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Abstract

Prior research on firm strategy in the presence of learning curves suggests that if learning is highly appropriable, early entrants can achieve sustained competitive advantage by rapidly building capacity and by pricing aggressively to preempt competition. However these studies all presume (1) rational actors and (2) equilibrium, implying markets clear at all points in time. We consider the robustness of the aggressive strategy in the presence of (1) boundedly rational agents and (2) a capacity acquisition lag. 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 the aggressive learning curve strategy becomes suboptimal when the market is dynamically complex. When capacity cannot be adjusted instantaneously, forecasting errors leading to excess capacity can overwhelm the cost advantage conferred by the learning curve. We explore the sensitivity of the results to the feedback complexity of the market and the rationality of the agents' decision making procedures. The results highlight the danger of extrapolating from equilibrium models of rational actors to the formulation of strategic prescriptions and demonstrate how disequilibrium behavior and bounded rationality can be incorporated into strategic analysis to form a 'behavioral game theory' amenable to rigorous analysis.

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1. Introduction

Learning curves have been identified in a wide variety of industries (Dutton and Thomas, 1984), and an extensive theoretical literature has explored their strategic implications. A learning curve creates a positive feedback loop by which a small initial market share advantage leads to greater production experience, lower unit costs, lower prices and still greater market share advantage. In general, the literature suggests that in the presence of learning curves – and when learning is privately appropriable – firms should pursue an aggressive strategy in which they seek to preempt their rivals, expand output and reduce price below the short-run profit maximizing level (Spence, 1981; Fudenberg and Tirole, 1983, 1986; 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 and building sustained competitive advantage until the firm dominates the market. The desirability of aggressive strategies in industries with learning curves has diffused widely in business education, the popular business literature, management texts, and public policy debates (Rothschild 1990, Hax and Majluf, 1984; Oster, 1990; Porter, 1980; Krugman, 1990), and learning curve strategies appear to have led to sustained advantage in industries such as synthetic fibers, bulk chemicals and disposable diapers (Shaw and Shaw 1984; Lieberman 1984, Ghemawat 1984, Porter 1984).

However in many industries, including televisions, VCRs, semiconductors, toys and games, lighting equipment, snowmobiles, hand calculators, tennis equipment, bicycles, chain saws, running shoes and vacuum cleaners, aggressive pricing and capacity expansion have led to substantial overcapacity and price wars that have destroyed industry profitability (Beinhocker, 1991; Salter, 1969; Porter, 1980; Saporito, 1992; The Economist, 1991; Business Week, 1992).

Existing models that consider the competitive implications of the learning curve utilize the traditional assumption that markets clear at all points in time. Market clearing in turn implies that a firm's production capacity and other resources can be adjusted instantaneously to equilibrium levels, or, if there are capacity adjustment lags, that firms have perfect foresight such that they can forecast their capacity requirements far enough in advance to bring the required capacity on line just as it is needed. Neither assumption is valid: it takes time to build new factories, expand existing ones, and decommission obsolete ones (Mayer 1960, Jorgenson and Stephenson 1967), and forecasting over typical planning horizons remains difficult and error-prone (Armstrong 1985, Makridakis et al. 1982, Makridakis et al. 1993). The presumption in the literature is that capacity adjustment and forecast error correction are fast relative to the dynamics of the learning curve so that the assumption of perfect market clearing is a reasonable approximation.

In this paper we 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. We begin with a review of the literature on strategy in the presence of learning curves. We then develop a model in which the assumptions of market clearing and rationality are replaced by a disequilibrium, behavioral framework in which firms face lags in adjusting capacity and use boundedly rational decision heuristics to set prices and forecast demand. We use the model to explore the impact of an aggressive learning-curve strategy in a variety of environments.

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 firms are sufficiently low, behavioral theory yields predictions observationally indistinguishable from those of equilibrium models. However in more dynamic environments, in which boundedly rational forecasting techniques become less accurate, the aggressive learning curve strategies prescribed in the game theory literature become inferior, as aggressive expansion leads to excess capacity. We close with implications for the study of strategic competition in general, arguing that the neoclassical assumptions of equilibrium and rationality may in many realistic circumstances prove to be a dangerous guide to action and a weak basis for empirical research.

2. Models of Learning Curve Strategy

Learning curves are a familiar phenomena. Numerous empirical studies have documented their existence in a wide variety of industries, as Hax and Majluf (1984, 112) note, "ranging from broiler chickens to integrated circuits" (see Dutton and Thomas 1984 for a review).

Spence (1979) examines the effect of competitive asymmetries on investment decisions in growth markets where there are learning effects. He notes that learning curves allow for creation of asymmetric advantage and thus create an incentive to preempt rivals. Spence (1981) further quantifies optimal production policy under a learning curve, finding that if firms can perfectly appropriate all the benefits of learning, and if they can be sure of a first mover position, then they should expand output beyond the short-run profit maximizing level in order to capture learning-induced cost advantage. Fudenberg and Tirole (1986) and Tirole (1990) present a dynamic analysis of a duopoly with a learning curve. Under quantity competition they find that an aggressive strategy always dominates. Under price competition the aggressive strategy succeeds in deterring rival entry and in causing rival exit, but when two existing players prefer accommodation there is no clearly dominant strategy a priori.

Other studies have examined the sensitivity of these results to differing demand conditions and appropriability assumptions. Majd and Pindyck (1989) show that uncertainty in future prices reduces the optimal expansion of output beyond the static equilibrium level. Ghemawat and Spence (1985) show that when the effects of learning spill over to competitors the incentives to expand output are also reduced. Similar conclusions are found in the literature on the effects of learning on international trade (Krugman, 1987).

Kalish (1983) addresses the interaction between learning and product diffusion dynamics (word of mouth, saturation). Word of mouth creates a shadow benefit of current sales that reinforces the incentive to cut price and expand production as current output builds the installed base of customers who in turn convey information on the benefits of the product to those who have not yet purchased, accelerating product adoption.

In sum, the literature 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. This recommendation has diffused widely in business education, the popular business literature, and public policy debates (Oster, 1990; Krugman, 1990). All these models assume equilibrium and market clearing so that the firm's capacity is always equal to demand, implying either that there are no capacity adjustment delays or that firms have perfect foresight so that they can forecast demand sufficiently far in advance to ensure that they always have exactly the correct capacity.

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 developed a disequilibrium, behavioral model of competitive dynamics in the presence of learning. Following Kalish (1983), we assume that the market goes through a life-cycle of growth, peak, and saturation. In contrast to the literature, we assume capacity adjusts with a lag, and that firms have only a limited ability to forecast future sales. These assumptions are consistent with a long tradition of experimental and empirical evidence (Brehmer 1992, Collopy and Armstrong 1992, Diehl and Sterman 1995, Kampmann 1992, Mahajan et al. 1990, 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 boundedly rational models, and assume that firms set prices with intendedly rational decision heuristics (Cyert and March, 1963/1992; Forrester 1961; Simon 1976, 1979, 1982; Morecroft 1985).

