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Boom and Bust Behaviour: On the Persistence of Strategic Decision Biases and their Collective Outcome

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Boom and Bust Behavior: On the Persistence of Strategic Decision Biases

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INTRODUCTION

Boom and bust or overshoot and collapse dynamics are common among firms in a large range of different industries. Durable consumer electronics (e.g. televisions, VCR's, calculators, etc.), telecommunications, medical equipment, chemicals, real estate, pulp and paper, agricultural commodities, natural resources, toys and games, tennis equipment, bicycles, semiconductors and running shoes, are examples of industries where boom and bust dynamics have occured (Paich & Sterman, 1993; Sterman, 2000; Sterman, Henderson, Beinhocker, & Newman, 2007). Such dynamics occur in both traditional cyclical industries (Meadows, 1970) as well as industries with pronounced product and/or category lifecycles (Klepper, 1996).

The common managerial behavior underpinning boom and bust dynamics (B&B) across all of these industries is aggressive capacity expansion in the boom period when demand typically outstrips supply. Aggressive capacity expansion strategies in the boom phase ultimately result in excess capacity turning the boom into bust (Bakken, Gould, & Kim, 1992; Moxnes, 1998; Paich & Sterman, 1993; Sterman, 1989a, 1989b; Sterman, 2000). The fundamental problem is that in many cases capacity adjustments cannot be made quickly enough to match demand. Time delays associated with expanding or reducing capacity require firms to forecast demand and make strategic decisions to initiate capacity changes far in advance. This combination of boundedly rational decision-making and capacity adjustment delays gives rise to boom and bust dynamics (Sterman et al., 2007). The combination is so difficult to manage that agents, including firms, rarely learn from boom and bust experiences. In some cases, the bust phase is so severe that the firms involved go bankrupt and disappear altogether. In other cases, the firms involved survive the bust only to fall into the same trap a few years later.

This chapter examines the underlying cognitive and behavioral factors responsible for strategic decisions driving B&B dynamics, discusses the reasons firms do not learn to avoid boom and bust, and identifies tentative strategies for mitigating B&B behavior. At the same time, we shall conjecturally conclude, there might be a positive collective side to B&B behavior fostering accumulation of knowledge and physical infrastructure, especially regarding new technological paradigms.

The next section discusses a number of real world cases of boom and bust dynamics. The examples illustrate quite common dynamic behaviors and highlight the crucial role of capacity investment decisions in B&B outcomes. Subsequent sections review the findings from prior experimental research on B&B dynamics and discuss some key decision biases and heuristics that play important roles in B&B decision-making. The final section outlines some tentative strategies for moderating B&B decision-making. In the conclusion, we highlight some of the collectively positive aspects of booms and busts.

EXAMPLES OF BOOM AND BUST DYNAMICS

There are numerous examples of companies that have experienced B&B dynamics. Examples include Atari in home video games (Coughlan, 2001, 2004), JDS Uniphase in telecommunications (Sterman et al., 2007), Worlds of Wonder in toys (" Toy Maker Finds a Buyer", 1989), Tensor Corporation in lighting (Salter, 1969), and Swatch in fashion watches (Pinson, 1987). This section discusses two brief case examples of organizational B&B dynamics – EMI in CT scanners and Lucent Technologies in telecommunications equipment. Both businesses experienced booming growth phases of tremendous success and then, within a very short period of time, suffered equally dramatic collapses and financial bust. These examples just scratch the surface of the wealth of cases documenting boom and bust.

EMI CT Scanners

EMI Laboratories invented Computed Tomography (CT) imaging, in 1972 and installed the first seven CT scanners in hospitals in 1973. Figure 1 provides time series data for the number of CT scanners sold in the United States from 1973-1980 along with the estimated remaining potential customers in the U.S. market (Bartlett, 1983a, 1983b; EMI, 1973-1980). By 1976, 17 companies were selling CT scanners, including a number of well-established medical equipment and devices firms such as GE and Siemens, and had installed over 475 CT scanners. At this stage, existing players invested rapidly to expand their production capacity to improve the 9-12 month delivery delays (Bartlett, 1983c). New entrants were also rapidly increasing the amount of capacity in the industry during this period. Unit sales across the industry were very strong in 1977, with approximately 40 scanners installed per month. However, during 1978 the unit sales rate fell by nearly half and then continued to fall further in 1979 and 1980. The precipitous decline in scanner sales in 1977 and 1978 caused many firms to exit the industry during this bust phase.

Figure 1 about here

As the first and dominant manufacturer of CT scanners for the first three years after they invented the CT scanner, EMI epitomized the B&B behavior of a number of companies in the CT market during the period 1973-1980. Following a $29.1 million profit in 1977, the medical electronics division of EMI, including the CT scanner business, incurred major losses in both fiscal years 1978 (-$28.7 million) and in 1979 (-$27.8 million). In December 1979, Thorn Electrical Industries acquired EMI, and several months later sold the CT scanner business to General Electric. In the eight years after inventing the CT scanner, EMI went through a spectacular boom period in which they could not keep up with demand, followed by an even steeper bust leading to large financial losses. A post hoc analysis of overall market potential compared with cumulative sales in 1976, reveals that the saturation point of the product lifecycle was being approached very rapidly even as capacity expansion was just starting to ramp up (Bartlett, 1983c). Figure 1b provides estimates of remaining "potential" US customers from 1973 to 1980. The subsequent period of excess capacity in the industry plummeted many firms into financial turmoil.

As is true in most B&B scenarios, EMI or other industry members could have, relatively easily, predicted the potential demand for CT scanners from the available knowledge of the number of hospitals and the required scanning capacity for CT diagnostics. Furthermore, almost all successful durable products follow a similar pattern of slow initial acceptance followed by rapid sales growth until the market becomes saturated. Demand stagnates and then falls to the level of replacement sales during the mature and decline phases of the lifecycle. Senior managers could have used the well-established product lifecycle curve plus knowledge of delays in adjusting production capacity in the industry when planning their strategies and capacity investment decisions to avoid the deep trough and losses of the bust.

