Getting Big Too Fast:
Strategic Dynamics with Increasing Returns and Bounded Rationality

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Abstract

Prior research on competitive strategy in the presence of increasing returns suggests that early entrants can achieve sustained competitive advantage by pursuing Get Big Fast (GBF) strategies: rapidly expanding capacity and cutting prices to gain market share advantage and exploit positive feedbacks faster than their rivals. Yet a growing literature in dynamics and behavioral economics, and the experience of firms during the 2000 crash, raise questions about the GBF prescription. Prior studies generally presume rational actors, perfect foresight and equilibrium. Here we consider the robustness of the GBF strategy in a dynamic model with boundedly rational agents. Agents are endowed with high local rationality but imperfect understanding of the feedback structure of the market; they use intendedly rational heuristics to forecast demand, acquire capacity, and set prices. These heuristics are grounded in empirical study and experimental test. Using a simulation of the duopoly case we show GBF strategies become suboptimal when market dynamics are rapid relative to capacity adjustment. Under a range of plausible assumptions, forecasting errors lead to excess capacity, overwhelming the cost advantage conferred by increasing returns. We explore the sensitivity of the results to assumptions about agent rationality and the feedback complexity of the market. The results highlight the risks of incorporating traditional neoclassical simplifications in strategic prescriptions and demonstrate how disequilibrium behavior and bounded rationality can be incorporated into strategic analysis to form a dynamic, behavioral game theory amenable to rigorous analysis.

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1. Introduction

It has become widely accepted that the core behavioral, institutional, and equilibrium assumptions of neoclassical economics are inconsistent with empirical observation (for example, Camerer, Loewenstein and Rabin 2004, Gilovich, Griffin and Kahneman 2002, Kahneman and Tversky 2000, Colander, Holt, and Rosser 2004). Though the tools of neoclassical theory have provided deep insight into a wide variety of strategic problems (for example, Besanko et al. 2003), a long standing tradition suggests that holding fast to the traditional simplifying assumptions of neoclassical theory may be dangerous in formulating normative policies, particularly settings with high dynamic complexity, in which managers are unlikely to be able to make optimal decisions (Nelson and Winter 1982, Dosi 1997, Gavetti and Levinthal 2000). Nevertheless, scholars have only begun to sketch out how alternative assumptions and tools might yield superior and robust implications for managerial action.

Here we focus on the case of increasing returns, and the commonly associated recommendation to "get big fast" (GBF) as a particularly compelling example of the risks of assuming that the classical assumptions of neoclassical theory are "good enough" to provide a basis for action. Research in strategy and economics has long identified increasing returns, or positive feedback effects, as a potentially potent source of competitive advantage. These positive feedbacks include learning by doing, scale economies, network effects, information contagion, and the accumulation of complementary assets. A large and fruitful literature suggests that in the presence of such positive feedbacks, firms should pursue an aggressive strategy in which they seek to grow faster than their rivals (e.g., Shapiro and Varian 1999, Fudenberg and Tirole 2000). Typical tactics include pricing below the short-run profit-maximizing level, rapidly expanding capacity, advertising heavily, and forming alliances to build positional advantage and deter entry (Spence 1981, Fudenberg and Tirole 1983, Tirole 1990).

Intuitively, such aggressive strategies are superior because they increase both industry demand and the aggressive firm's share of that demand, boosting cumulative volume, reducing future costs (or raising future demand) and building the firm's positional advantage until it

dominates the market. Aggressive strategies appear to have led to durable advantage in industries with strong learning curves such as synthetic fibers, chemicals and disposable diapers (Shaw and Shaw 1984; Lieberman 1984, Ghemawat 1984, Porter 1984), and in markets with network externalities and complementary assets, such as VCRs and personal computers. The logic of increasing returns, and these high profile successes, have led to the broad diffusion of the GBF strategy in business education, the popular business literature, management texts, and public policy debates (Shapiro and Varian 1999, Spector 2000, Saloner et al. 2001, Krugman, 1990). For example, in 1996 the *Wall Street Journal* noted the popularity of "the notion of increasing returns, which says that early dominance leads to near monopolies as customers become locked in and reluctant to switch to competitors. Now, dozens of companies are chasing market share" (Hill, Hardy, and Clark 1996).

The collapse of the technology bubble in 2000 has, of course, thrown Get Big Fast strategies into disrepute. As a typical example, consider fiber optic equipment maker JDS Uniphase (Figure 1). Throughout the boom of the late 1990s Uniphase aggressively expanded capacity, both internally and through acquisition. While sales nearly quadrupled in one year, Uniphase struggled to build capacity, and production (indicated by the cost of goods sold) lagged significantly behind. The collapse of demand caught Uniphase by surprise. Lags in reducing capacity and production meant costs could not drop as fast as sales: Uniphase operated with a negative gross margin for most of the next year, saw its stock collapse, laid off more than 15,000 employees (more than half), and posted losses of roughly $60 billion between 2001 and 2003. Similar dynamics plagued dozens of other firms that aggressively pursued GBF strategies.

Clearly these firms missed something. The question is, what? One possibility is that firms in these industries overestimated the strength of the positive feedbacks they hoped to exploit, or ignored important caveats to the GBF strategy discussed in the literature. Lieberman and Montgomery (1998), for example, point out that a blanket prescription to move first can be dangerous given the subtleties of many industries.

Here we explore an alternative hypothesis. We argue that the majority of existing models

addressing competitive strategy generally and increasing returns specifically rely on the traditional neoclassical assumptions of equilibrium and rationality. Equilibrium entails not only that agents adopt consistent strategies, but that firms and markets are in physical equilibrium, with key system states such as capacity, employment, and so forth constant at optimal levels (or in a steady state). Indeed, in many game theoretic models, including repeated games, there are no physical states and resource adjustment processes at all (e.g., the prisoner's dilemma)—the only change between periods arises from changes in agent beliefs and choices. Such models implicitly presume that a firm's capacity can be adjusted instantaneously to equilibrium levels, or, if there are adjustment lags, that firms have perfect foresight such that they can forecast requirements far enough in advance to bring capacity on line just as it is needed.

In practice, of course, neither assumption holds: it takes time to acquire and decrease capacity, human resources, distribution channels, and other resources, and forecasting remains difficult and error-prone (Armstrong 2001, Makridakis et al. 1993). However, the presumption in the literature is that resource adjustment is sufficiently fast, and managers sufficiently well-informed and rational, that the neoclassical assumptions are reasonable approximations and that therefore there is no need to consider disequilibrium dynamics or behavioral decision processes. The example of Uniphase shows that disequilibrium dynamics can play a major role. Most of their losses arose from their inability to adjust capacity fast enough to match the rapid rise and even faster collapse of orders. Lags in resource adjustment require firms to forecast demand and initiate capacity changes far in advance. If firms were well informed and could forecast accurately, capacity would match orders well (at least on average). Alternatively, even if forecasting ability were poor, capacity could match demand well if it could be adjusted rapidly and at low cost. The problem arises from the combination of adjustment rigidities and poor forecasting, the interaction of disequilibrium dynamics with boundedly rational decision-making.