The model is formulated in continuous time as a set of nonlinear differential equations. Since no analytic solution to the model is known, we use simulation to explore its dynamics[1] While the model portrays an industry with an arbitrary number of firms $i = \{1, ..., n\}$, we restrict ourselves to $n = 2$ in the simulation experiments below. We begin by laying out the equations describing the dynamics of demand. These are based on the standard Bass diffusion model (Bass, 1969; Mahajan et al. 1990). We then describe the physical and institutional structure of the firm, including order fulfillment, revenue and cost, the capacity acquisition lag, and the learning curve. Finally we discuss firm strategy. This section is the heart of the model and contains the key behavioral assumptions regarding demand forecasting, target capacity, and pricing.

Industry Demand

The total industry order rate, Q^O, is the sum of the initial and replacement purchase rates, Q^I and Q^R (time subscripts are omitted for clarity):

$$Q^O = Q^I + Q^R. \tag{1}$$

Initial orders are given by the product of the rate at which households choose to adopt the product and thus enter the market and the average number of units ordered per household, μ. The adoption rate is the rate of change of the number of adopters, M, thus:

$$Q^I = \mu(dM/dt). \tag{2}$$

Households are divided into adopters of the product, M, and potential adopters, N. Following the standard Bass diffusion model adoption arises through an autonomous component and through word of mouth encounters with those who already own the product:

$$dM/dt = N(\alpha + \beta M/POP) \tag{3}$$

where α is a constant fractional propensity for potential adopters to adopt, β is the fractional rate at which potential adopters choose to adopt given that they have an encounter with an adopter, and the ratio M/POP is the probability that a given nonadopter encounters an adopter (POP is the total number of households).

The number of potential adopters remaining, 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:

$$N = MAX(0, M^* - M) \tag{4}$$

where the MAX function ensures that N remains nonnegative even in the case where M^* drops below M (as could happen if the price suddenly rose after $M \approx M^*$).

The number of people who will eventually choose to adopt, M^*, is the equilibrium industry demand and is a function of the price of the product. For simplicity we assume a linear demand curve between the constraints $0 \le M^* \le POP$:

$$M^* = MAX(0, MIN(POP, POP^* + \sigma(P^{min} - P^*))) \tag{5}$$

where σ is the slope of the demand curve, P^{min} is the lowest price currently available in the market, and the reference price P^* is the price at which M^* equals the reference population POP^*.

The replacement order rate, Q^R, is the discard rate of old units, D, summed over all firms in the industry. For simplicity we assume exponential discards from the installed base of each firm:

$$Q^R = \Sigma_i D_i. \tag{6}$$

$$D_i = \delta I_i \tag{7}$$

where I_i is the installed base of firm i's product and δ is the fractional discard rate. The installed base is increased by shipments, Q_i, and decreased by discards:

$$I_i = \int (Q_i - D_i)dt + I_{i_0}. \tag{8}$$

Each firm receives orders O_i equal to a share of the industry order rate. The firm's order share, S^o_i, is determined by a logit model in which product attractiveness, A, depends on both price and availability. Availability is measured by the firm's average delivery delay, given (by Little's Law) by the ratio of backlog, B, to shipments, Q):

$$O_i = S^O{}_i \cdot Q^O \tag{9}$$

$$S^o{}_i = A_i / \Sigma_j A_j \tag{10}$$

$$A_i = [EXP(\varepsilon_p P_i/P^*)][EXP(\varepsilon_a (B_i/Q_i)/\tau^*)). \tag{11}$$

Both price and delivery delay are normalized by reference values (P^* and τ^*, respectively) in the determination of attractiveness. The parameters ε_p and ε_a are the sensitivities of attractiveness to price and availability, respectively. Note that because this is a disequilibrium model, orders and shipments need not be equal. Market share, defined as each firm's share of industry shipments, $S_i = Q_i/\Sigma_j Q_j$, will in general equal the firm's order share only in equilibrium.

The Firm

Firm profits are revenue, R, less total cost, C (the firm index i is deleted for clarity). Total cost consists of fixed cost C_f plus variable costs C_v:

$$\pi = R - (C_f + C_v). \tag{12}$$

Because it takes time to process and fill orders, the price of the product may change between the time customers place an order and receive the product. We assume customers pay the price in effect at the time they place their order. Revenue is thus the product of the quantity shipped and the average value each order in the backlog. The average value of each order in the backlog is the total value of the order book, V, divided by the number of units on order:

$$R = Q(V/B). \tag{13}$$

The value of the order backlog accumulates the value of new orders less the revenues received for orders shipped:

$$V = \int(P \cdot O - R)dt + V_0. \tag{14}$$

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

$$C_f = U_f \cdot K \tag{15}$$

$$C_v = U_v \cdot Q \tag{16}$$

$$U_f = U_{f_0} \cdot (E/E_0)^{\gamma} \tag{17}$$

$$U_v = U_{v_0} \cdot (E/E_0)^{\gamma} \tag{18}$$

$$E = \int Q dt + E_0 \tag{19}$$

where U_{f_0} and U_{v_0} 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.

For simplicity we assume the firm maintains no inventories and makes all product to order.[2] Shipments thus equal production, which is the minimum of desired production, Q^*, and capacity, K. Desired production is given by the backlog, B, and the target delivery delay τ^*. Backlog accumulates orders, O, less production:

$$Q = \mathrm{MIN}(Q^*, K). \tag{20}$$

$$Q^* = B/\tau^* \tag{21}$$

$$B = \int(O - Q)dt + B_0 \tag{22}$$

Capacity adjusts to the target level K^* with an average lag λ. Specifically, we assume K adjusts to K^* with a third-order Erlang lag, corresponding well to the distributed lag estimated in investment function research (Jorgenson and Stephenson 1967):

$$K = \mathcal{L}(K^*, \lambda) \tag{23}$$

where $\mathcal{L}$ is the Erlang lag operator. For simplicity the lag is symmetric for the cases of increasing and decreasing capacity.