Lucent Technologies

AT&T spun off Lucent Technologies in an initial public offering in 1996 and the new company morphed overnight into a hot technology stock. Deregulation of the telecommunications industry that same year fueled rapid growth in demand for telecommunications equipment by enabling new companies to sell phone services. These upstarts needed the networking equipment Lucent sold, and investors willingly furnished the cash required (Greenwald, Frank, & Taylor, 2001). The technology boom was in full swing. By the end of 2000, Lucent was the largest telecommunications equipment maker in the United States and had the leading share of the world's $250 billion market for communications infrastructure. Lucent provided products and services that included voice network switching products, fiber optic networking, wireless equipment, and network design and services. Revenues, profits, and the company's stock price soared as demand for high-speed networks seemed limitless (Waters, 2000).

During this rapid growth period, Lucent's capital expenditures continued to climb as the company tried to keep up with rising demand. However, in 2001 the global telecommunications market deteriorated as established service providers significantly reduced capital spending after building far too much capacity in the previous years. By 2001, the many telecommunications companies racing to build new fiber optic networks had installed over 39 million miles of fiber, enough to circle the earth 1,500 times (Bearden, August 31, 2001). Lucent had been one of the key beneficiaries of the race to wire the U.S. with high-speed fiber optic networks, but in 2001 demand for the company's products dried up and Lucent's sales collapsed as network capacity far outstripped demand.

This telecommunications bust intensified during 2002 and the market deterioration continued into 2003. New orders for equipment were lackluster, but even worse was that Lucent had approved $8.4 billion of loans for customers to buy their equipment. Many of the young telecommunications companies that received loans from Lucent went bankrupt and never repaid the loans (Waters, 2001). As shown in Figure 2a-d, the results for Lucent were plunging revenues, mounting losses, and imploding stock prices. The company posted losses for 2001, 2002 and 2003, and accordingly the stock price fell 99% from the record high and reached a low of 55 cents in 2002. At its peak, Lucent had a workforce of over 160,000, but in 2001 made plans to shed more than 60% of employees and initiated mass layoffs. After limping along for several years while the global telecommunications market slowly recovered, Alcatel acquired Lucent in 2006.

Figure 2 about here

The EMI and Lucent Technologies examples illustrate a pattern of dynamic behavior that is quite widespread. In fact, the evidence indicates that across a large range of industries, the product lifecycle exhibits a pattern characterized by rapid demand and output growth in the introduction phase, followed by market saturation in the mature phase, (Bass, 1969; Klepper, 1996; Klepper & Graddy, 1990). Correspondingly, there are a large number of case studies documenting B&B dynamics across a wide range of industry sectors. A few example industries where boom and bust has been prevalent include chainsaws (Porter, 1985), commercial (Bakken et al., 1992; Kummerow, 1999) and domestic (Hodgkinson, 1997, 2005) real estate, agricultural commodities (Meadows, 1970), oil tankers and bulk shipping (Bakken et al., 1992; Doman, Glucksman, Mass, & Sasportes, 1995), chemicals (Sharp, 1982), and airlines (Liehr, Größler, Klein, & Milling, 2001; Lyneis, 2000). The natural question to ask is: "Why does senior management fall prey to the B&B trap so often?" The next section begins to answer this question by reviewing the findings from experimental studies of dynamic decision-making.

EXPERIMENTAL RESEARCH ON BOOM AND BUST

A number of experimental studies on dynamic decision making have investigated the nature of the behavioral rules yielding B&B dynamics (Bakken et al., 1992; Diehl & Sterman, 1995; Moxnes, 1998; Paich & Sterman, 1993; Sterman, 1987, 1989a, 1989b). The findings from these studies suggest that individuals and groups suffer from misperceptions of feedback between decisions and the environment, in turn leading to boom and bust. This phenomenon has two components: 1) people typically have incomplete and inaccurate mental models or cognitive maps of complex decision environments and generally tend to ignore feedback, time delays, stock accumulation processes, and nonlinearities; and 2) decision makers are incapable of accurately inferring the dynamics of even relatively simple dynamic systems (Sterman, 2000). The implication of the second component is that even if managers had perfect mental models of their complex decision environments, they would still be incapable of accurately determining the consequences of their decisions. Both components of misperceptions of feedback are a direct consequence of "bounded rationality" in a broad sense.

In an experimental study examining boom and bust dynamics using a simulated new product launch task, participants made quarterly decisions for price and investments in production capacity (Paich & Sterman, 1993). The participants' goal was to maximize cumulative profit from the sales of their product through a forty-quarter simulation. Varying the strength of key feedback loops in the simulated market enabled the experimenters to test whether increasing feedback effects, nonlinearities and delays would affect participants' performance. Participants performed the task repeatedly, encouraging learning. However, typical participants' decisions led to boom and bust. Moreover, rising feedback complexity dramatically diminished performance relative to potential and accentuated the B&B dynamics.

Paich and Sterman (1993) estimated the capacity investment decision rules participants adopted when managing a new product launch. The information cues and parametric form of the decision rules were based on: "participants written reports of their strategies, prior models of similar decisions in the literature, and the feedback structure of the task" (Paich & Sterman, 1993, p. 1450). The decision rules identified through this analysis indicated participants in the simulated management environment: 1) selected the share of the market they sought to capture; 2) estimated future demand from information about current demand and recent demand growth; 3) and invested to balance capacity (supply) with demand. Estimated cue weights of the decision rules over trials suggested participants did not gain insight into the dynamics of the system, and experience did not mitigate the misperceptions of feedback, which resulted in B&B behavior. In short, despite repetition of the game, participants did not learn.

Another recent experimental study using a modified version of Paich and Sterman's (1993) simulated new product launch task, investigated the role of mental models on performance (Gary & Wood, 2007). After an initial learning phase, participants' completed a knowledge test as an assessment of their mental models of the task. One set of questions tested participants' recall of the bivariate causal relationships between pairs of variables from the management simulation. A second set of questions tested participants' ability to infer the dynamics of small sets of interdependent variables from the new product launch simulator. The knowledge test confirmed that participants had inaccurate and incomplete mental models of the environment that did not accurately account for feedback. On average, participants earned cumulative profits that were roughly 50% of the benchmark. The results also indicated that mental model accuracy is a significant predictor of performance. Participants with more accurate mental models of the new product launch simulator achieved higher performance levels and mitigated the B&B dynamics.