We develop a dynamic model to show that relaxing the assumptions of instantaneous market clearing and perfect foresight leads, in a variety of plausible circumstances, to competitive dynamics significantly different from those predicted by much of the existing

literature. Drawing on a behavioral framework in which firms face lags in adjusting capacity and use boundedly rational decision heuristics to set prices and forecast demand, we show that when the dynamics of the market are sufficiently slow, delays in information acquisition, decision making, and system response are sufficiently short, and the cognitive demands on the firm's managers are sufficiently low, our model yields predictions observationally indistinguishable from those of equilibrium models.

However in more complex and dynamic environments the aggressive strategies prescribed in the game theory literature may lead to disaster. Boundedly rational managers are not able to anticipate the saturation of the market in time to reduce capacity. As long as the industry is growing, all is well, but when sales peak and fall, firms find themselves with excess capacity. The more aggressive the firm's strategy, the more pronounced the overcapacity and the resulting losses. The failure of the aggressive strategy when the market dynamics are rapid is not due to the failure of the learning curve to confer cost advantage on the aggressive firm. Rather, the failure of the aggressive strategy is due to the interaction of capacity adjustment lags with the firm's boundedly rational forecasting heuristic.

In arguing for the explicit modeling of disequilibrium dynamics and bounded rationality we do not suggest that the traditional explanations for poor performance by GBF strategies are invalid. Equilibrium models of rational agents explain many important phenomena. For example, firms facing strong increasing returns have an incentive to price low and expand aggressively, but when multiple players simultaneously do so the result may be a price war that destroys profitability for all. Rather, we argue for the development of disequilibrium behavioral models for several reasons. First, systems, including the economy, are seldom if ever in physical equilibrium, where system states are unchanging or in a steady state (Beinhocker 2006): orders, production and shipments are rarely equal, causing ongoing unintended inventory and backlog accumulations, changes in delivery lead times, and product allocations; capacity, investment, and hiring change dramatically over the course of business cycles and product lifecycles; product functionality, costs, and other attributes evolve through R&D, process improvement, and other

investments, and so on. Second, a large body of evidence shows that human behavior, in both the laboratory and field, departs systematically and significantly from the predictions of rational models (for surveys, see Camerer, Lowenstein and Rabin 2004, Gilovich, Griffin and Kahneman 2002, and Kahneman and Tversky 2000). The bounds on rationality are particularly acute in complex dynamic systems, and slow learning that might cause behavior to evolve towards rational outcomes (Sterman 1994 provides a summary). Equilibrium models of rational agents provide an approximation to the behavior of real people in real markets, one that may work well if the dynamics are slow or the situation simple. Determining what constitutes "slow" and "simple" in models of competitive strategy requires the development of dynamic behavioral models that relax the core assumptions of equilibrium and rationality.

It's also worth pointing out what we do not assume. We do not assume that people are naïve automata, making myopic decisions without regard to strategic considerations. Our agents monitor market conditions. They monitor the plans and actions of their competitors, and adjust their behavior accordingly. However, their rationality is bounded: In the tradition of Simon (1982), Cyert and March (1963/1992), and Nelson and Winter (1982), the agents in the model make decisions using routines and heuristics because the complexity of the environment exceeds their ability to optimize even with respect to the limited information available to them.

The paper begins with a brief review of the relevant literature. Section 3 presents the model. For simplicity, we do not attempt to capture all sources of increasing returns, but focus on the learning curve, a source of positive feedback prevalent in many industries and well explored in the literature. Section 4 presents our results and explores their sensitivity to assumptions. We conclude with a discussion of implications and avenues for further research. Substantively, the results provide a rigorous account of a phenomenon—the widespread failure of the "get big fast" strategy"—largely unexplained by the existing literature. We also argue that the results have broader methodological implications. We suggest that in cases of high dynamic complexity, a reliance on the standard assumptions underlying much modern strategy research is not inconsequential—and that the use of analytical techniques that permit a wider (and more

realistic) set of assumptions may be of significant utility to the field.

2. Strategy Under Learning Curves and Increasing Returns

Spence (1979, 1981) was one of the first to rigorously examine the effects of increasing returns on competitive strategy, specifically the effect of competitive asymmetries on investment decisions in markets with learning effects. He showed that learning creates asymmetric advantage and thus an incentive to preempt rivals, particularly if firms can appropriate all the benefits of learning. His work has been been the basis for a lively literature exploring a range of extensions (e.g., Kalish 1983, Tirole 1990, Majd and Pindyck 1989 and Ghemawat and Spence 1985), which clarified the conditions under which aggressive strategies are likely to succeed.

Moving beyond the learning curve, research exploring industries in which strong network effects play an important role has also identified increasing returns as a central source of competitive advantage (Katz and Shapiro 1994, Shapiro and Varian 1999, Fudenberg and Tirole 2000, Parker and van Alstyne 2005). Arthur (1989, 1994) shows how positive feedbacks can lead to lock-in and path dependence. Sutton (1991) shows that increasing returns flowing from economies of scope in advertising can lead a few firms to dominate an industry, and has also suggested that under some circumstances learning in R&D can have similar effects (Sutton, 1998). Jovanovic (1982) and Klepper (1996) both build models in which dominant firms emerge as heterogeneous costs across firms are amplified by positive feedbacks.

In general, the literature strongly suggests that if learning is appropriable, if price is not highly uncertain, and if rivals can be relied on to behave rationally, then firms should pursue an aggressive strategy of preemption, higher output and lower prices. In the remainder of this paper we explore how robust this recommendation may be—not to traditional concerns such as the appropriability of learning—but to the core assumptions upon which these models rest.

3. A Boundedly Rational, Disequilibrium Model

To explore the robustness of the learning curve literature to the assumptions of perfect foresight and instantaneous market clearing, we develop a disequilibrium, behavioral model of

competitive dynamics in the presence of learning. In contrast to the literature, we assume

capacity adjusts with a lag, and that firms have only a limited ability to forecast future sales as

the industry progresses through the lifecycle of growth, peak and saturation. These assumptions

are consistent with a long tradition of experimental and empirical evidence (Armstrong 2001,

Brehmer 1992, Collopy and Armstrong 1992, Diehl and Sterman 1995, Kampmann 1992, Paich

and Sterman 1993, Parker 1994, Rao 1985, Sterman 1989a, 1989b, 1994). In models assuming

instantaneous market clearing and perfect foresight, the market-clearing price can be derived as a

necessary property of equilibrium, given the capacity decision. However in disequilibrium

settings, both price and capacity targets must be determined. Here we draw on the literature

cited above and the well-established tradition of bounded rationality (Cyert and March

1963/1992, Forrester 1961, Simon 1982, Morecroft 1985), and assume that firms set prices with

intendedly rational decision heuristics.

The model is formulated in continuous time as a set of nonlinear differential equations.

