness are essential in obtaining and subsequently retaining the market share when other firms already provide or are about to enter with technically superior products. We also hint on how to extend our model to study several other issues on industry dynamics.

Key words: Co-Evolution, Substitution-Diffusion, Manufacturing Strategy, Market Segmentation, Attractiveness, Responsiveness

1. Introduction

In this paper, we derive strategies for a firm to establish dominance of its product if the market segmentation develops through co-evolution of demand and supply under competition. Demand is induced by a substitution-diffusion process reflecting competition of firms for consumers based on product attractiveness. Supply levels depend on the production capacity, which is scaled in response to demand signals. Especially during the early stages of the product life-cycle, production scaling is conservative due to the market uncertainty. Service levels then affect substitution and thereby demand fluxes, which in turn affect future production targets.

We hereby depart from manufacturing strategy models that assume stationary demand or a micro-level perspective, and rather jump on the bandwagon of incorporating elements of evolutionary economics into business strategy models (Gavetti and Levinthal 2004). In this, we follow several others that have recently enriched manufacturing strategy models with diffusion (Ho et al. 2002, Kumar and Swaminathan 2003, Sterman et al. 2007).

In spite of its merits of analytical convenience, we drop the stationary demand assumption to do justice to, in particular, the demand dynamics in early phases of the product life-cycle, which is in part attributed to social diffusion processes. In the aggregate marketing model of diffusion by Bass (1969), there is non-linear, self-reinforced development of the market saturation. However, the Bass model does not feature supply-side factors but accounts for them (implicitly) in parameter estimates. Economic analysis has long indicated that supply factors strongly affect diffusion (Stoneman and Ireland 1983). If supply conditions change endogenously, these factors should be accounted for explicitly. Many studies have extended the Bass model with factors like price and advertising (for an overview, see Bass et al. 1994). Jain et al. (1991) introduce a term in the Bass

model for how much actually is supplied and then study the effect of the service level through (positive and negative) word-of-mouth on market saturation development.

Recent excursions from operations management into diffusion-driven demand follow Jain et al. (1991) and (implicitly) interpret the Bass model as a micro-level model in which a monopolistic supplier can completely stall diffusion. Ho et al. (2002) and Kumar and Swaminathan (2003) derive a strategy for production and product launch when the production is capacitated. They find that a 'delayed roll-out' strategy is preferred to a myopic, reactive strategy if inventory holding costs are relatively low compared to lost sales costs. The additional stock thus build up is then used to meet demand during the diffusion peak that would otherwise be lost sales.

We take two notions from evolutionary economics to relax (implicit) assumptions in these supply-constrained diffusion models. The first extension hinges on the notion that firms face technological and market uncertainty, especially during the early phases of the product life-cycle. Firms then do not follow a contrived, let alone optimal and rational production schedule -for which perfect foresight and instantaneous capacity adjustment is needed (Sterman et al. 2007)-, but rather adjust production capacity to demand figures gradually. This is due to both organizational inertia, as well as reluctance to engage in costly production scaling in absence of clear market signals. An obvious place to look for a responsive production scaling model is the bullwhip effect literature, as this body has response of a firm to demand pulses at its very core (See Lee et al. 1997, Sterman 1989). We adopt a model with roots in Forrester (1961) in which the production level P is scaled to the (desired) production level W with a delay T (c.f. Warburton 2004, Sterman 2000, Helbing et al. 2004, Nagatani and Helbing 2004):

$$\frac{dP}{dt} = \frac{W - P}{T}$$

The production level P determines how much of the demand actually is fulfilled, how much ends up as backorder and how much will end up as inventory. This Forrester delay capacity scaling heuristic reflects the boundedly rational and myopic routines of a firm (Nelson and Winter 1982, Simon 1955).

The second extension concerns acknowledging the likely presence of competing products, all subject to the same selective market pressures. In reality, consumers are likely to substitute one product for another if the product of first choice is not available soon enough, especially in case of consumables. The postponed product roll-out in Ho et al. (2002) and Kumar and Swaminathan (2003) is likely to result in a competitor filling the gap in demand, thereby offsetting diffusion of this competing product. In assuming this, we rely no more on substitutability than do these authors in arguing for presence of lost sales. This also further bolsters our first extension, as presence of competitors considerably clouds market projections. So, we abandon the implicit monopoly in these models for a competitive market model in which multiple firms compete with distinct products. We argue that, with low entry barriers, economic forces assure supply capacity and thereby an aggregate saturation dynamics that conforms the Bass diffusion curve.

A model that features endogenous development of market shares (from which we can derive instantaneous demand) and multiple, competing heterogeneous technologies is the substitution-diffusion model (Peterka 1978, Marchetti and Nakicenovic 1979, Fisher and Pry 1971). Peterka's formula (4.16) captures the development of the market share of product i driven by substitution of one technology for or by other technologies purely based on their costs:

$$\frac{df_i}{dt} = \frac{1}{\gamma} f_i \left(\sum_j c_j f_j - c_i \right) \quad (1)$$

This is also known as an Eigen (1971) replicator equation. In this equation, f_i is the market share of technology i , and coefficient γ an aggregate diffusion-substitution rate. We see that if the individual

costs c_i of a technology i exceed (are below) the industry average costs $\sum_j c_j f_j$, its market share declines (increases). If the c_i coefficients are time-invariant, this system does have a closed-form solution (see Peterka 1978, p.25), but upon slight extensions or introducing time-dependence, one has to resort to numerical solutions. Here, this model is reformulated to revolve around a conceptually encompassing 'product attractiveness', such that if a product is more attractive than average, its market share increases. As such, the Peterka model renders a concentrated market with a single dominant product, which seems to comply with notions of effects of Schumpeterian competition (Nelson and Winter 1982). However, both evolutionary economic (e.g. Windrum and Birchenhall 1998) and neoclassical economics-minded operations management (e.g. Xia et al. 2008) models have shown that stable segmentation is well possible. We will see that factors that consumers deem important like price and availability play a prominent role in the formation of long-lasting unstable or quasi-stable segmentations.

In Serman et al. (2007), we found kindred spirits in introducing evolutionary economic principles in manufacturing models with diffusion. These authors provide a conceptually rich model on oligopolistic competition of firms that provide a homogeneous product and divide the share of demand according to a formula weighing availability and price. They resort to simulations and show that firms scaling aggressively based on demand forecasts are likely to end up with excess capacity. As a consequence, the aptly called 'get big fast'-strategy, particularly appealing under increasing returns to scale, need not be optimal if capacity is expensive.