Firm Strategy

Under the traditional assumptions of perfect rationality and equilibrium, each firm's target capacity and pricing behavior would be given by the solution to the differential game defined by the physical and institutional structure of the market presented above. However, in reality firms do not determine their behavior by solving dynamic programming problems of such complexity (e.g. Camerer 1990, 1991). Business schools do not teach future managers how to formulate and solve dynamic programming problems when setting strategy. Rather, firms use intendedly rational heuristics to set prices and acquire capacity, and the analytic models in the literature reach the managerial audience in the form of rules of thumb. In the case of the learning curve, 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). In this spirit, we model target capacity and price with realistic boundedly rational heuristics, heuristics which 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. In particular, we assume the firm forecasts future market demand and then determines what share of that demand it would like to command. Target capacity therefore consists of the product of the firm's target market share, S^*, and its forecast of industry demand, D^e, adjusted by the normal rate of capacity utilization u^*:

$$K^* = MAX[K^{min}, S^*D^e/u^*] \tag{24}$$

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

Because of the capacity acquisition delay the firm must forecast demand λ years ahead. We assume firms forecast by extrapolating recent trends in observed industry demand (Collopy and Armstrong 1992). Specifically, the firms base their forecast on the reported value of the industry order rate, D^r, and exponentially extrapolate the recent growth in industry orders, g^e, over the forecast horizon λ^f:

$$D^e = D^r \mathrm{EXP}(\lambda^f g^e) \tag{25}$$

$$d(D^r)/dt = (O - D^r)/\tau^d \tag{26}$$

$$g^e = \ln(D^r{}_t / D^r{}_{t-\lambda^h}) / \lambda^h \tag{27}$$

where λ^h is the historical horizon used to compute the expected growth rate in demand G^e. The instantaneous, current value of industry orders is not available to firms because it takes time to collect and report the data, so the forecast is based on the reported order rate, given here by first-order exponential smoothing of actual industry orders with a smoothing time of τ^d (Sterman 1987 provides empirical evidence consistent with such forecasting procedures for both long-term energy demand forecasts and short-term inflation forecasts).

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 learning curve literature by seeking a market share large enough to move the firm down its learning curve faster than its rivals. In contrast, the conservative firm seeks accommodation with its rivals and sets a modest market share goal.

We also assume firms monitor the actions of their competitors. The aggressive strategy seeks to exploit the learning curve 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 sufficient 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

$$S^* = \begin{cases} \mathrm{MAX}(S^{min}, S^u) & \text{if Strategy = Aggressive} \\ \mathrm{MIN}(S^{max}, S^u) & \text{if Strategy = Conservative} \end{cases} \tag{28}$$

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 is the difference between the firm's forecast of industry demand and their forecast of competitor capacity. Expected uncontested market share is given by the expected uncontested demand, D^u, as a fraction of the projected industry demand:

$$S^u = MAX(0, D^u/D^e). \tag{29}$$

The MAX function maintains nonnegativity for S^u 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 the normal capacity utilization rate u^*:

$$D^u = D^e - u^* \Sigma_j K^e_j, \qquad j \neq i. \tag{30}$$

In the base case we make the strong assumption that firms accurately monitor their competitor's capacity plans. However, we assume there is a short delay of τ^c years required for the firm to carry out the competitive intelligence required to estimate the competitor's target capacity (exponential smoothing is assumed), so expected competitor capacity K^e evolves as:

$$d(K^e_j)/dt = (K^*_j - K^e_j)/\tau^c. \tag{31}$$

To model the price decision, we assume that due to administrative and decision making lags, price, P, adjusts to a target level, P^*, with an adjustment time τ^p:

$$dP/dt = (P^* - P)/\tau^p \tag{32}$$

The price setting rule assumes the firm does 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 form the target price. The current price forms the anchor, which is then adjusted in response to considerations of cost, demand/supply balance, and market share, forming a hill-climbing heuristic in which the firm searches for better prices in the neighborhood of the current price, using costs, demand/supply balance, and market share to assess the gradient. 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 never price below unit variable cost U_V. Thus

$$P^* = MAX\{U_V, P[(1+\alpha^c((P^C/P)-1))(1+\alpha^d((Q^*/(u^*K))-1))(1+\alpha^s(S^*-S))]\},$$

$$\alpha^c \geq 0; \alpha^d \geq 0; \alpha^s \leq 0. \tag{33}$$

The three adjustment terms capture the firm's response to unit costs, the adequacy of its capacity to meet demand, and its market share relative to its target share. The adjustment parameters α determine the sensitivity of price to each adjustment pressure. The first term, the adjustment for unit costs, moves target price towards a base price P^C given by unit costs and the normal profit margin m^*:

$$P^C = (1 + m^*)(U_v + U_f). \tag{34}$$

The firm also responds to the adequacy of its current capacity, measured by the desired rate of production Q^* divided by 'normal production', defined as the production rate given by current capacity and the normal capacity utilization fraction u^*. When this ratio exceeds unity, the firm has insufficient capacity and increases price above the current level; excess capacity creates pressure to lower price.

Finally, the firm attempts to price 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 finds it desires a greater share than it currently commands, it will lower price; conversely if market share exceeds its target it will increase 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), experimental evidence (Kampmann 1992), and econometric evidence from a similar model of interest rate setting behavior (Hines 1987). Paich and Sterman (1993) created a product lifecycle simulation microworld similar to the present model as an experimental system, and estimated a similar model for pricing which captured the pricing behavior of the subjects well.[3]

4. Results

We begin by confirming that under conditions of perfect foresight and instantaneous market clearing the model reproduces the conclusions of the existing literature. We then explore the effectiveness of the learning curve strategy as these assumptions are gradually relaxed by exploring the performance of the model in increasingly dynamic markets.

For the base case the model is calibrated to capture the dynamics of typical consumer electronics items such as camcorders (table 1). As scaling parameters we set the initial price at \$1000/unit, and the potential size of the market at the initial price to 60 million households, each seeking $\mu = 1$ unit. The product is assumed to be durable, with a 10%/year replacement rate. We assume a 70% learning curve (costs fall 30% for each doubling of cumulative production), a typical value for a wide range of products. The ratio of fixed to variable costs is 3:1. The sensitivity of order share to price is high ($\varepsilon_p = -8$), implying products are only moderately differentiated by non-price factors, an *a fortiori* assumption that favors the effectiveness of the learning curve strategy. We assume short delays of only one quarter year for the reporting of industry orders and the estimation of competitor target capacity. In general these parameters favor the success of a learning curve strategy (we present sensitivity analysis below).

We examine the behavior of the market for values of the word of mouth parameter $.5 \leq \beta \leq 2.5$. This range generates product lifecycle dynamics that span much of the variation in observed diffusion rates (Parker 1994, Klepper and Graddy 1990). For illustration, we define three scenarios for the evolution of industry demand: Fast, Medium, and Slow, defined by values of β = 2, 1, and .5, respectively. Figure 1 shows the evolution of the industry order rate generated by the demand sector of the model for each scenario, assuming no capacity constraints and assuming that prices follow unit costs down the learning curve (the target market shares for both firms = .5). All exhibit a period of rapid growth followed by a peak and decline to the equilibrium, replacement rate of demand. The stronger the word of mouth feedback, the greater the dynamic complexity of the market: 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, calculators, and many toys and games, often with only a few years from boom to bust.

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, large enough to provide the firm with a significant advantage in cumulative production and drive the learning curve in its favor yet not so large as to invite antitrust action (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.