Since no analytic solution is known, we use simulation to explore its dynamics. While the model

portrays an industry with an arbitrary number of firms, $i \in \{1, ..., n\}$, we restrict ourselves to $n =$

2 in the simulation experiments below. We begin with the dynamics of industry demand. We

then describe the physical and institutional structure of the firm, including order fulfillment,

capacity, and the learning curve. Finally we discuss the behavioral assumptions governing firm

strategy, including demand forecasting, capacity acquisition, and pricing. The online supplement

provides full documentation and the model itself, with the software needed to run it.

Industry Demand: We model the lifecycle of a durable good. Total industry orders evolve

according to the standard Bass diffusion model, modified to include both initial and replacement

purchases (Bass 1969, Mahajan et al. 1990). The population, *POP*, is divided into adopters of

the product, *M*, and potential adopters, *N*. Adoption arises from an autonomous component,

representing the impact of advertising and other external influences, and from social exposure

and word of mouth encounters with those who already own the good,

$$dM/dt = N(\alpha + \beta M/POP) \tag{1}$$

where α captures the strength of external influences such as advertising and β is the strength of social exposure and word of mouth arising from encounters with adopters.

The number of potential adopters, N, is the difference between the number of people who will ever adopt the product, M^*, and the number that have adopted the product to date:

$$N = MAX\left(0, M^* - M\right). \tag{2}$$

The equilibrium adoption level, M^*, depends on product price. For simplicity we assume a linear demand curve between the constraints $0 \leq M^* \leq POP$. The MAX function ensures that N remains nonnegative if M^* falls below M, say, because price rises suddenly.

Industry orders consist of initial and replacement purchases. Each household orders μ units when they adopt, so initial purchases are $\mu(dM/dt)$. Households also order replacements as their units wear out and are discarded from the installed base. The fractional discard rate, δ, is assumed constant and determines the durability of the product (see the supplement).

Market Share: Each firm receives orders O_i equal to a share of the industry order rate. The firm's order share, S_i^O, is determined by a logit choice model where product attractiveness, A_i, depends on both price and availability. Availability does not vary in models where markets clear at all times. In reality product availability varies substantially. For example, rapid growth often causes unintended backlog accumulation, product allocations and long delivery delays, as illustrated by the case of Uniphase (Figure 1). Availability is measured by the firm's average delivery delay, given (by Little's Law) by the ratio of backlog, B_i, to shipments, Q_i):

$$S_i^O = A_i \bigg/ \sum_j A_j \tag{3}$$

$$A_i = \exp\left(\varepsilon_p \, P_i/P^r\right)\exp\left(\varepsilon_a \left(B_i/Q_i\right)/\tau^r\right) \tag{4}$$

where ε_p and ε_a are the sensitivities of attractiveness to price and availability, respectively. Both price and delivery delay are normalized by reference values, P^r and τ^r, respectively, so that the sensitivities ε are comparable dimensionless quantities. Note that because orders and shipments need not be equal, market share, defined as each firm's share of industry shipments, $S_i = Q_i/\sum_j Q_j$,

will in general equal the firm's order share only in equilibrium.

The Firm: Firm profits are revenue, R, less fixed and variable costs, C^f and C^v, respectively (the firm index i is deleted for clarity):

$$\pi = R - \left(C^f + C^v\right). \tag{5}$$

Fixed costs depend on unit fixed costs, U^f, and current capacity, K; variable costs depend on unit variable costs, U^v, and production, Q.

$$C^f = U^f K; \ C^v = U^v Q \tag{6}$$

Both fixed and variable costs per unit fall as cumulative production experience, E, grows, according to a standard learning curve:

$$U^f = U_0^f \left(E/E_0\right)^\gamma; \ U^v = U_0^v \left(E/E_0\right)^\gamma \tag{7}$$

$$dE/dt = Q \tag{8}$$

where U_0^f and U_0^v are the initial values of unit fixed and variable costs, respectively, E_0 is the initial level of production experience and γ is the strength of the learning curve.

Production, Q, is the lesser of desired production, Q^*, and capacity, K.[1] Desired production is given by the backlog of unfilled orders, B, and target delivery delay τ^*. Backlog accumulates orders, O, less production:

$$Q = MIN\left(Q^*, K\right) \tag{9}$$

$$Q^* = B/\tau^* \tag{10}$$

$$dB/dt = O - Q \tag{11}$$

Capacity cannot be changed instantly, but adjusts to the target level K^* with an average lag λ. We assume K adjusts to K^* with a third-order Erlang lag, corresponding well to the distributed lags estimated in investment function research (e.g., Jorgenson et al. 1970, Senge 1980, Montgomery 1995).

Firm Strategy: Under the traditional assumptions of rationality and equilibrium, each firm's

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[1] For simplicity we assume the firm maintains no inventories and makes all product to order. Shipments thus equal production. Including inventories and distribution channels would intensify disequilibrium dynamics through the well-known "bullwhip effect" (Sterman 1989b); omitting inventories is thus an *a fortiori* assumption.

target capacity and pricing behavior would be given by the solution to the differential game defined by the structure of the market presented above. In reality, however, managers do not make decisions by solving dynamic programming problems of such complexity (e.g. Camerer et al. 2004, Camerer and Fehr 2006), and business schools do not teach future managers how to formulate and solve dynamic programming problems when setting strategy. Rather, managers use intendedly rational heuristics to set prices and acquire capacity, and the game theoretic models reach managers in the form of rules of thumb. In the presence of increasing returns, books and consultants prescribe rules such as "By slashing prices below costs, winning the biggest share of industry volume, and accelerating its cost erosion, a company [can] get permanently ahead of the pack...[and build] an unchallengeable long-term cost advantage" (Rothschild 1990, 181; Shapiro and Varian 1999 provide a more careful and nuanced version). In this spirit, we model target capacity and price with realistic boundedly rational heuristics, heuristics that allow us to capture different strategies for managing the product lifecycle and learning curve, including the 'market share advantage leads to lower costs leads to greater market share advantage' logic derived from the analytic literature.

Target Capacity and Demand Forecasting: Due to the capacity acquisition delay, and lacking perfect foresight, each firm must forecast future industry demand and then determine what share of that demand it seeks to capture. Firms pursuing GBF strategies will seek the dominant share of the market. Such a firm must acquire capacity sufficient to supply its target share, S^*, of the industry demand it forecasts, D^e (adjusted by the normal capacity utilization rate, u^*):

$$K^* = MAX\left(K^{\min}, S^* D^e / u^*\right) \tag{12}$$

where K^{min} is the minimum efficient scale of production.

The capacity acquisition delay requires the firm to forecast demand λ years ahead. Many studies show that forecasts are dominated by smoothing and extrapolation of recent trends (e.g., Collopy and Armstrong 1992). We capture such heuristics by assuming firms extrapolate demand λ years ahead on the assumption that recent growth will continue. The expected growth

rate in demand, g^e, is estimated from reported industry demand, D^r, over a historical horizon, h.

$$D^e = D^r \exp(\lambda g^e) \tag{13}$$

$$g^e = \ln(D^r_t / D^r_{t-h})/h \tag{14}$$

Forecasters face a strong tradeoff between responsiveness and overreaction. The longer the historic horizon h used to assess growth, the less vulnerable the firm will be to forecast errors arising from high-frequency noise in demand, but the greater the lag in responding to new trends. Sterman (1987, 2000) provides empirical evidence consistent with such forecasting procedures and shows how changes in growth trends led to significant overreaction in various industries. Note also that the instantaneous, current industry order rate is not available. Rather, firms rely on consultants, and industry associations to estimate current demand. It takes time to collect, analyze, and report such data, so the reported order rate lags current orders (see the supplement).