Gary and Wood (2007) further explored the implicit cue weights for the decision rules identified by Paich and Sterman (1993). The three cues in the target capacity decision rule included actual demand, demand growth rate, and the ratio of order backlog to actual production capacity[1]. Participants also made quarterly pricing decisions in the new product launch simulation, and the two cues for the pricing decision rule included unit variable cost and a markup based on the ratio of order backlog to current production capacity. Information weights were estimated for the capacity and pricing decision rules separately for each trial block for each participant. Table 1 presents the results, averaged across 360 decision trials, along with the results reported by Paich and Sterman (1993) for comparison.

[1] Paich and Sterman's (1993) decision rule for target capacity was: $C_t^* = s^*[D_0^{e(1-\alpha 0)} D_{t-1}^{\alpha 0}](1+g_{t-1})^{\alpha_1}(B_t/C_t)^{\alpha_2}$. Where s^* is a constant target market share of 50%, D^e is the prior estimate of market demand, D_{t-1} is the actual demand lagged by one time period), g_{t-1} is lagged demand growth, and the ratio of backlog/capacity. In both studies, the decision rule was estimated as: $\log(C_t^*) = c + a_0 \log(D_{t-1}) + a_1 \log(1+g_{t-1}) + a_2 \log(B_t/C_t) + \varepsilon_1$.

Insert Table 1 Here

Across both studies, the estimated decision rules captured the bulk of the variance in the participants' observed behaviors for each trial. On average, participants' target capacity decisions were primarily based on their prior expectations of market demand captured in the intercept term. This intercept term was a significant predictor of target capacity decisions in more than 86% of the instances (c = 3.870, $p<.000$). Actual industry demand had a weaker effect on participants' capacity decisions (a_0 = .062, $p<.10$) and was not significant in over 56% of the cases. Information about the ratio of backlog/capacity had a significant impact on target capacity decisions in almost 65% of the cases and was given moderate weight in the decision rule (a_2 = .221, $p<.05$). Surprisingly, participant's were insensitive to the demand growth rate in setting target capacity decisions (a_1 = .129, ns). Given the time delays associated with adjusting capacity, such information weights in the decision rules guaranteed that capacity fell far short of actual demand in the boom phase and resulted in excess capacity in the bust phase when the market saturated and demand declined down to the equilibrium replacement level.

For the pricing decision rule, unit cost was a significant predictor of participants' pricing decisions. In contrast, the backlog/capacity ratio had little effect on pricing behaviors. During the rapid growth phase of the product lifecycle – when demand often exceeded production capacity – decreasing price as unit costs fell only served to exacerbate the imbalance between demand and capacity and ensured a more painful bust phase when the market saturated.

In summary, participants' decision rules reflected "mental models" that were typically incomplete and dynamically deficient. In particular, participants' mental models did not incorporate time delays in adjusting capacity or feedback effects for market diffusion or saturation (Gary & Wood, 2007; Paich & Sterman, 1993).

In another experimental study of B&B dynamics in a completely different context, two different sets of managers with many years of experience in either commercial real estate development or the oil tanker industry have been shown to adopt myopic decision rules leading to B&B (Bakken et al., 1992). This study involved experienced managers making decisions in their own domains of expertise. Such results are important in that they highlight the fact that inaccurate and incomplete mental models can persist even after extensive experience and training (see also Hodgkinson, 1997, 2005).

The bottom line is that the widespread deficiencies of incomplete and inaccurate mental models are typically associated with the absence of accurate accounts of: (i) feedbacks between decision variables and state variables (that is the variables describing the environment in which agents operate); (ii) time lags, and even less so, (iii) possible non-linearities. Learning in dynamically complex environments is very difficult and, as a result, deficient mental models continue to serve as the basis for poor decision-making. In addition, these deficient mental models interact with equally widespread (and partly overlapping) biases and heuristics in decision-making processes. We discuss the role these biases and heuristics play in decisions leading to boom and bust in the next section.

ROLE OF DECISION BIASES IN BOOM AND BUST

It is now widely accepted that cognitive processing limitations prevent human beings from making objectively rational or optimum decisions when operating in complex decision environments for at least two reasons. First, decision makers cannot generate or identify all possible feasible alternative courses of action. Second, even for the alternative courses of action identified, decision makers are generally not likely to access and process all the information needed to value anticipated consequences accurately and to select among them (Cyert & March, 1963; Morecroft, 1985; Simon, 1976, 1979; Sterman, 2000). As a result, decision makers employ, consciously and unconsciously, a wide range of simple rules of thumb, routines and heuristics to make decisions in complex environments (Allison, 1971; Forrester, 1961; Kahneman & Tversky, 2000; Nelson & Winter, 1982; Simon, 1982). In fact, decision makers adopt such simple rules and heuristics even when provided with "full" information and when the decision tasks are not too difficult (cf. also the discussion in Dosi, Marengo, & Fagiolo, 2005).

Although some decision heuristics work reasonably well under some conditions, they generally yield systematic biases into decision processes (for discussions of different biases see for example, Camerer & Lovallo, 1999; Dosi & Lovallo, 1997; Hogarth, 1987; Kahneman & Lovallo, 1993; Kahneman & Tversky, 2000; Tversky & Kahneman, 1974). Such biases play important roles in B&B dynamics. Here we shall discuss in particular how two cognitive biases, *attribution errors* and *the inside view* frame, tend to both foster behaviors resulting in boom and bust, and, relatedly, act as impediments to learning.

Attribution Errors

Decision makers operating in complex and uncertain environments tend not to attribute negative outcomes to their own decision-making errors or management ability. The typical response is for decision makers to take too much credit for positive outcomes and to attribute negative outcomes to the environment (Nisbett & Ross, 1980; Repenning & Sterman, 2002). For example, in a firm that experiences boom and bust dynamics over several years, managers typically attribute firm success in the boom phase to their own decisions and actions. On the other hand, managers tend to point at exogenous factors in order to explain unexpected busts. It is easy to find external forces to blame for negative, unintended outcomes (e.g. fickle customers, over-aggressive competitors, or a downturn in the macro economy). Conversely, attributing success in the boom phase to management decision making ensures that the same decisions and behaviors continue after the boom. For instance, continued aggressive capacity expansion, based on extrapolated demand forecasts, worsen the bust when capacity surpasses demand and utilization falls. Moreover, managers attributing the bust to exogenous or external forces out of their control miss the opportunity to learn how their decision-making errors contribute to the bust.