The main contribution of this paper is the synthesis of evolutionary economic principles regarding the behavior of firms and consumers and operations management principles regarding capacity scaling responsiveness. We add competition on heterogeneous products and manufacturing capabilities to the supply-constrained diffusion models. To the best of our knowledge, we are the first to use the substitution-diffusion model in an operations management setting. The substitution-diffusion model is used in studying economic structural change (e.g. Silverberg et al. 1988, Metcalfe 1988), but the marketing literature and the operations management literature concerned with demand development is dominated by flavors of the Bass model.

Upon adopting evolutionary economic principles, we have to contend with understanding phenomena and deriving qualitative manufacturing strategies from that rather than deriving quantitative optimal scaling or launching policies as is customary in operations research. However, by appreciative theorizing, we nonetheless provide strategies to establish dominance. Seemingly in contrast with Serman et al. (2007), the analytical and numerical results translate to recommendations on entering early on in the onset phase, aggressive scaling and predatory pricing, either to compensate for inferior technical performance or to preemptively appropriate market share in anticipation of entrants.

The structure of the paper is as follows. In section 2, we formulate a concise mathematical model for the co-evolution of demand generated by substitution-diffusion and supply for which production capacity is tuned reactively to meet demand. We investigate the effect of (constant) product attractiveness on the development of market segmentation over time, thereby controlling for the responsiveness of firms in adjusting production capacity. In section 3, we study dynamics in some numerical examples with extended operational definitions for product attractiveness (which is then no longer constant, but dependent on scale of production or backlogs) and see that both quasi-stable and unstable segmentations emerge. In section 4, we provide conclusions, insights and strategy recommendations, and a range of ideas for further research.

2. Model and Basic Dynamics

We model a business-to-consumer market with product replacement. There are M firms, where firm i produces a distinct product i . The N consumers order a product by comparing the attractiveness of the M products on offer. We assume universal consumer preferences (no a priori segmentation).

Firms hence compete on what consumers deem important (performance, price, service). We assume that there is an intrinsic attractiveness of a product i in the form of a unique technical performance $\alpha_i \geq 0$. We take α_i to be constant, so we refrain from incorporating product innovation (which is reasonable in case of consumables). In this section, we investigate the dynamics and asymptotic outcome if consumers only care about technical performance. In section 3, we study more involved and (non-constant) 'product attractiveness' operationalizations accounting for scale-sensitive price and service level. Despite our evolutionary economic outlook in supplier behavior, we limit supply market conditions to features reflecting in product attractiveness.

In terms of substitutability (related to patience, importance of availability and costs of switching), innovation and technological complexity (a single, constant technical performance characteristic) and properties of the manufacturing system (mass production rather than job shop), the products we deal with are more like consumables than like durables.

The developments in the industry are driven by two processes. The first process concerns consumers placing new orders and canceling backorders to order another product. Each period t , a fraction $0 < \rho < 1$ of the X_j consumers of product j wears out its unit of product j and a fraction σ_{ji} orders a unit of product i , while a fraction σ_{ji} of the B_j consumers backlogged (those that were not supplied in previous periods) decides to cancel the outstanding order for product j and instead order some other product $i \neq j$. The demand for product i at time t hence becomes:

$$d_i = \sum_j \rho X_j \sigma_{ji} + \sum_{j \neq i} B_j \sigma_{ji} \quad (2)$$

We omit the period reference t where confusion is unlikely.

The second process concerns the scaling of production capacity to demand and the final supply of the products. At the end of a period, the firms produce and supply a quantity s_i . At the beginning of the next period, the number of consumers X_i then increases with the number s_i of units supplied and decreases with all consumers that disposed their unit last period:

$$\Delta X_i = s_i - \rho \sum_j X_i \sigma_{ij} = s_i - \rho X_i \quad (3)$$

We assume that $\sigma_{ii} = 1 - \sum_{j \neq i} \sigma_{ij}$. We refer to X_i as the market share of i . We write $\Delta W = v$ for $W(t+1) = W(t) + v(t)$. Furthermore, also at the beginning of the next period, the number of backorders B_i increases with the number $d_i - s_i$ of orders that have not been met and decreases with the consumers that impatiently canceled their backorder just to order another product:

$$\Delta B_i = (d_i - s_i) - \sum_{j \neq i} B_i \sigma_{ij} \quad (4)$$

We assume that the rate at which backlogged consumers become impatient is higher than the replacement rate ρ . We take, without loss of generality, the impatience rate to be 1, such that a fraction $(1 - \sigma_{ii})$ of backlogged consumers cancels its order each period.

We assume a make-to-order policy in which, at the end of period t , firm i produces a quantity s_i which is ample s_i^a at best (so there is no inventory build-up) and cannot exceed the current capacity c_i :

$$s_i = \min\{c_i, s_i^a\} \quad \text{with} \quad s_i^a := B_i + d_i - B_i \sum_{j \neq i} \sigma_{ij} = B_i \sigma_{ii} + d_i = \sum_j (\rho X_j + B_j) \quad (5)$$

All demand and backorders in the current period not being met at this level of supply become backorders in the next period.

The production capacity c_i is adjusted heuristically to the desired production level $d_i + \xi_i B_i$ with

a Forrester delay ϕ_i . At the beginning of a new period, the production capacity c_i is adjusted to facilitate supply levels that meet demand and backlogs observed last period:

$$c_i(t+1) = s_i(t) + \frac{(d_i(t) + \xi_i B_i(t)) - s_i(t)}{\phi_i} \quad (6)$$

The Forrester delay $\phi_i \geq 1$ reflects that production capacity adjustments occur gradually. The scaling is purely reactive reflecting the need to have clear demand signals in times of market uncertainty. The higher ϕ , the slower the capacity adjustments are implemented. The backlog consideration rate $0 \leq \xi_i \leq 1$ governs the response to the existence of backorders. Both ϕ and ξ reflect the underlying scaling cost structure as well as managerial prudence in attuning to demand signals. The level of ξ reflects implicit assumptions about how the firm balances lost sales due to impatient backorders being canceled, especially during diffusion peaks, and having to install additional capacity to prevent these lost sales while this might be unused in the future.

Any discrepancy between the current sales level and the actually required production level is fed forward into the level of production in the next period.

Only when demand drops (very) steeply, the prudent capacity adjustment heuristic (6) does not downscale production capacity fast enough, causing the ample production constraint to hold.