The firm's target market share, S^*, depends on its strategy. We consider two strategies, 'aggressive' and 'conservative'. In the aggressive strategy, the firm follows the recommendation of the increasing returns literature by seeking greater market share than its rivals, lowering prices and expanding capacity to do so. In contrast, the conservative firm seeks accommodation with its rivals and sets a modest market share goal.

Firms also monitor the plans of their competitors. The aggressive player seeks to exploit increasing returns not only by setting an aggressive market share goal but also by taking advantage of timidity, delay or underforecasting on the part of its rivals by opportunistically increasing its target when it detects insufficient industry capacity relative to its demand forecast (denoted uncontested demand). The conservative strategy seeks accommodation with its rivals, but fears overcapacity and will cede additional share to avoid it. Thus target share is given by

$$S^* = \begin{cases} MAX(S^{\min}, S^u) & if \quad Strategy = Aggressive \\ MIN(S^{\max}, S^u) & if \quad Strategy = Conservative \end{cases} \tag{15}$$

where S^{min} and S^{max} are the minimum and maximum acceptable market share levels for the aggressive and conservative strategies, respectively, and S^u is the share of the market the firm expects to be uncontested. Expected uncontested demand, D^u, is the difference between a firm's

forecast of industry demand λ years ahead, when the capacity it orders today will be available, and its forecast of the capacity its competitors will have at that time. The uncontested share of the market is expected uncontested demand as a fraction of projected industry demand:

$$S^u = MAX\left(0, D^u / D^e\right). \tag{16}$$

The MAX function maintains nonnegativity even when there is excess industry capacity. Expected uncontested demand is the firm's forecast of industry demand less the sum of the firm's estimates of expected competitor capacity, K^e, adjusted by normal capacity utilization, u^*:

$$D^u = D^e - u^* \sum_{j \neq i} K^e_j \tag{17}$$

In the base case we assume firms can accurately assess each competitors' *target* capacity, including capacity plans not yet publicly announced and capacity under construction, with only a short delay required for the firm to carry out the required competitive intelligence (see the supplement). Assuming capacity plans are known favors the GBF strategy by limiting overbuilding due to failure to account for the competitors' supply line of capacity on order or under construction (Sterman 1989a, 1989b, 2000).

Pricing: Due to administrative and decision making lags, price, P, adjusts to a target level, P^*, with an adjustment time τ^p:

$$dP/dt = \left(P^* - P\right) / \tau^p \tag{18}$$

Firms do not have the ability to determine the optimal price and instead must search for an appropriate price level. We assume firms use the anchoring and adjustment heuristic to estimate target prices. The current price forms the anchor, which is then adjusted in response to unit costs, the demand/supply balance, and market share. The price discovery process constitutes a hill-climbing heuristic in which the firm searches for better prices in the neighborhood of the current price, using price relative to unit costs, demand/supply balance, and market share relative to its target to assess the gradient (Sterman 2000). For simplicity we assume the target price is a multiplicatively separable function of the various adjustment factors, and that each adjustment is linear in the input variables. Finally, the firm will not price below unit variable cost U^v. Thus

$$P^* = MAX\left[U^v, P\left(1 + \alpha^c\left(\frac{P^C}{P} - 1\right)\right)\left(1 + \alpha^d\left(\frac{Q^*}{u^*K} - 1\right)\right)\left(1 + \alpha^s(S^* - S)\right)\right],$$

$$\alpha^c \geq 0; \; \alpha^d \geq 0; \; \alpha^s \leq 0. \tag{19}$$

The three adjustment terms capture the firm's response to unit costs, the adequacy of its capacity to meet demand, and market share relative to its target share. The adjustment parameters α determine the sensitivity of price to each of these pressures. The first term moves target price to a base price P^C determined by total unit costs and a constant target markup, m^*,

$$P^C = \left(1 + m^*\right)\left(U^f + U^v\right). \tag{20}$$

The firm also responds to the adequacy of its current capacity, measured by the ratio of desired production Q^* to the rate of output defined by current capacity and normal capacity utilization, u^*. When this ratio exceeds unity, the firm has insufficient capacity and increases price; excess capacity causes prices to fall. Finally, the firm prices strategically in support of its capacity goals by adjusting prices when there is a gap between its target market share S^* and its current share S. When the firm desires a greater share than it currently commands, it will lower price; conversely, if market share exceeds the target the firm increases price, trading off the excess market share for higher profits and signaling rivals its desire to achieve a cooperative equilibrium. The price formulation is consistent with the behavioral model of price in Cyert and March (1963/1992), and experimental evidence (Paich and Sterman 1993, Kampmann 1992).

4. Results

We begin by confirming that under conditions of perfect foresight and market clearing the model reproduces the conclusions of the increasing returns literature. We then explore the effectiveness of the GBF strategy as these assumptions are relaxed. For the base case the model is calibrated to capture the dynamics of typical consumer electronics items such as camcorders (Table 1). As (arbitrary) scaling parameters we set the initial price at \$1000/unit, and the potential size of the market at that price to 60 million households, each seeking $\mu = 1$ unit. The replacement rate is 10%/year. We assume a 70% learning curve (costs fall 30% for each doubling of cumulative production), a typical value. The ratio of fixed to variable costs is 3:1.

The sensitivity of order share to price is high, implying products are only moderately differentiated by non-price factors, an *a fortiori* assumption that favors the effectiveness of the GBF strategy. We assume short delays of only one-quarter year for the reporting of industry orders and the estimation of competitor target capacity. These parameters favor the success of the aggressive strategy (we present sensitivity analysis below).

We examine the behavior of the market for values of the word of mouth parameter 0.5 $\leq \beta \leq 2.5$, generating product lifecycle dynamics that span much of the variation in observed diffusion rates (Parker 1994, Klepper and Graddy 1990). For illustration, we define three industry demand scenarios: Fast, Medium, and Slow, defined by $\beta = 2, 1$, and 0.5, respectively. Figure 2 shows the evolution of industry orders for each case, assuming no capacity constraints and that prices follow unit costs down the learning curve. In all cases a period of rapid growth is followed by a peak and decline to the equilibrium, replacement rate of demand. The stronger the word of mouth feedback, the faster the growth, the earlier and higher the peak rate of orders, and the larger the decline from peak to equilibrium demand. Demand in the slow scenario peaks after about 20 years, while in the fast scenario, the peak comes at about year 6. Even faster dynamics have been documented, such as black and white televisions, toys and games and other consumer electronic items, often with only a few years from boom to bust (Parker 1994).