To test whether the model reflects the competitive dynamics analyzed in the existing literature, we begin by assuming that capacity can instantly adjust to the level required to provide the target rate of capacity utilization at all times:

$$K = Q^*/u^*. \tag{23'}$$

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 rational expectations and perfect foresight so that they can perfectly anticipate the capacity acquisition lag. The market always clears with no unintended backlog accumulations, and capacity utilization always equals the target rate. Prices thus respond only to unit costs and the gap between the firm's target and actual market share. The price rule yields behavior consistent with the recommendations in the literature: the aggressive player will respond to the initial gap between target and actual market share by reducing price below the short-term equilibrium.

Table 2 shows discounted cumulative profits for the three market scenarios. (Throughout the paper 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. Even though the payoff to the cooperative, conservative strategy [C, C] maximizes the net present value of cumulative profit for both the individual firms and the industry, each player has a strategic incentive to defect to exploit the learning curve if they believe the other player will cede and continue to play the conservative strategy. However, a firm that finds itself playing conservative while the other pursues the learning curve strategy would improve their position by defecting, so [A, A] is the dominant strategy. Aggressively exploiting the learning curve is the dominant strategy if firms must irrevocably and independently choose their strategy at the beginning of the industry, if the firm can credibly commit to the aggressive strategy and persuade its rival to acquiesce, or if the first mover gains sufficient advantage before rivals can respond.

The faster the dynamics of the market unfold, the greater industry profits are for any strategy combination (figure 2 shows the relative payoffs in the market clearing case as functions of the word of mouth parameter β). Stronger word of mouth brings people into the market sooner, hence boosting cumulative profit. Consistent with Kalish (1983), the advantage of the aggressive strategy, and thus the strategic incentive to defect, increases with the speed of the product lifecycle. Similarly, sensitivity analysis shows that the stronger the learning curve, the greater is the strategic incentive to play the aggressive strategy.

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

We now examine the case where the firm faces the capacity adjustment lag and must therefore forecast industry demand and competitor responses, as specified by the behavioral rules in equations 23-34. Figure 3 shows the payoffs as they depend on the word of mouth parameter; table 3 shows the payoff matrices for the different scenarios. The capacity adjustment lag and behavioral decision rules dramatically alter the payoffs to the different strategies. As long as the market dynamics are sufficiently slow, the firm's capacity forecasts are accurate enough 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 the aggressive strategy, contrary to the prescription of the equilibrium models. Neither firm has any incentive to defect, and [C, C] becomes the unique Nash equilibrium. Note the penalty imposed when both firms play the aggressive strategy is much greater than in the market clearing case.

To identify why the payoffs change so dramatically when the equilibrium and perfect foresight assumptions are relaxed, figure 4a shows the dynamics of the [A, C] case for the fast market scenario, while figure 4b shows the same scenario for the case where capacity adjusts instantaneously. In both cases, the aggressive firm immediately perceives a gap between its initial share of 50% and its goal of 80%, and cuts price. In the case with the capacity lag, the aggressive firm also sets target capacity to 80% of its forecast of industry demand. The demand forecast extrapolates the rapidly rising industry order rate. After about one year, the firm expects industry demand to grow at a rate in excess of 100%/year, causing target capacity to increase well above the firm's current capacity requirements and swelling the supply line of capacity on order. Due to the capacity acquisition lag and the delay in perceiving industry orders, both firms reach full capacity utilization after about .5 years. 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 price bubbles are often observed during the growth phases of highly successful products, as occurred for example with radios, black and white television, and color televisions (Dino 1985) and more recently with 1 Mbit DRAM chips and Harley-Davidson motorcycles.

Beginning in about year 2, and accelerating dramatically after about year 4, the market, though growing, experiences a decline in the fractional growth rate. As the data are reported, the firm lowers its forecast of future growth rates, but due to the lags in the reporting of industry orders, in assessing the growth rate from historical order rates, and in adjusting capacity to the target, actual capacity begins to overshoot the required level, and capacity utilization falls below normal. As industry orders peak and decline, shortly before year 6, both firms find their forecasts have gone badly wrong, leaving them with excess capacity. The aggressive firm suffers the most, since it has not only been growing to meet the forecasted growth of industry demand, but has during the same period been growing at an additional rate to increase its market share (note that the aggressor's capacity peaks later as well as higher than that of the conservative firm). As boom becomes bust, the aggressive firm finds capacity utilization drops below 50%. The conservative firm also experiences excess capacity, but the magnitude and duration of the problem is significantly less since the conservative player has been steadily giving up market share during the growth phase, partially offsetting its excessively optimistic forecasts. The pattern of capacity overshoot is widespread in maturing industries (Porter 1980), and was frequently observed in Paich and Sterman's (1993) experimental product lifecycle task, even when subjects had experience with the dynamics. As a result of the excess capacity generated by the saturation of the market, both firms experience a period of losses as revenues drop below fixed costs. The losses of the aggressive firm, however, are substantially larger than those of the conservative firm. The aggressor generates a net loss of more than $2 billion per year as industry sales peak around year 6. Though the aggressive firm earns superior profits after year 8 these fail to compensate for its earlier losses, leaving it with discounted cumulative profits of -$1.7 billion by year 40.

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. 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 is due entirely to the combination of the capacity adjustment lag with a boundedly rational forecasting heuristic.

When capacity adjusts perfectly the aggressive strategy always dominates the conservative strategy and faster market evolution increases the advantage of the aggressive strategy (figure 2). 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 3). As the dynamic complexity of the market environment grows, or as the capacity acquisition lag increases, the likelihood of significant capacity overshoot grows, and an aggressive strategy becomes significantly less profitable than the conservative strategy even if a firm is able to commit to an aggressive strategy secure in the knowledge that its rival will cede.

Sensitivity Analysis

Before drawing any general conclusions from the results it is important to explore the degree to which they are sensitive to assumptions. Despite substantial variations in key parameters (table 4), the critical value of the word of mouth parameter above which the learning curve strategy becomes inferior, β^{CRIT}, remains in the range from 2.0 to less than .5, corresponding to sales peaks from five to twenty years after product launch, well within the range documented for numerous real products (Parker 1994).

We have made a number of assumptions that reduce the attractiveness of a learning curve strategy. 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 assume there are no returns to scale or other positive feedback processes such as network externalities. Additional positive feedbacks or other sources of increasing returns favor the aggressor just as a stronger learning curve increases the advantage of the aggressive strategy (see e.g. Arthur 1989). 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 reduces the dynamic complexity of the market and the magnitude of the decline from peak to replacement sales rates.

One of our key behavioral assumptions is that firms forecast industry demand by extrapolating past demand and have no advance knowledge of the market's saturation point. In the case of durable goods, extrapolative methods necessarily overshoot as growth gives way to saturation. 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) experimental version of the present model, 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 and Mahajan et al. 1990 review the extensive literature). In practice, diffusion models often miss the turning point as well, 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 percent forecast errors averaged more than 40% across all models and products. The extrapolative models generally outperformed the diffusion models.