The switching rate σ_{ji} plays a pivotal role in the dynamics and is defined as:

$$\sigma_{ji} = \eta X_i (\alpha_i - \alpha_j)^+ \quad (7)$$

With $(a)^+ = \max\{a, 0\}$. In the basic model, the unique $\alpha_i > 0$ forms the attractiveness of product i . We hence assume that all consumers find the same product equally attractive. There is no a priori segmentation. The normalization constant is $\eta = 1/N$. Due to the X_i term, demand for product i is self-reinforcing by means of word-of-mouth. The $(\alpha_i - \alpha_j)^+$ term reflects the fact that the *net* flux between product i and j is positively directed toward product i if α_i is higher than α_j .

Clearly, these two processes interlock whereby demand and supply co-evolve. Since supply s_i is constrained by capacity c_i , while capacity is scaled to demand d_i and backorders B_i with a certain responsiveness $1/\phi_i$ and backlog consideration ξ , we see that supply follows changes in demand. Demand d_i in turn is strongly affected by word-of-mouth of X_i current consumers. On the other hand, if capacity is insufficient to meet demand, orders are backlogged but these might get lost due to impatience. The supply service level hence drives product substitution and future demand, whereby firms compete on product attractiveness as well as supply process characteristics.

2.1. Basic dynamics

Let us elaborate on the basic properties and dynamics of the model. We predominantly focus on asymptotic segmentation outcomes and we answer the question whether the technically superior product can be beaten by competitors with technically inferior products by employing different scaling heuristics.

In the analysis of this model, we use the convenient properties that the system is closed with respect to the number of consumers ($N = \sum_i \{X_i(t) + B_i(t)\}$ for all t) and has defined upper- and lower-bounds ($0 \leq X_i(t) \leq N$ and $0 \leq B_i(t) \leq N$). The proofs are straight-forward. To exclude trivial cases, we assume that any product i has $X_i(t_i) + B_i(t_i) > 0$ upon introduction $t_i \geq 0$. It is easy to show that if $X_i(t) + B_i(t) = 0$, $X_i(\tau) + B_i(\tau) = 0$ for all $\tau > t$.

The first lemma tells us that results are well-known for our model under ample supply.

LEMMA 1. *Under ample supply from period t onward, the system behaves like a Peterka replicator dynamics system from $t+1$ onward.*

Proof. If supply is ample from period t onward, there are no backorders from $t+1$ onward. After substituting $s_i = d_i = \rho \sum_j X_j \sigma_{ji}$, algebra reveals equivalence of equations (3) and (1). \square

In such a replicator dynamic system (with non-trivial settings), the dynamics and asymptotic outcome are known. Shares inevitably converge to a situation in which the most attractive product is absolutely dominant with market share $X_i = N$, no matter how small (but non-zero) the difference in attractiveness values (c.f. Peterka 1978).

However, in early phases of the industry, when there is high market uncertainty, production scaling is expected to be responsive to clear demand signals, so supply generally is less than ample. What dynamics and emerging segmentation are we to expect now?

We now provide definitions and a lemma to eventually prove a theorem that this most attractive product eventually emerges as absolutely dominant. Essentially, supply restricts fundamental developments driven by the switching rates σ . Although we conceptually regard the switching rate as the *net* flux (there might still be consumers going back to a less attractive product, but this is just less than going the other way), we can and do treat it formally as if consumers only switch from the less to the more attractive product. As a consequence, the switching rates are non-circularly oriented, and since we can treat consumers as if they never return to less attractive products, products with high attractiveness 'drain' products with low attractiveness. Let us provide definitions to prove this 'draining' at an aggregate level.

We call a flux of switching consumers a positive influx from (out of) product i into product j if $(\rho X_i + B_i)\sigma_{ij} > 0$. We define the influx set $H_i(t)$ of all products that potentially generate demand for product i at time t as $H_i(t) := \{ j \neq i \mid X_i > 0 \Rightarrow \sigma_{ji} > 0 \}$ and the outflux set $L_i(t)$ of all products potentially receiving demand of product i at time t as $L_i(t) := \{ j \neq i \mid X_j > 0 \Rightarrow \sigma_{ij} > 0 \}$. Clearly, $H_i(t)$ and $L_i(t)$ are disjoint and any product $j \neq i$ is in $H_i(t)$ or $L_i(t)$. All kinds of properties on flux orientation and flux set nestings hold.

LEMMA 2 (Draining). *Under non-trivial scaling heuristics ($1 \leq \phi_j < \infty$ and $0 < \xi_j \leq 1$), the more attractive products in $L_i \cup \{i\}$ with a non-zero market share drain the less attractive products in a non-empty H_i .*

Proof. Let $X_k(0) + B_k(0) > 0$ for some $k \in H_i$ and $X_j(0) > 0$ for some $j \in L_i \cup \{i\}$. First of all, note that, if we ignore the influx into set $L_i \cup \{i\}$ (let us add superscript r to signal this restriction), i.e. ignore consumers of product $j \in H_i$ switching to a product in $L_i \cup \{i\}$, the total number of consumers in backlog for or using products in $L_i \cup \{i\}$ is constant:

$$\begin{aligned} \Delta^r \sum_{j \in L_i \cup \{i\}} (X_j + B_j) &= \sum_{j \in L_i \cup \{i\}} \{s_j^r - \sum_k \rho X_j \sigma_{jk} + \sum_{k \in L_i \cup \{i\}} (\rho X_k + B_k) \sigma_{kj} - s_j^r - \sum_k B_j \sigma_{jk}\} \\ &= - \sum_{j \in L_i \cup \{i\}} \sum_k (\rho X_j + B_j) \sigma_{jk} + \sum_j \sum_{k \in L_i \cup \{i\}} (\rho X_k + B_k) \sigma_{kj} \\ &= 0 \end{aligned}$$

In the first step, we simplified the expression and further algebra by using that we can safely enlarge the set we sum over given that the terms thus added are zero (due to $\sigma_{jk} = 0$). We see that every change in number of actual and backlogged consumers in $L_i \cup \{i\}$ is due to an influx from H_i :

$$\Delta \sum_{j \in L_i \cup \{i\}} (X_j + B_j) = \sum_{k \in H_i} (\rho X_k + B_k) \sum_{j \in L_i \cup \{i\}} \sigma_{kj} \geq 0 \quad (8)$$

and, since $\Delta \sum_j (X_j + B_j) = 0$, $\Delta \sum_{k \in H_i} (X_k + B_k) \leq 0$. As long as $\sum_{k \in H_i} (X_k + B_k) > 0$, this last inequality is strict. \square

Since the most attractive product k has $X_k(t) + B_k(t) > 0$ at the point in time t of introduction, we know from the draining lemma that $X_k + B_k$ is increasing from t onward. Clearly, it does not imply *absolute* dominance $\lim_{t \rightarrow \infty} X_k(t) = N$. The next theorem however claims exactly that.