The Inside View

The *inside view* is a mindset decision makers commonly adopt when facing complex problems. Decision makers have a strong tendency to consider problems as unique and thus focus on the particulars of the case at hand when generating solutions (Kahneman and Tversy, 1979; Kahneman & Lovallo, 1993). They draw mainly on knowledge about the specific characteristics of the current situation, focus on obstacles to the pursuit of the intended strategy and typically extrapolate from current trends (Kahneman and Tversky, 1979; Kahneman & Lovallo, 1993).

By adopting an inside view, managers in a firm struggling to meet growing demand in the boom phase may build bottom-up forecasts of future demand. Managers typically construct such forecasts by anchoring on the firm's sales from the most recent year, extrapolating the growth in firm sales from the previous year, and often factoring in additional demand growth expected from their own managerial decisions such as new marketing efforts. Subsequently, in the throws of the bust phase, managers using an inside view would typically look for the unique factors of the problem situation responsible for the bust. For example, executives at EMI re-organized their CT scanner manufacturing and marketing operations in the bust phase in the belief that this could restore the division's health – it did not. They did not recognize that the CT scanner market, like so many other markets with pronounced product lifecycles, was approaching saturation. Instead, they believed specific problems in the manufacturing and marketing functions were driving the company's performance downturn.

Adopting an inside view activates numerous cognitive biases (Lovallo and Kahneman, 2003). Perhaps, the most relevant to boom and bust dynamics is anchoring and adjustment – the tendency to insufficiently adjust estimates away from a salient (frequently meaningless) anchor (Tversky & Kahneman, 1974). There is strong empirical support indicating that the anchor and adjustment heuristic is incorporated into a wide range of decision rules such as expectation formation, forecasting, aspiration and goal adaptation, and updating of perceptions (Lant, 1992; Sterman, 1988). As a concrete example, when setting the price of a product or service each month or quarter, marketing managers are likely to anchor on the previous price level and make insufficient adjustments around that value. Also, in forecasting demand, the planning or marketing department will likely base their forecast on simple extrapolations anchored on the most recent demand levels as in the decision rule identified in Paich and Sterman (1993) discussed previously. Using the anchor and adjustment heuristic for forecasting demand is particularly insidious in markets where boom and bust is possible, since the anchoring process ensures managers will form expectations that future demand will continue growing without end while they are in the boom phase of rapid growth. If managers respond to such forecasts by investing aggressively in expanding capacity, the hazard of ending up with excess capacity and the associated financial bust becomes far more likely.

It is also important to notice that cognitive biases, which are identified at the level of individual behaviors, tend to "scale up" to the collective organizational level. Part of the reason for this is that relatively few people make the largest firm decisions. A recent McKinsey survey reports that only one or two people make nearly 40% of all large firm decisions. While it is beyond the scope of this work to examine the vast literature on individual and organizational decision-making, there are good reasons to believe that organizations, in many instances, reinforce rather than mitigate individual decision biases (see, for example, Kahneman & Lovallo, 1993; March & Shapira, 1987). Escalation situations are well studied examples of a "scale free" phenomenon applying at widely different units of analysis, ranging from individual choices under experimental conditions all the way to enormous collective tragedies such as the Vietnam War (cf. Janis, 1982; Staw & Ross, 1978). More broadly, organizations are not simple aggregations of independent individuals but rather hierarchically nested structures that often tend to amplify cognitive and behavioral biases throughout their hierarchical layers. Indeed, this is likely to apply even more so when the decision process occurs top-to-bottom, as typically in strategic commitments (e.g. investment/production capacity decisions).

We have discussed the role of both inaccurate mental models and cognitive biases in strategic decision-making resulting in B&B dynamics. These factors also impede learning. Next, we discuss additional impediments to learning that may partially explain the widespread nature of boom and bust.

IMPEDIMENTS TO LEARNING

The widespread and repeated incidences of B&B dynamics across a wide range of firms and industries suggest there are strong underlying impediments to learning at work. The lack of learning is particularly surprising in chronically cyclical industries that repeatedly experience boom and bust episodes (e.g. almost all basic materials industries). Together with the cognitive and behavioral factors discussed above, this section discusses two additional (even if related) barriers to learning. The low frequency of B&B episodes within a particular executive's career is one such obstacle. In addition, causal ambiguity in understanding the reasons for boom and bust is another obstacle (clearly overlapping with the inaccurate and incomplete mental models and cognitive biases discussed above) discussed in this section.

The long length of time between boom and bust cycles likely act as an impediment to learning. Quick, high frequency feedback cycles facilitate learning, while delayed, low frequency feedback cycles impair learning. Boom and bust cycles typically operate on a time period of at least several years if not a decade or more in some industries (Sterman, 2000). Managers who make the decisions resulting in B&B dynamics may not immediately recognize their decision-making errors were responsible for the unintended behavior. In order to learn that decision errors are causing the problem and to discover how to avoid B&B behavior, repeated observations are likely to be necessary (although possibly not sufficient: cf. the earlier discussion of the *inside view*). However, the low frequency of B&B episodes implies that managers may well move to a different company, move to a different industry, or even leave the workforce altogether before they can experience several B&B cycles. In addition, when there are long lags between B&B cycles, individual decision makers or the organization as a whole may well forget the lessons learned several years or a decade or more before even if they participated in them. Managerial turnover within organizations just augments the problem in that the institutional memory about B&B episodes in the company's history may well walk out the door when key managers involved depart the company.

Conditions for learning are best when there is also clear feedback about how to improve performance and avoid mistakes. However, the feedbacks between actions, environmental responses and payoffs, are typically ambiguous for managers going through a boom or bust. Clear, unambiguous feedback is not readily available during either the boom or the bust phase. For example, in the bust phase it is often very difficult to disentangle the real causal factors responsible for the decline. This *causal ambiguity* makes it very difficult for managers to learn how their sequence of decisions contributes to B&B dynamics (cf., Powell, Lovallo, & Caringal, 2006).