On the other hand a number of our assumptions tend to increase the advantage of an aggressive strategy. We assume learning is perfectly appropriable, increasing the ability of firms to gain sustained cost advantage. 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 more realistic adjustment costs would significantly 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 might not survive the losses of the transition from boom to bust, again favoring the aggressive strategy. 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. 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.

The assumption that firms know their rivals' planned capacity levels bears closer examination. Extensive experimental studies (Sterman 1989a, 1989b, Paich and Sterman 1993, Diehl and Sterman 1995, Kampmann 1992) show in a wide range of experimental markets that people ignore or give insufficient weight to the supply line of pending capacity or production. The tendency to ignore the supply line (and more generally, failing to account for delays, e.g. Brehmer 1992) is robust: it occurs even in settings where the contents of the supply line are available costlessly and at all times, are prominently displayed, and are highly diagnostic, and where subjects had financial incentives to perform well. Failure to account for time delays and supply lines appears to be common in real markets as well. Studies show few real estate developers, for example, take account of the supply line of projects under development (Thornton 1992, Bakken 1993), leading to periodic overbuilding. Figure 5 shows the payoffs in the case where we assume firms do not account for the supply line of pending capacity but instead use the competitors' current capacity to estimate uncontested demand:

$$K^e_j = K_j. \tag{31'}$$

When the supply line is ignored the aggressive strategy is inferior for all the market environments tested. Ignoring the supply line ensures that during the growth phase each firm erroneously believes its rival is expanding capacity much less than it actually is, and overestimates uncontested demand. The aggressive player opportunistically increases its target capacity still further and the conservative player fails to cede sufficiently, leading to a much larger overshoot of capacity and much larger losses when the market saturates. The aggressive strategy is dominated by the conservative strategy even in the slow scenario where demand for the product peaks 20 years after its introduction and the decline from peak to equilibrium sales is small.

5. Discussion and Conclusions

Prior research has shown that under assumptions of equilibrium and perfect rationality, the optimal strategy for a firm facing a learning curve is to aggressively preempt competitors, cutting price and boosting output beyond the static optimum levels. We have shown that under a more realistic set of assumptions, the normative result can be reversed. When there are capacity adjustment lags, commonly used forecasting heuristics lead to capacity overshoot as a market saturates. Investing in additional capacity and lower prices to achieve learning benefits 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. 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 rational model to fail.

These conclusions are consistent with experimental and empirical evidence. The results predict that learning curve strategies will perform best in industries where there is slow demand growth (or where customer awareness of the product category is already high), the product has a high repeat purchase rate and is fairly undifferentiated, or where capacity can be adjusted rapidly at low cost. Observations that learning curve strategies generally led to sustained advantage in industries such as synthetic fibers, bulk chemicals, and disposable diapers (Shaw and Shaw 1984, Porter 1984, Lieberman 1984, and Ghemawat 1984 respectively) are broadly consistent with this prediction. Similarly, our results predict poor performance for aggressive strategies in industries with high word of mouth, durable, differentiated products, or long capacity adjustment delays. The overcapacity, excess inventory, and price wars observed in industries such as televisions and VCRs, toys and games, lighting equipment, snowmobiles, hand calculators, tennis equipment, bicycles, chain saws, semiconductors, and running shoes cited earlier support this proposition.

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. The recommendation to pursue a learning curve strategy must always be treated with caution. Current texts and theory suggest firms should assess the strength and appropriability of learning curves in their industry and recommend aggressive preemption in the presence of strong, appropriable learning curves or other positive feedbacks that confer increasing returns. Our results show that firms must also determine whether they are vulnerable to capacity overshoot or underestimation of competitor capacity plans. A firm electing to pursue a learning curve driven 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 less aggressive players will not unintentionally overbuild. To prevent competitor overbuilding, it may find it optimal to share its 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. Rather, it appears that when high dynamic complexity increases the risk of capacity overshoot, firms should consider conservative strategies even in the presence of learning curves and other sources 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.

On the methodological front, our results suggest that the equilibrium and rationality assumptions of game theory and microeconomics are not robust. More realistic physical, institutional and behavioral assumptions can reverse the neoclassical result and reveals a much more complex relation between the learning curve, the dynamics of demand and firm strategy.

When the system dynamics are sufficiently slow, the delays in information acquisition, decision making and system response sufficiently short, and the cognitive demands on the agents sufficiently low, behavioral theories 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. The case of the learning curve in a dynamic market shows these differences can matter greatly, and their impact can be examined rigorously. We speculate that relaxing the assumptions of rationality and equilibrium may lead to similar differences in a variety of other contexts. Such cases are likely to include settings in which there are long time delays between action and effect or in the reporting of information, where there are positive feedback processes (increasing returns), and where there are significant nonlinearities (Sterman 1994, Arthur 1994). Likely examples include markets such as shipbuilding, real estate, paper, and many others plagued by chronic cyclicality, and industries with network externalities and standard formation issues such as telecommunications and software. We suggest the combination of game theoretic reasoning with behavioral simulation models can help create a meaningful 'behavioral game theory' (Camerer 1990, 1991), that is, a behaviorally grounded, empirically testable, and normatively useful theory of disequilibrium dynamics in strategic settings.

NOTES

1. The model is solved by Euler integration with a time step of .0625 years. The results are not sensitive to the use of smaller time steps or higher-order integration methods.

2. Including inventories would substantially destabilize the system (Sterman 1989b); omitting inventories is thus an *a fortiori* assumption.

3. Paich and Sterman (1993) estimated a slightly different form of the model, in which there was no market share effect. They found the cost effect was very strong, while the response to the demand/supply balance was quite weak.

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Table 1. Parameters and initial conditions for the base case.