For each of the three market scenarios identified above we test the effectiveness of the Aggressive (A) and Conservative (C) strategies. For ease of comparison, both firms have identical parameters and initial conditions, so the playing field is level. Only the strategy each uses for capacity planning and pricing may differ. Note in particular that the forecasting procedure used by each firm is identical, so the two firms have consistent beliefs about industry demand and competitor capacity. In the aggressive strategy, the firm seeks at least 80% of the market (the aggressive player will increase its market share goal above 80% if it perceives there is additional uncontested demand). The conservative player is willing to split the market with its rival, but will cede if it perceives a 50% share would result in excess capacity.

We begin by assuming that capacity can instantly adjust to the level required to provide

the target rate of capacity utilization at all times, $K = Q^*/u^*$. The 'perfect capacity' case corresponds to the equilibrium assumption that the market always clears, either because capacity can be adjusted instantly, or because agents have and perfect foresight so that they can anticipate the capacity acquisition lag. The market always clears, capacity utilization always equals the target rate, and delivery delays are always normal. Prices thus respond only to unit costs and the gap between the firm's target and actual market share, and order share responds only to price.

Table 2 shows the net present value of cumulative profits for the three market scenarios. (We use a discount rate of 4%/year and simulate the model for 40 years. The results are robust to rates from 0 to at least 20%/year.) In all cases the result is a prisoner's dilemma. Though the NPV of profit is maximized when both firms play the conservative strategy, [C, C], each firm has a strategic incentive to defect to exploit increasing returns and thus the Nash equilibrium is for both firms to play the aggressive strategy.

The faster the dynamics of the market unfold, the greater industry profits are for any strategy combination. Figure 3 shows payoffs to each strategy combination in the market clearing case as the word of mouth parameter β varies. Stronger word of mouth brings people into the market sooner, increasing the NPV of profits and the advantage of the GBF strategy, consistent with Kalish (1983). Also consistent with the literature, the strategic incentive to play the aggressive strategy increases with the strength of the learning curve (table 3).

These results show the model conforms to the game-theoretic result when we assume instantaneous and perfect capacity adjustment. With an appropriable learning curve it is optimal to price below the short-run profit-maximizing level and expand capacity rapidly. The stronger the learning curve, the greater is the incentive to pursue the aggressive strategy. Likewise, the faster the growth of the market, the greater is the advantage of the aggressive strategy.

Now consider the realistic case where firms face capacity adjustment lags and must therefore forecast industry demand and competitor responses, as specified by the behavioral rules above. Table 2 shows the payoff matrices for the different scenarios; Figure 3 shows how the payoffs depend on the speed of product diffusion. When the market dynamics are sufficiently

slow, the firm's demand forecasts are accurate enough, capacity closely follows desired capacity, and the aggressive strategy dominates. However, for market dynamics faster than those given by a critical value of the word of mouth parameter, $\beta^{CRIT} \approx 1.3$, the conservative strategy dominates, contrary to the prescription of the equilibrium models. Neither firm has any incentive to defect, and [C, C] becomes the dominant strategy.

To identify why the payoffs change so dramatically when the market clearing and perfect foresight assumptions are relaxed, Figure 4 shows the dynamics of the [A, C] case for the fast market scenario, while Figure 5 shows the same scenario for the case where capacity adjusts instantaneously. In both, the aggressive firm immediately cuts price to gain market share. In the case with the capacity lag, the aggressive firm also sets target capacity to 80% of its forecast of industry demand. After about one year, the firm responds to the rapid growth in industry demand by increasing target capacity. Due to the delay in perceiving industry orders and in capacity acquisition, actual capacity lags behind orders, and both firms quickly reach full utilization. Capacity remains inadequate until year about 1.5. During this time, excess backlogs accumulate and customers are forced to wait longer than normal for delivery. The capacity crunch causes both firms to boost prices above normal levels, though the aggressive firm continues to price below the conservative firm. Such transient shortages and price bubbles are often observed during the growth phases of successful products, for example radios, black and white television, and color televisions (Dino 1985), and more recently, DRAM, iPods, and Harley-Davidson motorcycles.

Demand continues to grow rapidly, though at a declining fractional rate. As these data are reported, both firms gradually lower their demand forecasts. However, due to the adjustment lags, capacity begins to overshoot the required level, and utilization falls below normal. As industry orders peak and decline, shortly before year 6, both firms find themselves with significant excess capacity. The aggressive firm suffers the most, since it expands capacity faster to increase its market share. As boom becomes bust, the aggressive firm finds utilization drops below 50%. The conservative firm also experiences excess capacity, but the magnitude and

duration of the problem is substantially less since the conservative player has been steadily giving up market share during the growth phase. The pattern of capacity overshoot is widespread in maturing industries, and was frequently observed in Paich and Sterman's (1993) experimental product lifecycle task, even when subjects had experience with the dynamics. Both firms experience excess capacity as the market unexpectedly saturates, causing large losses. The aggressive firm, however, loses far more than its conservative rival.

The failure of the aggressive strategy when the market dynamics are rapid is not due to the failure of increasing returns to confer cost advantage on the aggressive firm. As in the perfect capacity case, the aggressive strategy achieves its intended goal: low prices and rapid expansion quickly give the aggressor a cost advantage, which steadily widens as the industry moves through its lifecycle. Indeed, at the end of the simulation, the aggressive firm has unit costs only 42% as great as its rival, a *larger* advantage than it enjoyed in the perfect capacity case. The failure of the aggressive strategy arises from the interaction of the disequilibrium dynamics of the market and the boundedly rational heuristics the firms' managers use to forecast demand, plan capacity, and set prices.

When capacity adjusts perfectly the aggressive strategy always dominates the conservative strategy and faster market evolution increases the advantage of the aggressive strategy (figure 3a). In contrast, when firms face a capacity adjustment lag, the costs of excess capacity induced by forecast error increase with the speed of the product lifecycle. Eventually, the costs of excess capacity overwhelm the cost advantage of the learning curve, and the aggressive strategy becomes inferior (Figure 3b). As the dynamic complexity of the environment grows, or as the capacity acquisition lag increases, the greater is the likelihood of capacity overshoot.

Sensitivity Analysis: Before turning to conclusions we explore the sensitivity of results to assumptions. Despite substantial variations in key parameters (table 3), the critical value of the word of mouth parameter above which the aggressive strategy becomes inferior remains in the

range from 2.0 to less than 0.5, corresponding to sales peaks from five to twenty years after product launch, well within the range documented for many real products (Parker 1994).

We have made a number of assumptions that reduce the attractiveness of aggressive GBF strategies. First, to the extent capacity can be used to make follow on products the costs of capacity overshoot will be mitigated. Second, we assume there are no economies of scope allowing follow-on or related products to share in the benefits of learning. To the extent learning can be passed on to other products, thereby conferring advantage to them, the costs of capacity overshoot are offset even if capacity is not fungible with successor products. Third, we subsume returns to scale and other positive feedback processes such as network externalities within the learning curve. Additional positive feedbacks arising from other sources of increasing returns favor the aggressor, just as a stronger learning curve increases the advantage of the aggressive strategy. Fourth, we assume there is no growth in the underlying pool of potential customers. This too would reduce the severity of the saturation peak. Fifth, we assume a durable product. More frequent repurchases reduce the dynamic complexity of the market and the magnitude of the decline from peak to replacement sales rates.