The well-known B&B story of Atari in home video games and the subsequent repeated boom and busts of Worlds of Wonder in toys illustrate the damaging effects of failing to learn how decision errors contribute to B&B dynamics. In the six years from 1976 to 1982, Atari's revenues streaked from $35 million to nearly $2 billion (WarnerCommunications, 1976-1983). However, by 1983 the console market had reached saturation point and the company's operating income fell from a healthy $300 million at the end of 1982, to $536 million in losses by the end of 1983. Everyone who wanted a home videogame system had bought one, and yet Atari and their rivals kept churning out units. Worlds of Wonder (WoW) was an American toy company founded in 1985 by former Atari employees including Donald Kingsborough, the former president of Atari. WoW achieved one of the fastest two-year growth spurts of any major US manufacturing start-up. The company's talking bear, Teddy Ruxpin, and Lazer Tag, a gun game, were among the toy industry's biggest hits during 1985 and 1986. The high-tech, high-priced Teddy Ruxpin was selling so fast, toy stores could not keep him on the shelves.

> "We're building them as fast as we can build them. We certainly can't meet demand. Even if we had six more factories, we still can't meet demand." (Paul Rago, vice president of Worlds of Wonder Inc., interview quote in New York Times article on December 20, 1985)

WOW had shown explosive growth, going from zero sales to $93 million in just a year and to more than $300 million at the end of its second year. However, sales of Teddy Ruxpin and Lazer Tag began to collapse in 1987 turning the boom to bust, and the company posted a $43 million quarterly loss in mid 1987. Battered by high inventories swollen by unexpectedly poor sales, the company tried unsuccessfully to obtain additional funds from investors. By the end of 1987, WoW filed for bankruptcy protection. Many of WOW's senior managers had also been part of Atari's senior management, but they failed to learn from the previous experiences, and repeated their mistakes a few short years later at Worlds of Wonder.

Clearly, if strategic behaviors resulting in B&B dynamics are so endemic one can hardly imagine a "magic bullet" remedy. However, it is worth investigating prescriptions aimed at mitigating such episodes.

TENTATIVE STRATEGIES FOR MODERATING BOOM AND BUST BEHAVIOR

How can management practices be refined in order to overcome the cognitive and behavioral biases leading to overshoot and collapse? Let us consider two possible (partial) remedies entailing, first, the construction of *schemata* of the common structure underlying B&B dynamics and, second, a greater reliance on the "outside view" (as opposed to the "inside view" discussed above). If developed, schemata of the high-level causal structure underpinning B&B dynamics guide decisions instead of deficient mental models. The outside view focuses on a set of reference cases similar to the case at hand and derives forecasts based on the statistics of similar past cases.

Building Schemata of the Underlying Structures of Boom and Bust

While it is common to think about different classes of problems in natural sciences, engineering and medicine and to identify the similarities of problems and solutions within the same class, it has not been common in management practice. However, findings from a large body of research in psychology and cognitive science suggest that developing schemata identifying different classes of management problems could dramatically improve managerial decision-making. Research findings across a range of problem domains indicate that experts develop schemata to organize their knowledge of different classes of problems within the domain and use these schemata to represent problems at a deeper, "structural" level.
For example, in the domain of medicine, research indicates that experienced physicians diagnose routine cases using knowledge organized in schemata of different illness categories to accurately diagnose and treat patients (Schmidt & Boshuizen, 1993). These illness schemata emerge from continuing exposure to patients and are, therefore, largely the result of extended practice. Novice physicians and students do not have these knowledge structures. Schmidt and Boshuizen (1993) found that the illness schemata used by experienced physicians consisted of high-level, simplified causal models explaining signs and symptoms of different illness categories combined with a "script" for how to effectively treat an illness in different categories.

In the management domain, recent research indicates managers often use analogical reasoning to make strategic choices, but are typically not aware they are reasoning by analogy (Gavetti & Rivkin, 2005) and they often do so in rather undisciplined ways. Drawing on prior experience and applying relevant insights to solve similar problems can be a powerful approach for solving complex problems. Barnett and Koslowski (2002) compared problem solving approaches and solutions of management consultants, restaurateurs and novices (non-business undergraduates) in solving a common problem about a change in road conditions that would affect the patronage of a restaurant. Despite a lack of restaurant experience, the consultants performed better than the restaurateurs and undergraduates, who did not differ significantly from one another. Barnett and Koslowski (2002) attributed the consultants' higher performance to a wide repertoire of schemata of managerial problems developed through the substantive variability in their career experiences. Consultants work on different problems in different companies and – so it seems – are accustomed to applying insights gained from previous projects to similar problems encountered in other firms or industries. These findings hint at the efficacy of structured, disciplined analogical reasoning involving schemata of simplified causal models germane to entire classes of phenomena or problems.

Enduring causal models underpin many recurring managerial problems and challenges such as product lifecycle diffusion (Bass, 1969; see also the survey in Dosi, 1992), commodity production cycles (Meadows, 1970)[2] and inventory management in supply chains (Sterman, 1989b). The causal models of these common managerial problems display sufficient invariance across different instantiations to allow for formation of schemata identifying crucial state variables and relationships between system variables and the high-leverage control (or strategic) variables in the hands of the decision-makers. Based on substantial evidence from other problem domains, we suggest managers armed with schema of these and

[2] Meadows (1970) expanded the original Cobweb model (Ezekiel, 1938) to provide a more comprehensive endogenous explanation for commodity cycles and recent research on cyclical industries continue to use this model (Aramburo, 2006).

other managerial problems would likely make better decisions when faced with such challenges.

For example, schemata of product lifecycle diffusion could easily guide managers to collect and consider information about the potential number of customers in the total market, the industry growth rate, competitors' aggregate capacity investments, and the average useful lifetime of the product. Managers possessing a schema for logistic product lifecycle diffusion would understand that as new customers purchase the product, fewer potential customers remain and that when most potential customers have purchased the product, demand tends to approach the level of replacement purchases determined by the average useful lifetime of the product. Fundamental uncertainties would remain about, for example, the rate of technical progress, which in turn affects the number of future potential customers, their preferences, and rates of substitution of new for old products. Such uncertainties would imply significant forecasting errors. Still, our claim is that using any naïve logistic product lifecycle schemata instead of grossly deficient mental models might reduce errors even by an order of magnitude. Yet the disciplined use of schemata composed of high-level causal models is not a "natural" part of decision making in business. So for example, if EMI's and Lucent Technologies' managers had applied even utterly simple schemata of the product lifecycle diffusion model they may have recognized earlier that the markets for CT scanners and telecommunications networking equipment, respectively, could not expand exponentially forever. Staying alert for signals of market saturation, EMI's and Lucent's managers might have curtailed aggressive capacity expansion.