THEOREM 1 (Absolute dominance of the most attractive). *Under non-trivial scaling heuristics, the most attractive product eventually dominates absolutely.*

Proof. Let $\alpha_k > \max_{j \neq k} \alpha_j$. We show that the market segmentation converges to a state with $X_k = N$.

Suppose there is some $0 < \varepsilon < N$ and for all t , $X_k(t) + B_k(t) \leq N - \varepsilon$. Take $\varepsilon = N - \lim_{t \rightarrow \infty} (X_k(t) + B_k(t))$. This limit exists due to (a) boundedness ($0 \leq X_k + B_k \leq N$) and (b) applying the draining lemma 2 to product k , which asserts that $\Delta(X_k + B_k)$ is strictly increasing as long as $\sum_{j \in H_k} (X_j + B_j) > 0$.

The idea is to show that there is a jump in $X_k + B_k$ larger than or equal to δ closer than δ to $N - \varepsilon$, thereby jumping over the supposed limit. We propose the following constant δ :

$$\delta = (N - \varepsilon) \frac{\chi}{1 + \chi} \quad \text{where} \quad \chi = \eta \rho \varepsilon \min_{h \neq k} \{\alpha_k - \alpha_h\}$$

We first derive a lower bound for the jump-size $\Delta X_k + \Delta B_k = \sum_{j \neq k} (\rho X_j + B_j) \sigma_{jk}$. Since we assumed that (for all t), $X_k + B_k \leq N - \varepsilon$, we know that

$$\sum_{j \neq k} X_j + B_j = N - (X_k + B_k) \geq N - (N - \varepsilon) = \varepsilon$$

Suppose that $\sum_{j \neq k} X_j + B_j = S$. Given that $\rho < 1$, we see that the jump-size $\sum_{j \neq k} (\rho X_j + B_j) \sigma_{jk}$ is minimal if all of these S consumers would be regular consumers, not backorders, i.e. if $\sum_{j \neq k} X_j = S$. Since $\sum_{j \neq k} \rho X_j + B_j \geq \rho S \geq \rho \varepsilon$, we then know of the increase in $X_k + B_k$:

$$\Delta X_k + \Delta B_k = \sum_{j \neq k} (\rho X_j + B_j) \sigma_{jk} \geq \min_{h \neq k} \sigma_{hk} \sum_{j \neq k} (\rho X_j + B_j) \geq \eta X_k \rho \varepsilon \min_{h \neq k} \{\alpha_k - \alpha_h\} = X_k \chi$$

We assumed that $X_k + B_k \rightarrow N - \varepsilon$. Since $X_k + B_k$ is increasing, eventually $s_k \rightarrow c_k \leq s_k^a$, so we know $\Delta B_k = d_k - s_k \rightarrow d_k - (d_k + \xi_k B_k) = -\xi_k B_k$. However, since B_k is bounded, we know that $B_k \rightarrow 0$ and $X_k \rightarrow N - \varepsilon$. So, we can pick a τ such that $X_k(\tau) > N - \varepsilon - \delta$. We then know (at point in time τ):

$$\Delta X_k + \Delta B_k \geq X_k \chi > (N - \varepsilon - \delta) \chi = \delta(1 + \chi) - \delta \chi = \delta$$

We hence see that:

$$X_k(\tau + 1) + B_k(\tau + 1) = X_k(\tau) + B_k(\tau) + \Delta X_k(\tau) + \Delta B_k(\tau) > N - \varepsilon - \delta + \delta = N - \varepsilon$$

This violates our assumption that there is some $\varepsilon > 0$ such that $X_k + B_k \leq N - \varepsilon$ for all t . So, $X_k + B_k \rightarrow N$ and due to the capacity scaling heuristic $B_k \rightarrow 0$ and $X_k \rightarrow N$. \square

So, if attractiveness purely relates to a constant feature like technical performance, the most attractive product eventually dominates absolutely. This is regardless of the responsiveness $1/\phi$ or backlog considerateness ξ , that is, as long as they are not trivial.

2.2. Illustrations

Despite these analytical results, developments are not trivially induced by the attractiveness levels α_j , but still strongly relate to the responsiveness $1/\phi$ of the manufacturers. We study a market in which, at time $t = 0$, 98 percent of the consumers possesses a null-product (the alternative of not having a product) and two products each have a 1 percent market share. The null-product has an attractiveness of zero, while product 2 ($\alpha_2 = 0.5$) is more attractive than product 1 ($\alpha_1 = 0.4$). We decided not to introduce separate equations for the null-product, so we interpret backorders for the null-product as potential adopters that still own the null-product. In the numerical studies in

the remainder of this paper we simply plot $X_0 + B_0$ for the market share of the null-product.

In this setting, we distinguish two phases in the dynamics. During the 'onset' phase, the fluxes mainly consist of null-product consumers that order product 1 or 2. We call these consumers first-buyers, for obvious reasons. The development of the total consumer base (excluding the null-product) over time thus realized resembles that of the Bass model, qualitatively. During the 'replacement' phase, which starts when $X_0 + B_0$ approaches zero, fluxes mainly consist of consumers that have consumed and now replace their non-null-product.

In figure 1, we plot the development of variables X , B , s and d for each product over time for two extreme cases. Figure 1a shows the results for equal Forrester responsiveness values. We see that some first-buyers purchase the inferior product, but upon replacement later, they still switch to the superior product. Figure 1b shows the results in case the manufacturer of the inferior product is much more responsive. We see that an extremely large market share is realized for the inferior product and that the superior product only very gradually gains market share. The low responsiveness causes much of the influx to end up as backorders, while both the low responsiveness and low backlog consideration ($\xi = 0.1$) cause the production capacity and supply rate s_2 to be adjusted only gradually. Higher responsiveness would result in a faster increase in X_2 , which would in turn increase the influx.

Clearly, the technically superior product dominates the market eventually, in both cases. However, our time scale for simulation ($T = 1500$) does not need to coincide with the real industry lifespan. In high-tech, short life-cycle industries, new radical inventions might render the products in the industry obsolete long before the end of the period we simulate. As a consequence, it might be that the inferior product is still dominant upon the start of industry demise.