A key behavioral assumption is that firms forecast industry demand by extrapolating past demand and have no advance knowledge of the market's saturation point. Clearly, better forecasting would favor the aggressive learning curve strategy, as shown by the results of the market clearing case. The evidence is not encouraging. In Paich and Sterman's (1993) product lifecycle experiment, subjects consistently failed to forecast the sales peak, leading to excess capacity and large losses similar to those simulated here—even after extensive experience with the task. Outside the laboratory, a wide range of new product diffusion models have been developed which, in principle, allow forecasting of the sales peak (Parker 1994, Mahajan et al. 1990, Armstrong 2001). In practice, diffusion models often miss the turning point, since, as Mahajan et al. (1990) write, "by the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes." Rao (1985) examined the ability of ten popular models to predict sales of typical durable goods. Mean absolute forecast

errors averaged more than 40% across all models and products. The extrapolative models generally outperformed the diffusion models. Collopy et al. (1994) also found extrapolation outperformed diffusion models in predicting spending on information technology.

On the other hand a number of our assumptions favor the aggressive strategy. We assume learning is perfectly appropriable, increasing the ability of firms to gain sustained cost advantage. Spillovers allow conservative firms to benefit from the cost advantage of larger rivals, dissipating the cost advantage of aggressors pay so dearly to acquire (Ghemawat and Spence 1985). We assume market share is quite elastic so that modestly lower prices bring significant share advantage, strengthening the positive feedbacks created by the learning curve. We also assume that production adjusts instantaneously at constant marginal cost (until capacity utilization reaches 100%), and that capacity can be adjusted continuously with an average lag of just one year, less than the typical lags estimated in the literature. There are no capacity adjustment costs or exit costs. A longer capacity lag or realistic adjustment costs would increase the magnitude and cost of forecast errors. We omit balance sheet considerations and thus the risk of bankruptcy: aggressive firms that ultimately do well in the simulation may not survive the losses of the transition from boom to bust (Oliva, Giese and Sterman 2001), a common phenomenon in the collapse of the dot.com bubble. The information on which the firm bases its decisions is free of noise, measurement error, bias, or other distortion. We assume firms can base their forecasts on industry orders, reported with only a one-quarter year lag, when in most industries order data are unavailable and firms must rely on estimates of industry revenues or shipments for forecasting, introducing an additional delay and also confounding demand (orders) with capacity (which may constrain shipments below the rate of incoming orders during periods of rapid demand growth). Most importantly, we assume that the competitor's *planned* capacity target is fully known with only a short delay, while in reality the determination of competitor plans is difficult and time consuming. Relaxing any of these assumptions strengthens our results and causes the aggressive strategy to be dominated by the conservative strategy at lower rates of market growth and for less durable products (see the supplement).

5. Discussion and Conclusions

The belief that practicing managers are boundedly rational has a long tradition in organizational theory, evolutionary economics, and strategy, and has been broadly confirmed by work in psychology and behavioral economics. Yet in general the literature continues to draw on traditional neoclassical assumptions, largely under the assumption that they are "good enough" to yield insight into many critical strategic problems. In this paper we have highlighted some conditions under which these assumptions are likely to be dangerous, and attempted to illustrate how the combination of behavioral assumptions and dynamic modeling techniques may provide powerful alternative sources of insight.

We focused our analysis on cases of increasing returns. Prior research shows that under traditional assumptions of equilibrium, full information and perfect rationality, the optimal strategy for a firm in an environment with increasing returns is to aggressively preempt competitors, cutting price and boosting output beyond the static optimum levels. We have shown that this result is not robust to relaxation of these assumptions. Investing in additional capacity and lower prices to benefit from increasing returns is only optimal when the dynamic complexity of the market, and hence the risk of capacity overshoot, is low. In these circumstances, fully and boundedly rational decision making converge, just as Newtonian physics gives good approximations to relativistic dynamics for small speeds and low masses. However, as the dynamic complexity of the market increases, disequilibrium effects and systematic decision making errors become more important, and cause the predictions of the traditional models to fail.

These conclusions are consistent with experimental and empirical evidence. Our results predict that GBF strategies will perform best in industries where demand growth is steady and the product has a high repeat purchase rate (lowering the risk of excess capacity caused by market saturation), or where capacity can be adjusted rapidly at low cost (lowering the cost of forecast error). Consistent with this observation, aggressive strategies generally led to sustained advantage in synthetic fibers, bulk chemicals, and disposable diapers (Shaw and Shaw 1984,

Porter 1984, Lieberman 1984, and Ghemawat 1984), with high repurchase rates and reasonably steady demand growth, and in certain e-commerce sectors (e.g., Amazon.com) where capacity can be adjusted quickly. Similarly, our results predict poor performance for aggressive strategies in industries with rapid demand growth and long-lived products, or long capacity adjustment delays where commonly used forecasting heuristics are particularly likely to lead to capacity overshoot. Examples include televisions and VCRs, toys and games, lighting equipment, snowmobiles, calculators, tennis equipment, bicycles, chain saws, semiconductors, running shoes, and, most obviously, telecommunications during the technology bubble of the 1990s.

The results have implications both for practicing managers and for the larger issue of the modeling tools most appropriate for the study of strategic behavior. Most obviously, any recommendation to pursue an increasing returns GBF strategy must be treated with caution. Current theory suggest firms should assess the strength and appropriability of learning and other sources of increasing returns in their industry and recommend aggressive preemption in the presence of strong, appropriable learning curves or other positive feedbacks that confer cumulative positional advantage. Our results suggest that firms must also determine whether they are vulnerable to capacity overshoot or to systematic underestimation of competitor capacity plans, including capacity acquired by new entrants. A firm electing to pursue a GBF strategy must devote significant effort to understanding the dynamics of market demand so that it is not caught unprepared by market saturation. It must clearly and credibly signal its capacity intentions in a rapidly growing market so that other players will not unintentionally overbuild. To prevent competitor overbuilding, managers may find it optimal to share their forecasts and market intelligence with rivals. Experience and experimental studies suggest that this is both hard medicine to take and difficult to carry out successfully. Alternatively, when the risk of capacity overshoot is high, firms should consider conservative strategies even in the presence of increasing returns, allowing less sensible rivals to play the aggressive strategy, then buying these rivals at distress prices when they fail during the transition from boom to bust. Jack Tramiel followed just such a strategy, purchasing Atari from Warner Communications after the peak in

the video game market for $160 million in unsecured debt and no cash, while Warner took a $592 million writeoff of Atari assets on top of $532 million in Atari losses. Similarly, many internet and telecom firms have been bought since 2001 at distress prices.

On the methodological front, our results suggest that assuming that the equilibrium, information and rationality assumptions of game theory and microeconomics are "close enough" to provide robust frameworks for action is risky. More realistic physical, institutional and behavioral assumptions can dramatically reverse the neoclassical result and reveal a much more complex relation between increasing returns, the dynamics of demand and firm strategy.