n	number of firms in industry	2
μ	Average number of units per household (units/household)	1
α	Propensity for nonadopters to adopt the product autonomously (1/years)	.001
β	Propensity for nonadopters to adopt the product through word of mouth (1/years)	1
POP	Total population (households)	100e6
σ	Slope of the demand curve (Households/($/unit))	$-.2(POP^*/P^*)$
POP^*	Population that would adopt at the reference price P* (households)	60e6
P^*	Price at which industry demand equals the reference population POP* ($/unit)	1000
δ	Fractional discard rate of units from the installed base (1/years)	.10
ε_p	Sensitivity of product attractiveness to price	-8
ε_a	Sensitivity of product attractiveness to availability	-4
U_{v0}	Initial unit variable cost ($/unit)	$(P_{i0}/(1+m^*))/(1+c)$
U_{f0}	Initial unit fixed cost ($/unit)	$c(P_{i0}/(1+m^*))u^*/(1+c)$
c	Ratio of fixed to variable costs (dimensionless)	3
γ	Strength of the learning curve (dimensionless)	$\log_2(.7)$
τ^*	Target delivery delay (years)	.25
λ	Capacity acquisition delay (years)	1
u^*	Target capacity utilization rate (dimensionless)	.8
K^{min}	Minimum efficient scale (units/year)	1e5
λ^f	Forecast horizon (years)	λ
τ^d	Time delay for reporting industry order rate (years)	.25
λ^h	Historic horizon for estimating trend in demand (years)	1
τ^c	Time delay for estimating competitor target capacity (years)	.25
τ^p	Adjustment time for price (years)	.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)	.5
α^s	Weight on market share in determination of target price (dimensionless)	-.10
m^*	Target profit margin (dimensionless)	.2
M_0	Initial number of adopters (households)	$.001M^*$
I_{i0}	Initial installed base of product for firm i (units)	$.5\mu M$
V_{i0}	Initial value of order backlog of firm i ($)	$P_i \cdot B_{i0}$
B_{i0}	Initial order backlog of firm i (units)	$.5Q_0\tau^*$
E_{i0}	Initial cumulative production experience of firm i (units)	10e6
K	Initial capacity of firm i (units/year)	K^*
K^e_j	Initial estimate of competitor j's target capacity (units/year)	K^*_j
D^r_{i0}	Initial value of reported industry demand (units/year)	Q^0
P_{i0}	Initial price of firm i ($/unit)	1000

Table 2. Payoffs for the perfect capacity case in three industry evolution scenarios (NPV of cumulative profits, Billion $).

SLOW (β=.5)		**Aggressive**	**Conservative**
	A	3.2, 3.2	5.1, 2.1
	C	2.1, 5.1	3.8, 3.8

MEDIUM (β=1)		**Aggressive**	**Conservative**
	A	4.8, 4.8	7.3, 3.2
	C	3.2, 7.3	5.7, 5.7

FAST (β=2)		**Aggressive**	**Conservative**
	A	6.5, 6.5	9.4, 4.8
	C	4.8, 9.4	7.6, 7.6

Table 3. Payoffs for the capacity adjustment lag case in three industry evolution scenarios (NPV of cumulative profits, Billion $).

SLOW (β=.5)		**Aggressive**	**Conservative**
	A	-7.0, -7.0	4.8, 0.9
	C	0.9, 4.8	3.5, 3.5

MEDIUM (β=1)		**Aggressive**	**Conservative**
	A	-11.1, -11.1	5.2, 1.0
	C	1.0, 5.2	4.4, 4.4

FAST (β=2)		**Aggressive**	**Conservative**
	A	-19.7, -19.7	-1.7, 0.2
	C	0.2, -1.7	1.9, 1.9

Table 4. Sensitivity analysis. The critical value of the word of mouth parameter, β^{CRIT}, is the value of β such that the aggressive strategy is inferior for values of $\beta > \beta^{CRIT}$. The larger the value of β^{CRIT}, the more robust is the learning curve strategy to a rapid product lifecycle. § denotes the base case value.

Parameter			β^{CRIT}
σ:	Demand	$0.0(POP^*/P^*)$	1.4
	Curve Slope	$-0.2(POP^*/P^*)$ §	1.3
		$-1.0(POP^*/P^*)$	1.1
ε_p:	Sensitivity of Product	-4	<.5
	Attractiveness	-8 §	1.3
	to Price	-12	2.0
δ:	Fractional Discard Rate	.10 §	1.3
	of Products	.20	1.6
		.50	1.4
c:	Ratio of fixed	3 §	1.3
	to variable cost	1	1.5
		1/3	1.9
λ:	Capacity	1.0 §	1.3
	Adjustment Delay	0.5	1.9
γ:	Learning	$\log_2(.8)$	1.3
	Curve	$\log_2(.7)$ §	1.3
	Strength	$\log_2(.5)$	1.6

Parameter			β^{CRIT}
u^*:	Normal	.6	1.2
	Capacity	.8 §	1.3
	Utilization	1.0	1.6
τ^d, τ^c:	Information	.25, .25 §	1.3
	Reporting Delays	.0625, .0625	1.7
α^c:	Strength of Cost	1.0 §	1.3
	Adjustment in Price	0.5	1.2
α^d:	Strength of	0.50	1.1
	Demand/Supply	0.25 §	1.3
	Effect on Price	0.00	1.0
α^s:	Strength of	0.00	1.3
	Market Share	.10 §	1.3
	Effect on Price	.20	1.3
		.50	1.3
S^{min}:	Minimum	1.00	1.0
	Market Share Target	.80 §	1.3
	for Aggressive Strategy	.60	0.8

Figure 1.. Diffusion dynamics for three values of the word of mouth parameter, β (Slow, Medium, Fast: β = .5, 1, 2 respectively), for the perfect capacity case with target market share for both firms = 50%. From top to bottom: Adopters, Industry Order Rate, Price.