One remarkable feature of the dynamics is what we came to call the demand and sales peak. Note that the sales peak itself is an inherent feature of the classical Bass model and extensions thereof with replacement demand (Sterman 2000, p.342). In figure 1, we see that during the onset phase, in case of a responsive manufacturer, both supply and demand skyrocket and then suddenly drop sharply. This peak is caused by the reinforced switching of first-buyers. Not surprisingly, the more the manufacturers take into account backorders (the higher ξ) in setting production level targets, the higher the peak. The manufacturing strategy should balance serving this peak to prolong the presence of the inferior product and accepting possible sunk costs for capacity installed that is unused later.

3. Model extensions

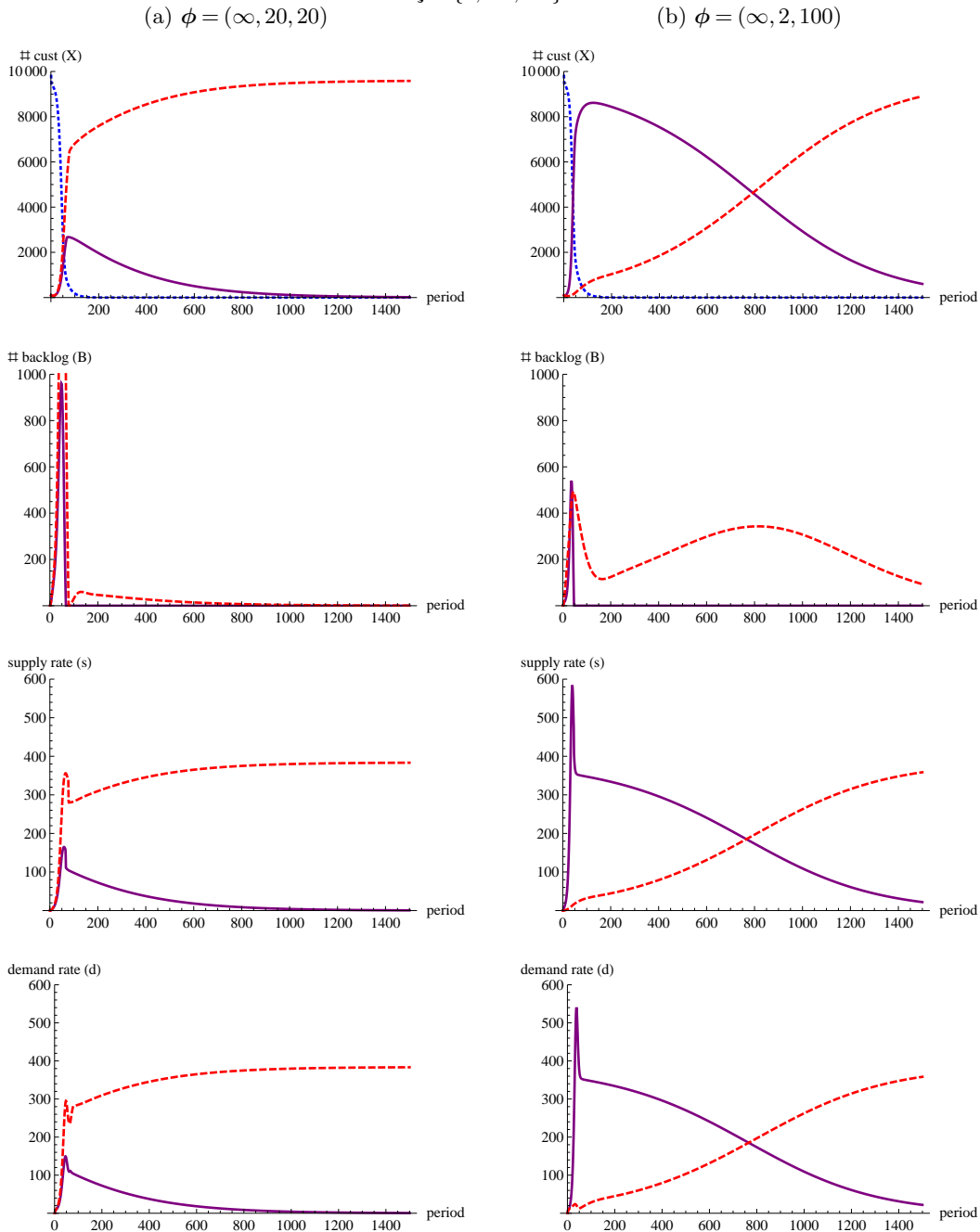
The analytical results obtained so far hinge on the constant nature of product attractiveness. Here, we show numerically that absolute dominance does not depend on the time of entry.

Now what if consumers also care about other features? As far as these are constant they can of course be accounted for in attractiveness and the results obtained previously still fully apply. However, consumers care about price, which is likely to be dependent on production scale. Consumers might also care about the service level, or availability, which is related to backlogs. In this section, we show that both the dynamics and asymptotic market segmentation -and the mediating effect of responsiveness- strongly depend on which comprehensive 'attractiveness' concept applies to an industry.

3.1. Time of entry

The time of entry also determines the period required to realize a certain market share (and even dominance), and whether this market share can be realized in the first place. If consumers care only about technical performance, a technically inferior product needs a head-start in market share or in time of entry or a more responsive upscaling if it is to gain a large market share temporarily. We extend the case studied in subsection 2.2, i.e. with $\alpha = \{0, 0.4, 0.5\}$, $\phi = \{0, 20, 20\}$ and we

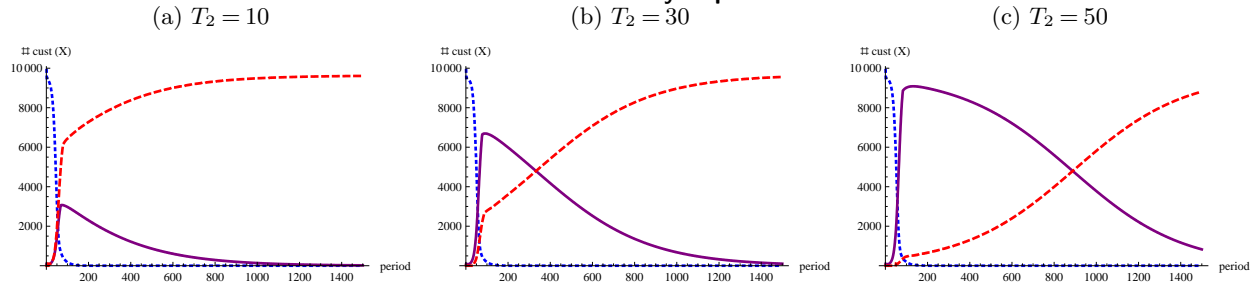
Figure 1 The figures show the development of X , B , s and d over time with the null-product (dotted), product one (continuous) and product two (dashed) for two different settings of ϕ . We used $\alpha = \{0, 0.4, 0.5\}$ and $\xi = \{0, 0.1, 0.1\}$



postpone the entry of the technically superior product from $T_2 = 0$ to $T_2 = 10, 30, 50$. Postponing the entry of the technically inferior product is less interesting.