When the dynamics of the system are sufficiently slow, the delays in information acquisition, decision-making and system response sufficiently short, and the cognitive demands on the agents sufficiently low, dynamic behavioral models will yield predictions observationally indistinguishable from those of equilibrium models. However, in cases of high dynamic complexity, boundedly rational people can and do behave significantly differently from their equilibrium counterparts. The case of increasing returns in a dynamic market shows that these differences can matter greatly and their impact examined rigorously.

Though further work is required to explore the relationship between behavior and dynamic complexity beyond the two-firm case under increasing returns, we speculate that relaxing the assumptions of equilibrium and complete rationality may lead to similar differences in a variety of other contexts. Such cases are likely to include settings in which there are long lags between action and effect or in the reporting of information, where there are positive feedback processes, and where there are significant nonlinearities. We suggest the combination of game theoretic reasoning with behavioral simulation models can contribute to a behaviorally grounded and normatively fruitful theory of disequilibrium dynamics in strategic settings.

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Table 1. Key parameters. The supplement provides full documentation.

POP	Total population (households)	100e6
μ	Units purchased per adopter (units/household)	1
α	Propensity for nonadopters to adopt the product autonomously (1/years)	0.001
β	Propensity for nonadopters to adopt the product through word of mouth (1/years)	1
ε_d	Elasticity of demand at the reference price and population (dimensionless)	-0.2
δ	Fractional discard rate of units from the installed base (1/years)	0.10
ε_p	Sensitivity of product attractiveness to price	-8
ε_a	Sensitivity of product attractiveness to availability	-4
c	Ratio of fixed to variable costs (dimensionless)	3
γ	Strength of the learning curve (dimensionless)	$\log_2(0.7)$
λ	Capacity acquisition delay (years)	1
u^*	Target capacity utilization rate (dimensionless)	0.8
K^{min}	Minimum efficient scale (units/year)	1e5
h	Historic horizon for estimating trend in demand (years)	1
τ^d	Time delay for reporting industry order rate (years)	0.25
τ^c	Time delay for estimating competitor target capacity (years)	0.25
τ^p	Adjustment time for price (years)	0.25
α^c	Weight on costs in determination of target price (dimensionless)	1
α^d	Weight on demand/supply balance in determination of target price (dimensionless)	0.5
α^s	Weight on market share in determination of target price (dimensionless)	-0.10
M_0	Initial number of adopters (households)	$0.001M^*$
E_{i0}	Initial cumulative production experience of firm i (units)	10e6
P_{i0}	Initial price of firm i ($/unit)	1000

Table 2. Payoffs in three industry evolution scenarios (NPV of cumulative profits, Billion $).

		Perfect Capacity			*Capacity Adjustment Lag*	
SLOW		**Aggressive (A)**	**Conservative (C)**		**A**	**C**
($\beta = 0.5$)	**A**	3.2, 3.2	5.1, 2.1	**A**	-7.0, -7.0	4.8, 0.9
	C	2.1, 5.1	3.8, 3.8	**C**	0.9, 4.8	3.5, 3.5
MEDIUM		**A**	**C**		**A**	**C**
($\beta = 1$)	**A**	4.8, 4.8	7.3, 3.2	**A**	-11.1, -11.1	5.2, 1.0
	C	3.2, 7.3	5.7, 5.7	**C**	1.0, 5.2	4.4, 4.4
FAST		**A**	**C**		**A**	**C**
($\beta = 2$)	**A**	6.5, 6.5	9.4, 4.8	**A**	-19.7, -19.7	-1.7, 0.2
	C	4.8, 9.4	7.6, 7.6	**C**	0.2, -1.7	1.9, 1.9

Table 3. Sensitivity analysis. The aggressive strategy is inferior for values of $\beta > \beta^{CRIT}$. The smaller the critical value β^{CRIT}, the less robust is the aggressive strategy. § = the base case value.

Parameter		β^{CRIT}	Parameter		β^{CRIT}
ε_d: Industry demand	0.0	1.4	u^* : Normal	0.6	1.2
Elasticity at	-0.2 §	1.3	Capacity	0.8 §	1.3
Reference price	-1.0	1.1	Utilization	1.0	1.6
ε_p: Sensitivity of Product	-4	<0.5	τ^d, τ^c: Information	0.25, 0.25 §	1.3
Attractiveness	-8 §	1.3	Reporting Delays	0.0625, 0.0625	1.7
to Price	-12	2.0			
			α^c: Strength of Cost	1.0 §	1.3
δ: Fractional Product	0.10 §	1.3	Adjustment in Price	0.5	1.2
Discard Rate	0.20	1.6			
	0.50	1.4	α^d: Strength of	0.50	1.1
			Demand/Supply	0.25 §	1.3
c: Ratio of fixed	3 §	1.3	Effect on Price	0.00	1.0
to variable cost	1	1.5			
	1/3	1.9	α^s: Strength of	0.00	1.3
			Market Share	0.10 §	1.3
λ: Capacity	1.0 §	1.3	Effect on Price	0.20	1.3
Adjustment Delay	0.5	1.9		0.50	1.3
γ: Learning	$\log_2(0.8)$	1.3	s^{min}: Minimum	1.00	1.0
Curve	$\log_2(0.7)$ §	1.3	Market Share Target	0.80 §	1.3
Strength	$\log_2(0.5)$	1.6	for Aggressive Strategy	0.60	0.8

Figure 1. Sales, Cost of Goods Sold and stock price for JDS Uniphase.
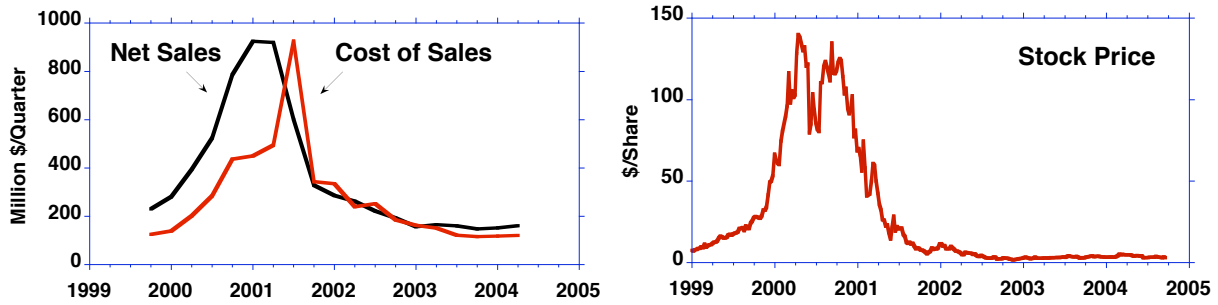