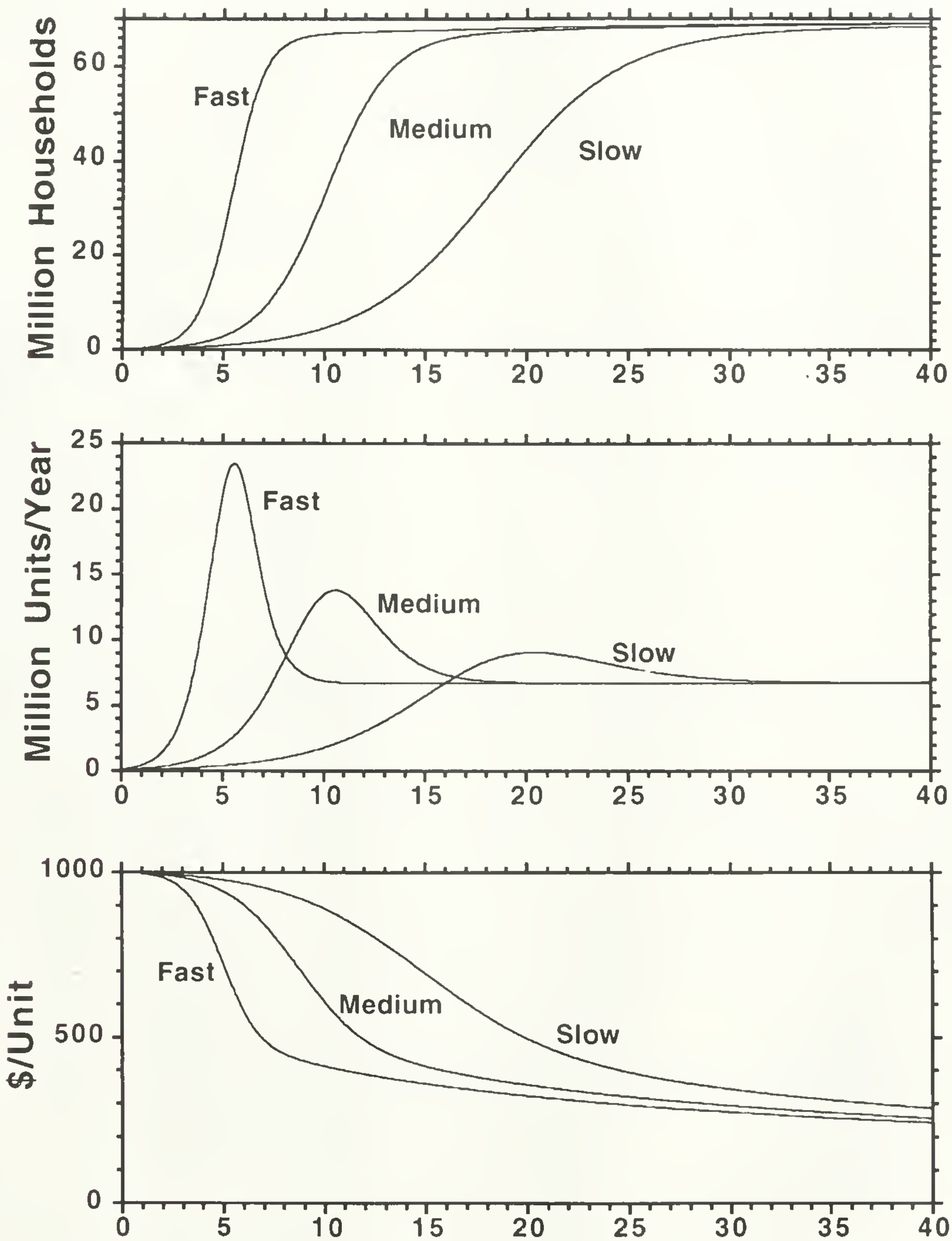

Figure 2. Firm Payoffs as they depend on the speed of the product lifecycle, perfect capacity case. The aggressive strategy always dominates.

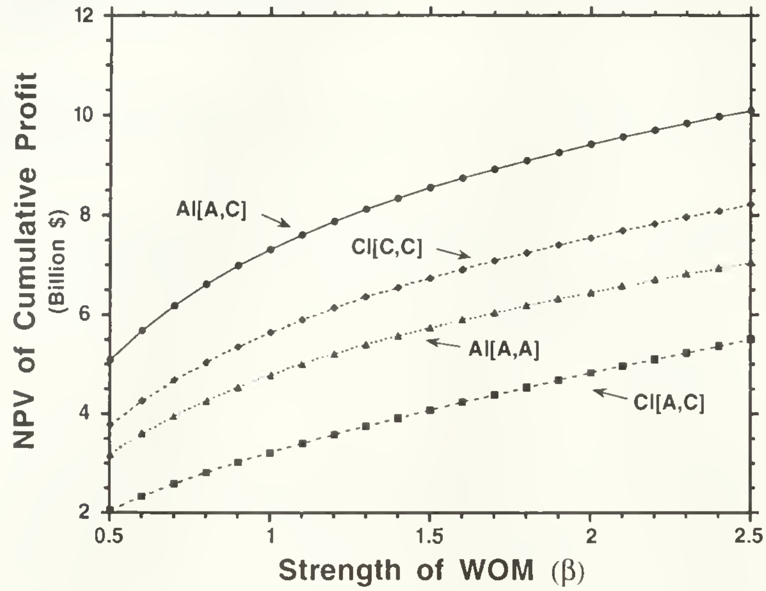

Figure 3. Firm Payoffs as they depend on the speed of the product lifecycle when capacity adjusts with a one-year lag. The aggressive strategy is inferior for values of $\beta > \beta^{CRIT}$. Compare to figure 2.

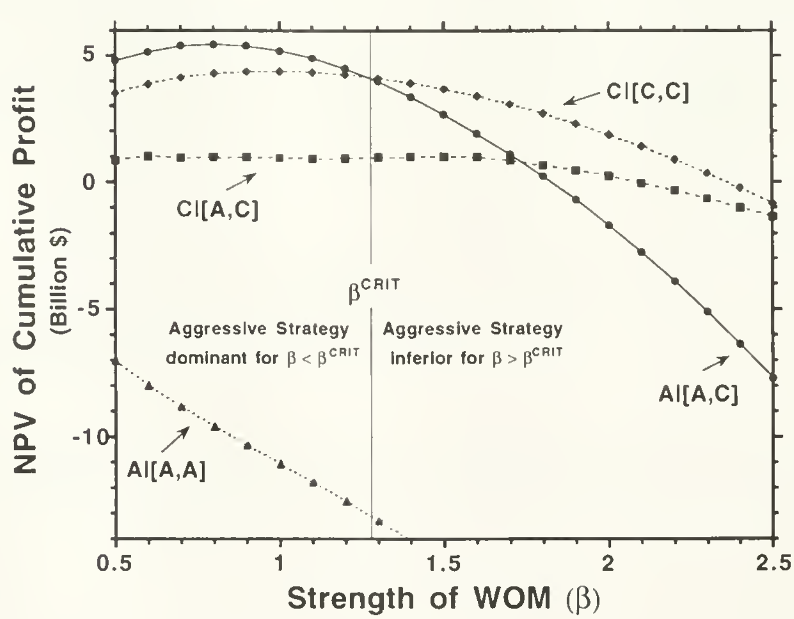

Figure 4a. Dynamics of the aggressive vs. conservative strategies in the fast market scenario (β = 2), with the capacity acquisition lag.