From the three subfigures in figure 2 for each of these three cases, we conclude that upon entering increasingly later, less first-buyer influx is received by the later entrant and it takes increasingly longer before the market growth takes off. Given that both entrants have equal responsiveness, the slow take-off is caused purely by the late entry. We conclude that it is crucial to be a quick follower, even for a firm with a technically superior product.

Figure 2 Figures show the development of the market shares \mathbf{X} over time (in the same linetypes as before) for different times of entry of product 2.



3.2. When price matters

Consumers generally weigh (constant) technical performance of a consumable against the price of it, e.g. when choosing between the genuine brand and a cheap, low-quality clone.

The price that is charged often depends on costs on the supply side through a markup and these costs arguably drop with the scale of production. Such scale economies consist of both learning as well as efficiency gains. Learning and experience cost advantages relate to how many units R have been produced cumulatively throughout the lifespan, and generally follow a power law like $c^f + c^v R^{\lambda-1}$ (where $0 < \lambda \leq 1$) (See e.g. Sterman et al. 2007, Cachon and Harker 2002). We argue that learning and experience effects dominate in a job shop production environment, while efficiency and volume gains dominate in a mass production system. In a consumable market, we object to the long, flat tail and explosion to infinity for $R \rightarrow 0$ and rather look for a more gradual function with reasonable end-points reflecting the per period volume advantages. We propose the following equation for the price π as a function of production scale s :

$$\pi_j = 1 + e^{-\left(\varepsilon \frac{s_j}{\rho N}\right)} \quad (9)$$

Arguably, other price curves featuring economies of scale are expected to yield qualitatively similar insights. After numerical experimentation, we decided to take $\varepsilon = 4$ as this provides a decline of the curve that is not too steep nor too gradual.

We redefine product attractiveness as α/π and the switching rate (eq. 7) as:

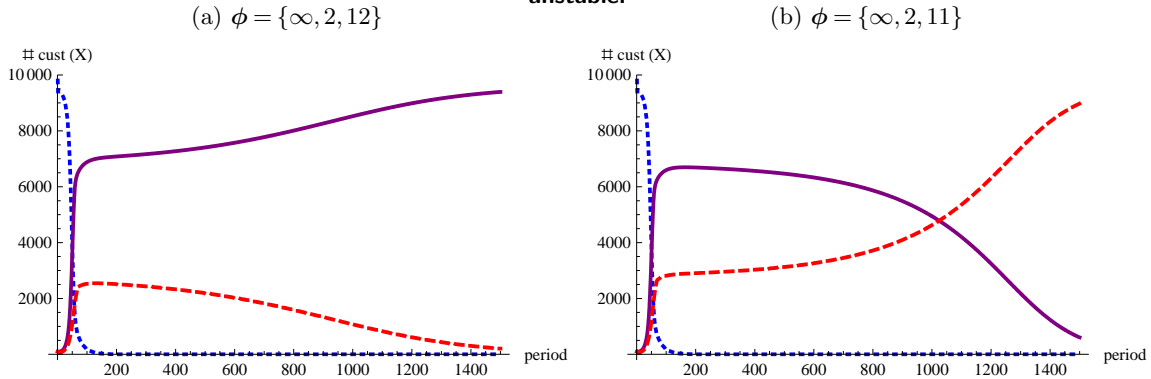
$$\sigma_{ji} = \eta X_i \left(\frac{\alpha_i}{\pi_i(s_i)} - \frac{\alpha_j}{\pi_j(s_j)} \right)^+ \quad (10)$$

We hence assume that if a product is produced on a very small scale (s close to 0), the price is close to 2, which makes the product only half as attractive as to when that product is produced on a very large scale (s around ρN) when the price is close to 1.

Figure 3 shows the development of market shares \mathbf{X} over time of the null-product and the two newly introduced products. In both cases, the manufacturer of the technically inferior product ($\alpha_1 < \alpha_2$) is more responsive ($\phi_1 < \phi_2$). We see that, dependent on the actual ϕ values, the industry eventually tips to dominance of either product one or product two. Due to the higher responsiveness and the reinforced switching rates, the lion share of the first-buyers switch to product 1. In some cases, the production scale s_1 renders such a low price that attractiveness of the technically inferior product exceeds that of the superior product. This reverses the switching flux between the two products and makes the market tip to dominance of that inferior product. We see this confirmed in figure 3a. However, if we make manufacturer 2 only slightly more responsive by changing $\phi = \{\infty, 2, 12\}$ into $\phi = \{\infty, 2, 11\}$, the production of the superior product reaches a scale large enough to invoke a tip toward absolute dominance of the superior product.

Exploiting the notion that backorders vanish asymptotically, the critical tipping point in scale, which also is an unstable equilibrium in market segmentation, can be easily found analytically by solving $\alpha_i/\pi_i(s_i^*) = \alpha_j/\pi_j(s_j^*)$ for $\sum_k s_k^* \rightarrow \rho N$ and deriving the shares X_k from that.

Figure 3 Figures with development of market shares X over time (in the same linetypes as before) when also price determines the attractiveness. Here $\alpha = \{0, 0.4, 0.5\}$ and $\xi = \{0, 0.1, 0.1\}$. The market segmentation is unstable.



A remarkable feature of the curves in figure 3 is the plateau in the segmentation between, say, $t = 100$ and $t = 500$. Since economies of scale drive down the price, the lower technical performance is compensated. Once the attractiveness values are about the same, the switching rates are nearly zero. As this slows down developments, such a plateau in segmentation emerges.

3.3. When availability matters

Purchasing decisions might also depend on some service level, e.g. the immediate availability of a product. Whenever a consumer has decided to renew its product, the product of first choice might not be available immediately, making alternatives relatively more attractive.

We define availability by using the relative number of backorders for that product. The idea is that if there are only few backorders, the probability of being served within a reasonable period of time or finding a product in the store of choice is high. Other interpretations are well possible.