Adopting the "Outside View"

Developing schemata of the underlying structure for classes of phenomena and managerial problems involves explicit efforts aimed to form *reference classes* of similar problems. In turn, this very process facilitates the adoption of an *outside view*. In contrast to the inside view discussed above, managers adopting an outside view ignore the details of the case at hand and simply focus on understanding the historical statistics and patterns of similar phenomena. For example, awareness of logistic product lifecycle diffusion dynamics might have straightforwardly led managers to an attempt to estimate the near-saturation level of demand in CT scanners by drawing on the diffusion patterns of other medical devices (e.g., X-ray machines, sonograms, etc). Similarly, an appreciation of the short and pronounced lifecycles in toy demand should have sent loud warnings of potential boom and bust dynamics to Atari's management.

Using the statistical history of analogous situations to predict not just the quantity of next quarter's demand but the structure of demand over time is not immediately intuitive. Adopting an outside view takes deliberate effort, but the rewards for predictive accuracy can be substantial. For instance, EMI's executives could have responded differently to the decline in unit sales and financial results. At the time, management responded by allocating resources to reorganize the company's manufacturing and marketing operations. Instead, adopting an outside view may have helped executives at EMI understand that the CT scanner market was approaching saturation. Armed with an understanding that the market was saturating, EMI may have been able to either sell the firm at an optimal time or change their strategy to one more compatible with their firm's skills. Instead, they sustained substantial losses before selling out for a minimal sum once GE and Siemens became dominant.

CONCLUSIONS

Strategic decisions leading to boom and bust dynamics are widespread and persistent. The cases we have briefly discussed are just a few out of an enormous number of examples including both individual companies and whole industries. As experimental evidence shows, decisions resulting in B&B dynamics are rooted in grossly incomplete and inaccurate mental models of the problem domain and pervasive cognitive biases. One important bias leads managers to frame the decision setting as involving a unique problem (the "inside view"), even though it actually belongs to a whole category of decision problems sharing the same basic features.

We have identified two tentative strategies for overcoming B&B behavior. The first strategy focuses on developing schema of commonly recurring management problems or challenges. In other domains, expert knowledge is organized through schemata composed of simplified but powerful causal models linking underlying reference categories for information processing and decision-making. Such schemata replace deficient mental models of the problem/challenge and provide guidance about the high-leverage points of the system and decisions for effective management in such situations. We propose that developing schemata of logistic demand growth in managing product lifecycles may well mitigate boom and bust behaviors. A second tentative strategy for overcoming boom and bust decisions is to ensure managers adopt an outside view by paying attention to historical time series of similar cases of diffusion/capacity building in order to detect inflection or turning points. These two strategies would likely offer remarkable performance improvements. What is surprising is that they are not part of the standard "tool box" of managers and management training. As a result, problems such as boom and bust persist and are repeated, many times over.

Over 250,000 telecommunications workers lost jobs as part of the telecoms bust during 2001. At the time, the telecommunications industry as a whole had an estimated $500 billion in outstanding loans that could have gone into default. In fact, the decision errors yielding the fiber optic boom and bust are not new. In the 19th century, a US railroad boom began in 1869 with the completion of the Transcontinental Railroad spanning east to west across the country. A railroad building frenzy ensued and rival railroads laid four additional routes to the Pacific financed by large loans from the bond market. The bust arrived just four years later and 90 heavily indebted railroads went bankrupt.

However, there may be a collective brighter side to boom and bust. In fact, what is likely to be a catastrophe from the point of view of individual or company-level returns might well correspond to a *collective bonanza* in the accumulation of knowledge and infrastructure development. As Perez (2006) convincingly argues, the establishment of all major infrastructures associated with dominant techno-economic paradigms has been intimately linked to major *technological bubbles* entailing the euphoric and reckless build-up of overcapacities of various kinds. This applies to canals, and later, railroads, to fiber optic networks and the dot.com bubble. Prior research suggests that cognitive biases may, under some circumstances, lead to collective social gains such as the collective value of overconfidence that often drives individual entrepreneurial decisions (Dosi & Lovallo, 1997). Similarly, it may well be that collectively boom and bust behaviors, at least in some circumstances, drive private investors to develop externalities and collective physical infrastructures that no sober exclusively profit-motivated actor would have done otherwise. We all enjoy cheaper phone calls due to the boom in fiber optic infrastructure and, more importantly, the expansive race in medical diagnostic imagining has saved countless lives.

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Figure 1a US Total CT Scanner Unit Sales 1973-1980