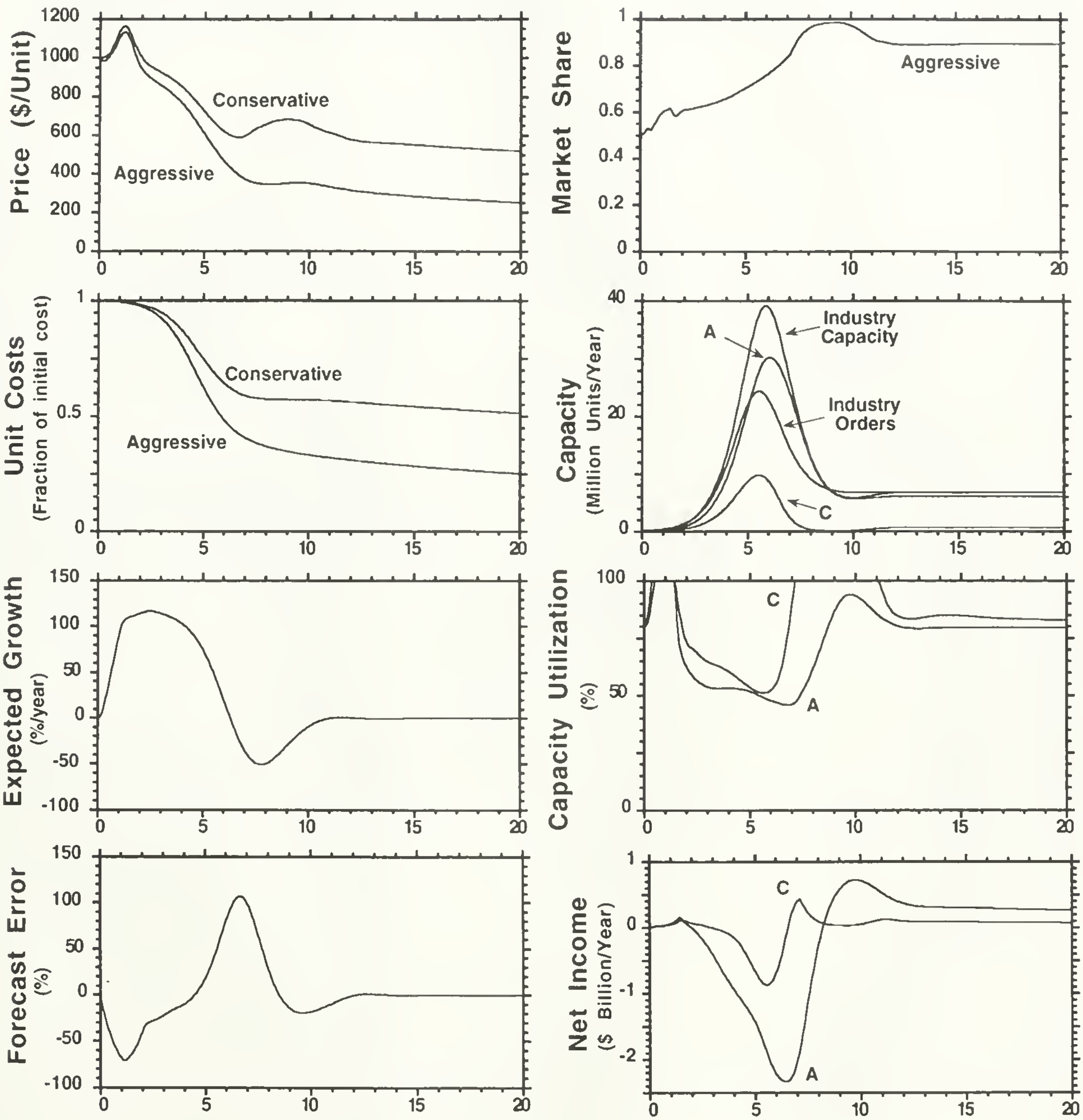

Figure 4b. Aggressive vs. Conservative Strategies in the market clearing case with fast market dynamics ($\beta = 2$). Compare to figure 4a.

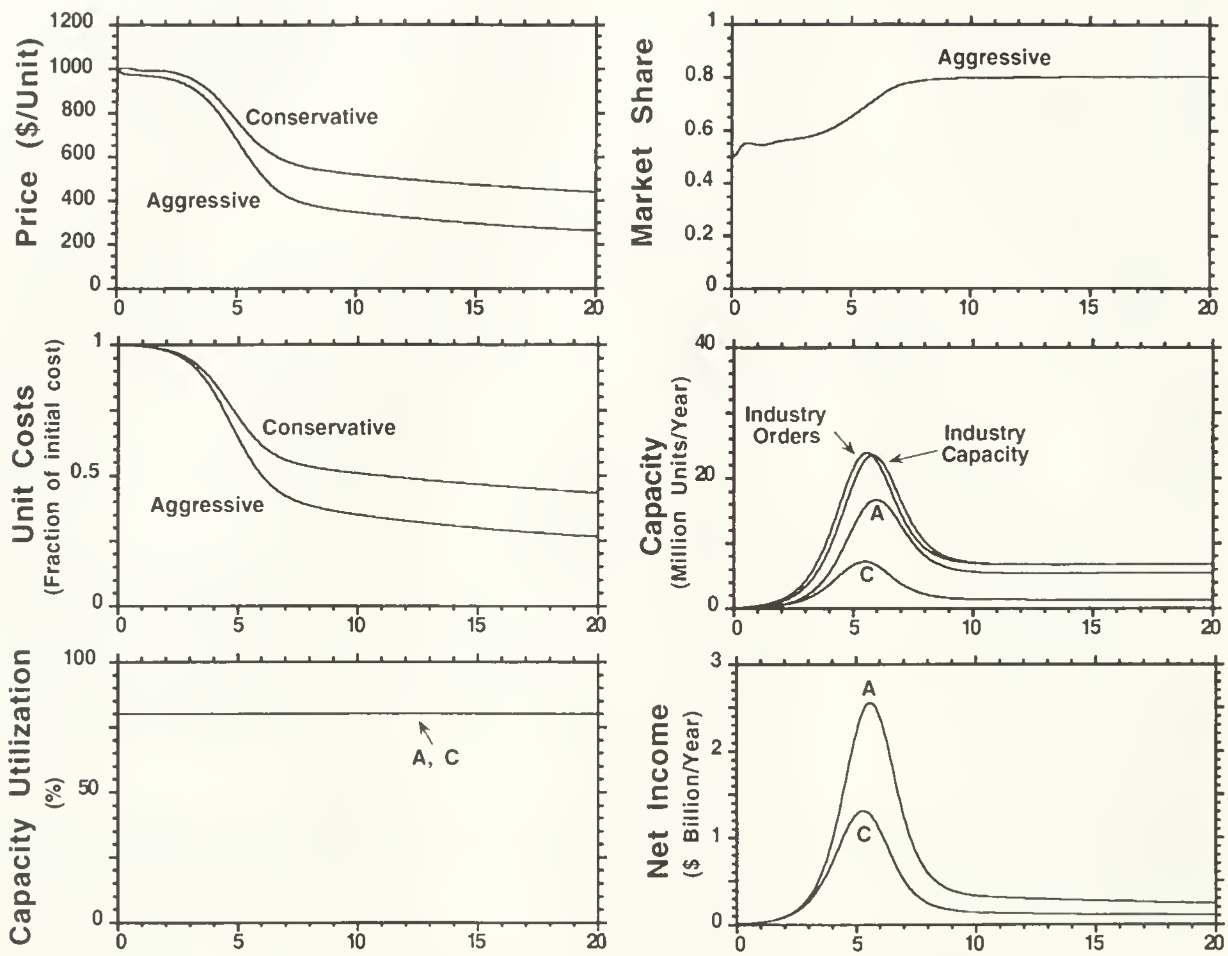

Figure 5. Firm Payoffs as they depend on the speed of the product lifecycle when competitor capacity is estimated without regard to the supply line of pending capacity. The aggressive strategy is inferior for $\beta > .5$.