We define availability γ_i of product i as:

$$\gamma_i = \zeta + (1 - \zeta) \frac{\sum_{j \neq i} B_j}{\sum_j B_j + 1} \quad (11)$$

The ζ coefficient determines the extent to which consumers weigh availability against technical performance. If $\zeta \rightarrow 0$, then $\gamma_k < \gamma_i$ means that manufacturer k has relatively more backorders. Consumers then expect to have to wait longer to get hold of a unit of product k , making the competing product i relatively a more attractive option. If $\zeta \rightarrow 1$, consumers value products primarily for their technical performance.

We redefine product attractiveness as $\alpha\gamma$ and the switching rate (eq. 7) as:

$$\sigma_{ji} = \eta X_i (\alpha_i \gamma_i - \alpha_j \gamma_j)^+ \quad (12)$$

If ζ is relatively large, the dynamics resembles that of an industry in which consumers mainly care about performance. If ζ is relatively small, the dynamics become more intricate.

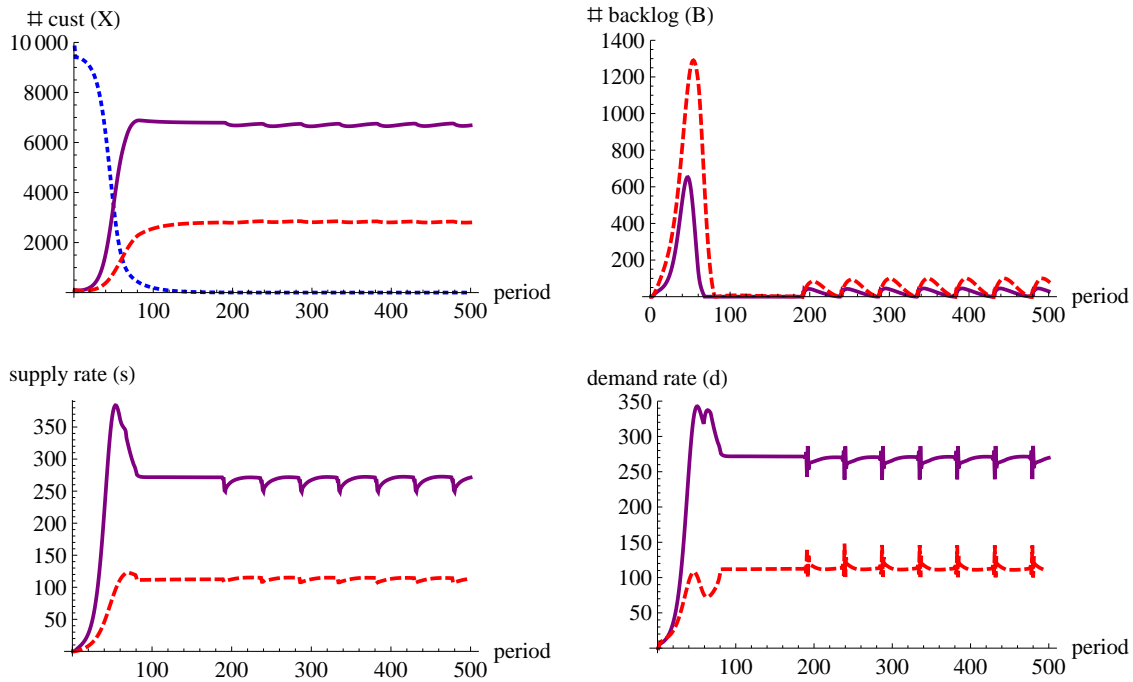
Particularly interesting is the non-trivial case in which the most responsive manufacturer has the technically inferior product. For figure 4, we took one of a wide range of non-trivial parameters settings for which a quasi-stable, cyclically developing market segmentation emerges in which both

firms co-exist. This is explained as follows. Due to positive backlog consideration ($0 < \xi \leq 1$) in equation (6), $\mathbf{B} = \mathbf{0}$ is a global attractor. Any model tends to the zero backorder situation. However, in the vicinity of that zero backorder situation, the second term in (11) becomes small and ordering decisions are again based on technical performance. So, the manufacturer of the superior product receives all the replacement orders. Due to the low responsiveness $1/\phi$ of that manufacturer, the backlogs for the technically superior product accumulate, making it less attractive. This eventually renders a switch flux reversal. Both new replacement orders and impatiently switching consumers now generate demand for the technically inferior product. At first this will of course also render some backorders. So, the 'corrective' effect of availability on attractiveness makes the $\mathbf{B} = \mathbf{0}$ point a local repulsor.

The manufacturer of the inferior product however is more responsive so rids itself of backlogs fast, while the backlog of the technically superior product is drained. So, the switch flux reversal that causes draining plus the ordinary Forrester production adjustment causes \mathbf{B} to drop to zero again. We thus see a cyclical process of attraction and repulsion based on the backlogs that explains the wobbly nature of the market shares curves.

Generally, under a sufficiently more responsive manufacturer of the technically inferior product,

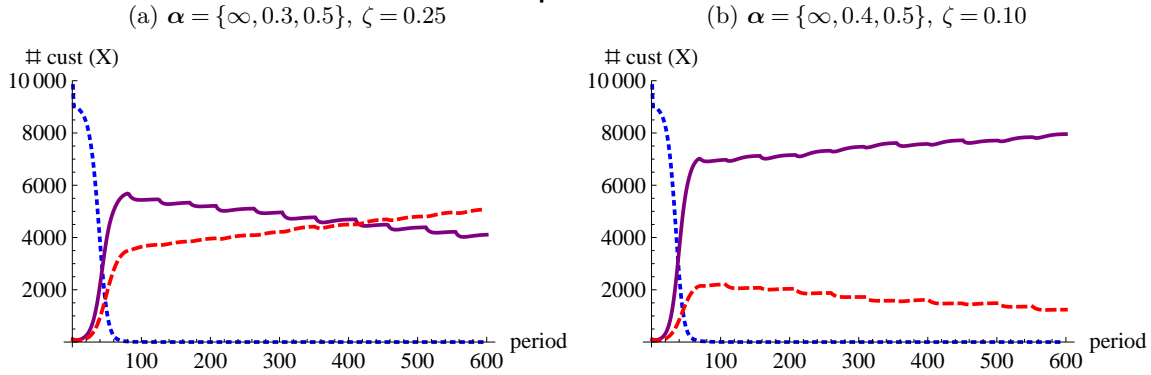
Figure 4 Figure showing development of major variables over time (in the same linetypes as before) when attractiveness depends on availability. Here $\zeta = 1/4$, $\alpha = \{0, 0.3, 0.5\}$, $\phi = \{\infty, 5, 40\}$ and $\xi = \{0, 0.1, 0.1\}$. The market segmentation is quasi-stable.



and sufficient sensitivity of consumers to availability (ζ small enough), the market share of the inferior product reaches a level at which the instabilities in attractiveness under near-zero backlogs are absorbed: the repulsion does not catapult the system into another basin of attraction of market segmentation.