Figure 2. Diffusion dynamics for three values of the word of mouth parameter (Slow, Medium, Fast: $\beta = 0.5$, 1, 2 respectively), for the perfect capacity case with target market share for both firms = 50%. Left: Industry Orders; Right: Price.
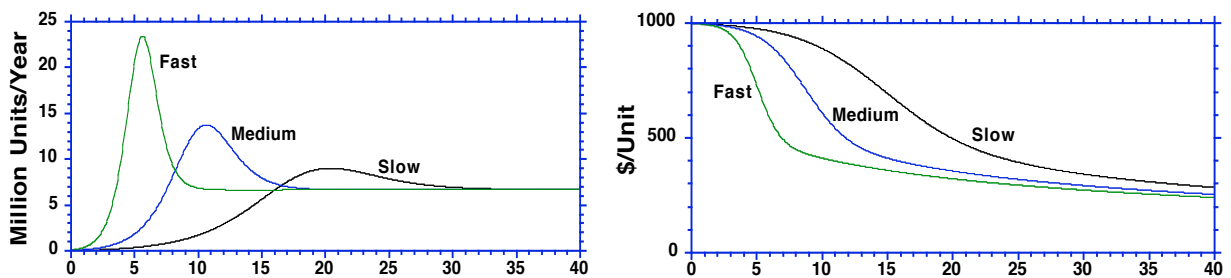

Figure 3. Firm Payoffs as they depend on the speed of the product lifecycle. (a; left): perfect capacity case; the aggressive strategy always dominates; (b; right): capacity acquisition lag; the aggressive strategy is inferior for values of $\beta > \beta^{CRIT}$.
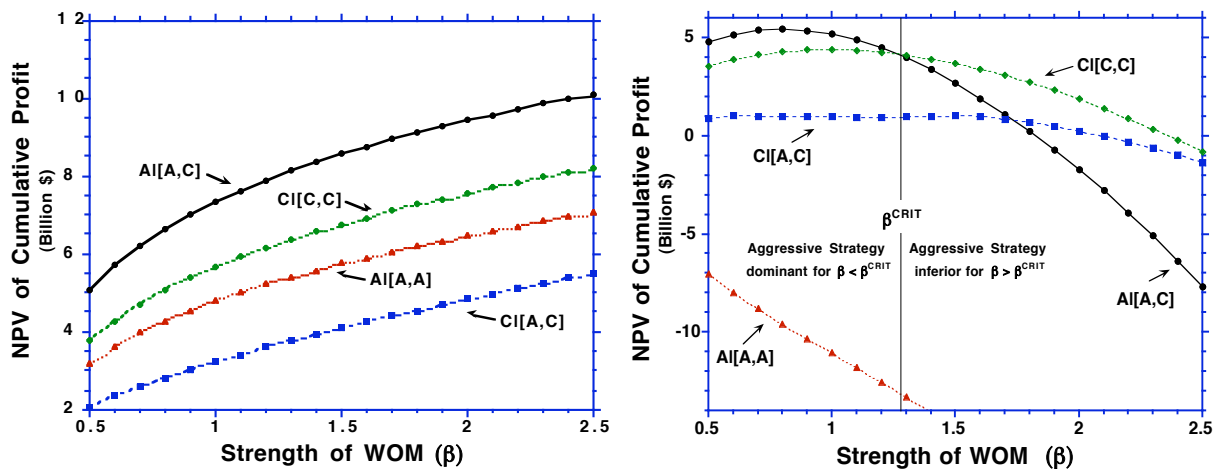
Figure 4. Dynamics of the aggressive vs. conservative strategies in the fast market scenario (β = 2), with the capacity acquisition lag.
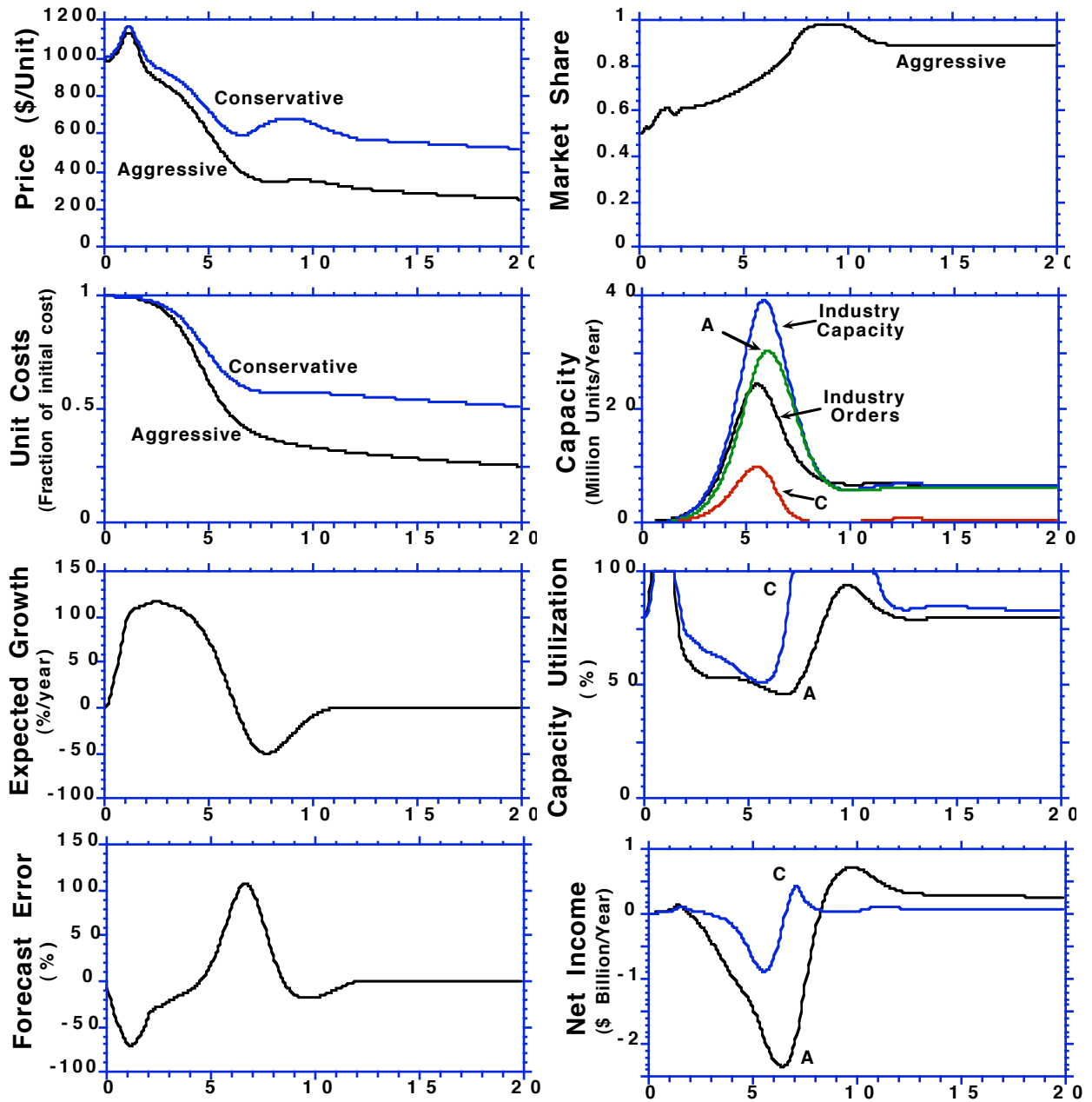
Figure 5. Aggressive vs. Conservative Strategies in the market clearing case with fast market dynamics ($\beta = 2$). Compare to figure 4.