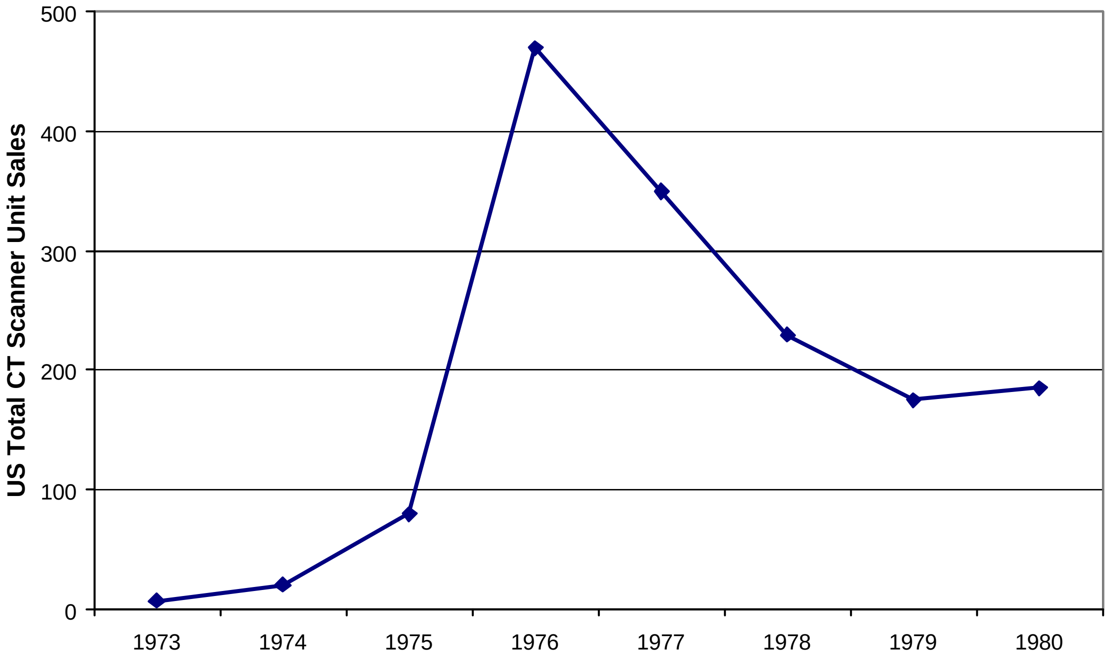

Figure 1b Remaining US Potential Customers 1973-1980 (Source, Bartlett, 1983c)

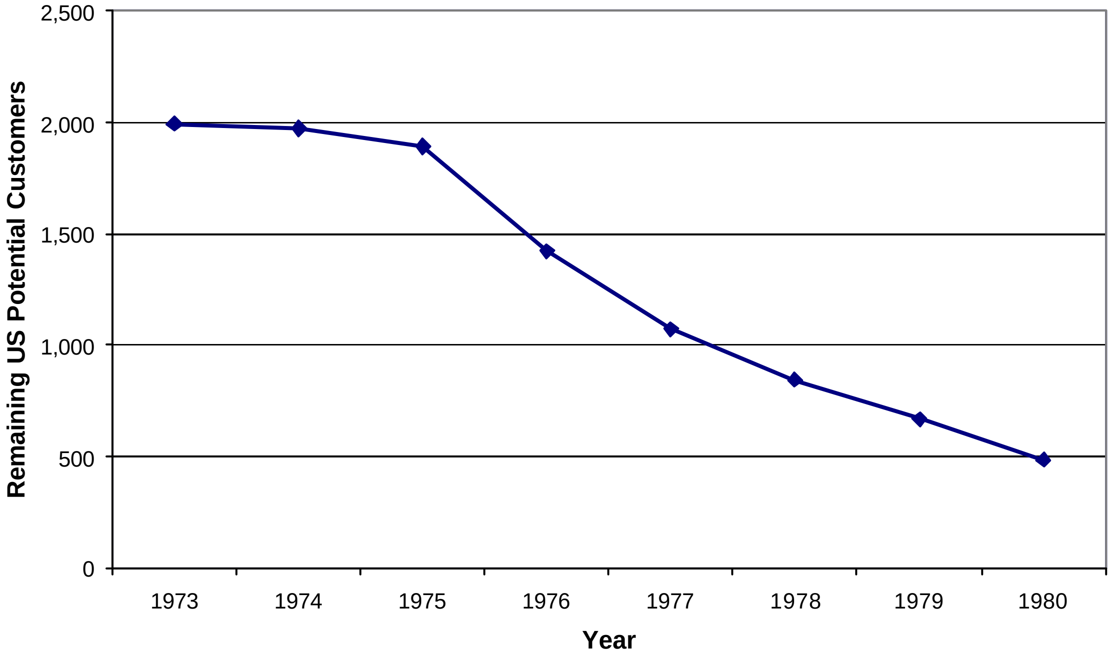

Figure 2a Revenues ($ million) for Lucent Technologies 1996-2006 (Source, Bloomberg)

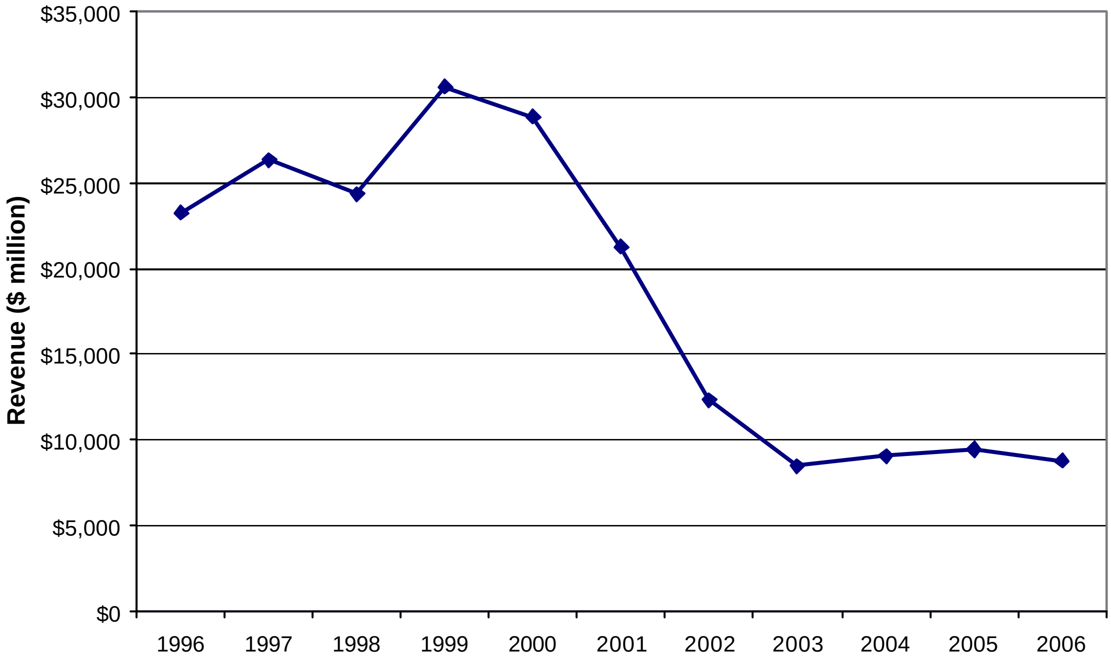

Figure 2b Net Profit ($ million) for Lucent Technologies 1996-2006 (Source, Bloomberg)