If the difference in responsiveness is relatively small, which ordinarily is in favor of superior products, dynamics under high sensitivity to availability (ζ is low) turn out to be non-trivial. Each wave of repulsion causes a shift toward absolute dominance of either the inferior (figure 5b) or superior product (figure 5a). If consumers care little about technical performance and the difference

Figure 5 Figures with development of market shares X over time (in the same linetypes as before) when availability also determines attractiveness. Here $\phi = \{\infty, 5, 20\}$, $\xi = \{0, 0.1, 0.1\}$ and $\rho = 0.08$. The segmentation is not quasi-stable.



is small anyhow, the slightly higher availability of the inferior product renders dominance of that product. If the sensitivity for availability decreases and difference in performance increases, the superior product emerges as absolutely dominant.

If for a certain $\zeta = \zeta^*$ a non-trivial, quasi-stable market segmentation emerges, then this also is the case for all $\zeta < \zeta^*$. The actual value $\zeta < \zeta^*$ determines the sizes of the market segments. Note that the segment of the less attractive product is necessarily the largest anyhow.

4. Conclusions and Further Research

From the model on co-evolution of demand and supply under competition, we learn that the dynamics and asymptotic outcome of the market segmentation strongly depend on the operationalization of product attractiveness and the responsiveness of the manufacturing scaling. Firms should attune their manufacturing strategy to the factors that consumers deem important and the timescale of the life-cycle.

In section 2.1, we have seen that with constant attractiveness, as with technical performance, aggressive launches allow for temporary dominance for inferior technology. Not compensating inferiority of technology with an early entry and aggressive scaling strategy means a sure and quick demise. In short life-cycle industries, dominance might last the whole industry lifespan. In long life-cycle industries, it is likely a superior product will overtake within the lifespan. The firm with a dominant inferior product should either exploit the financial luxury for cannibalistic succession or -given the then inevitable demise- devise an exit strategy.

In subsection 3.2, we have seen that if attractiveness correlates positively with production scale, as -presumably- with price, any non-trivial segmentation is unstable and the market tips to dominance of one of the products. Aggressive entry with predatory pricing yields prolonged presence (the segmentation plateau in figure 3) or even a favorable market tip, so returns are likely to cover the deep pockets required for such a practice. In the vicinity of tipping points, only minor interventions of either one of the competitors are required to leverage the top-heavy behavior of the market. If consumers care only about price and low-dimensional technical quality, intrinsic market dynamics tend to slow down at a high-price-high-quality and low-price-low-quality segmentation as products then have near-equal attractiveness values.

In subsection 3.3, we have seen that if consumers value availability or factors otherwise related to service levels, the manufacturer of a inferior product can enforce a (quasi-)stable segmentation relatively soon. Apart from the required head-start or aggressiveness in establishing a large market share, the manufacturer should be sufficiently resilient to market shocks upon reaching equal service levels. Higher responsiveness spans a basin of attraction for the segmentation. This is a

comfortable competitive position to either fend off head-on attacks or to bring about a shift toward total dominance.

Regardless of which factors matter most to consumers, timely entry, particularly during the onset phase, is recommended to capture first-buyer influx and influx from inferior products. Early entry and aggressive creation of market share is more important than having a superior product in establishing dominance, especially in the short and medium-long run. So, we do recommend to 'get big fast' in most industries. On the other hand, missing the first-buyer influx can best be compensated by leap-frogging and providing superior products, especially in industries with long life-cycles and ample opportunity to reap returns on R&D investments.

Our recommendation to enter early and upscale aggressively seems in conflict with the warning of Sterman et al. (2007) not to get big too fast. In our model, however, the scaling is responsive rather than anticipative, thereby limiting excess capacity. We do endorse their notion that firms should strike a balance in responsiveness for first-buyers and sensitivity for backorders in scaling, especially for inferior products. Indeed, capacity installed to serve the first-buyer peak and not the regular replacement demand will turn out to be excess capacity. However, ignoring backorders too much results in losing consumers to competitors. In our case this might even have disproportional consequences. Managers can best deal with this first-buyer peak demand through contingent production forces, soothing consumers to prevent them from turning impatient, or -if there is commitment to target market dominance- upscale to levels required in the 'replacement' phase long before the demand peak to produce inventory in advance (c.f. Ho et al. 2002).

The root cause of the seemingly conflicting recommendations is that we have heterogeneous products. The best response to either already offering a technically inferior product or anticipating the entry of a firm with a technically superior product is conquering as large a market share as soon as possible. Compensation of this sort is not required if products are intrinsically the same.

Finally, we make our point in the segmentation and dominant design discussion. We have seen that it strongly depends on what consumers deem important whether the market tips to a dominant product or whether a (quasi-)stable or seemingly stable (plateau) segmentation emerges. The possible effect of innovation in this is in fact subject in our first proposal for further research.

We plan to shed light on the dynamics in case innovation improves technical performance, either at firm level or through endogenous entry. Our guess is that the impact of innovation strongly depends on the actual operationalization of innovation. If innovation is an isolated jump process improving α , we expect it to merely amplify the qualities described in this paper. If firms are able to imitate and leapfrog the technology of competitors, we expect firms to engage in waiting games, to enter during takeoff and thus drive emergence of a certain technology paradigm. We plan to extend experiments with endogenous entry to study the takeoff findings of Agarwal and Bayus (2002).

In further research, we also plan to alter the Peterka model to do justice to the fact that entry of a competing product can in fact increase the market size and the adoption rate of other products (e.g. Krishnan et al. 2000, Norton and Bass 1987). Currently, the market size is fixed and the immediate effect of presence of one on the other products is negative.

We also plan on relaxing the universal performance perception of consumers by introducing a priori preference niches possibly combined with multiple technical product dimensions. We also consider an extension with positive switching costs or brand loyalty, e.g. by using $\sigma_{ji} = \eta X_i (\alpha_i - \alpha_j - \nu)^+$ as this is expected to facilitate further segmentation.

As far as changes on the supply side of the model is concerned, we want to investigate the effect of both lumpy and forward looking capacity adjustments. It is furthermore suggested to also have an overflow inventory to relax the ample supply constraint.

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