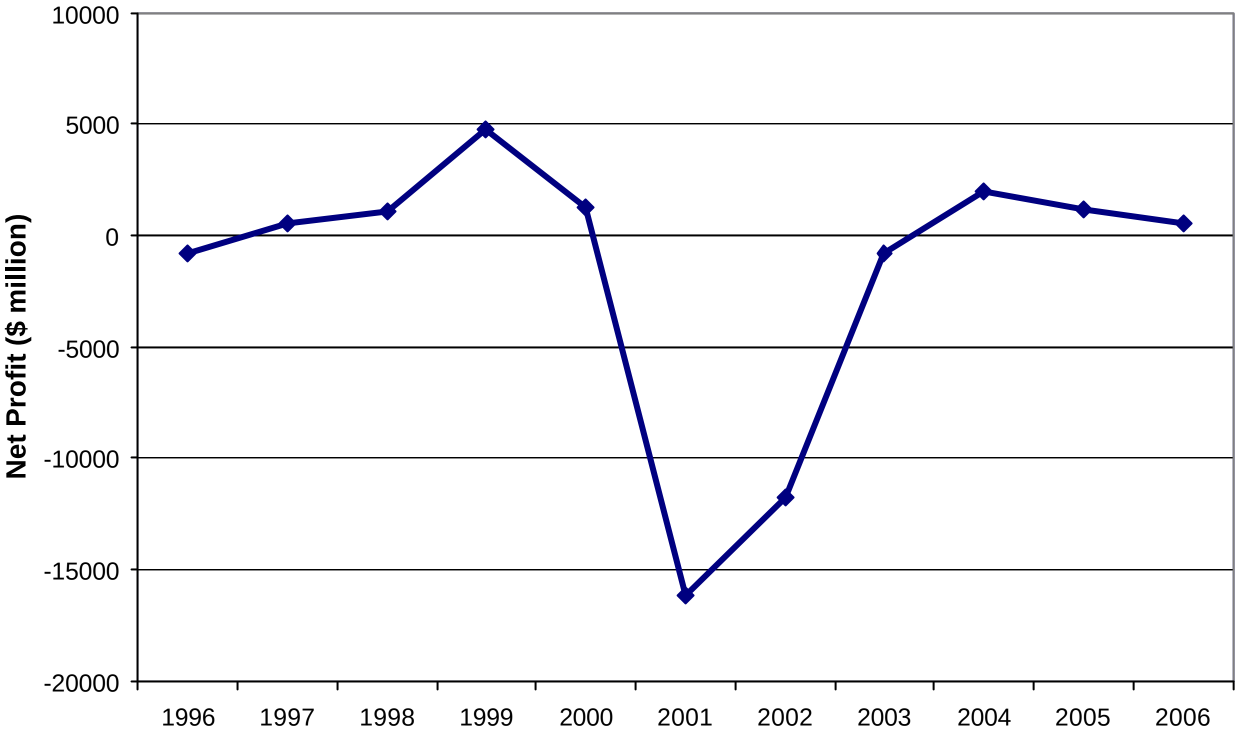

Figure 2c Stock Price ($) for Lucent Technologies 1996-2006 (Source, Bloomberg)

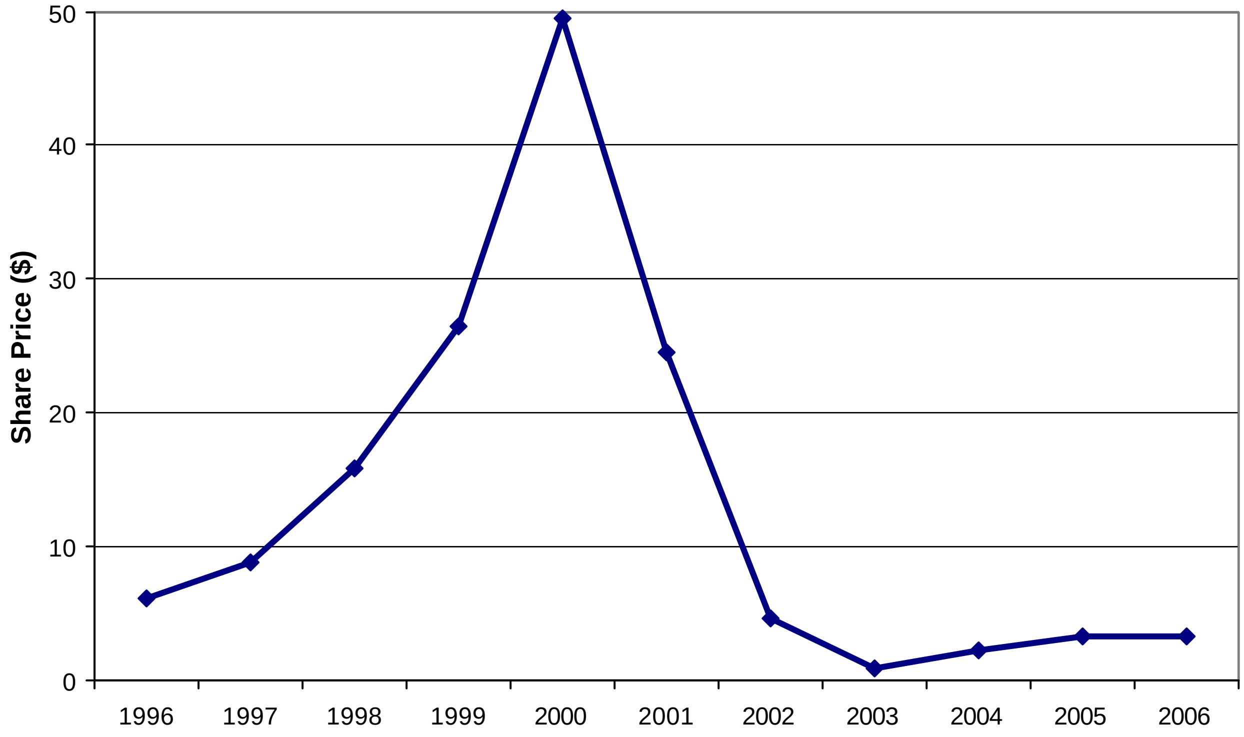

Figure 2 d Capital Expenditure ($ million) for Lucent Technologies 1996-2006 (Source, Bloomberg)

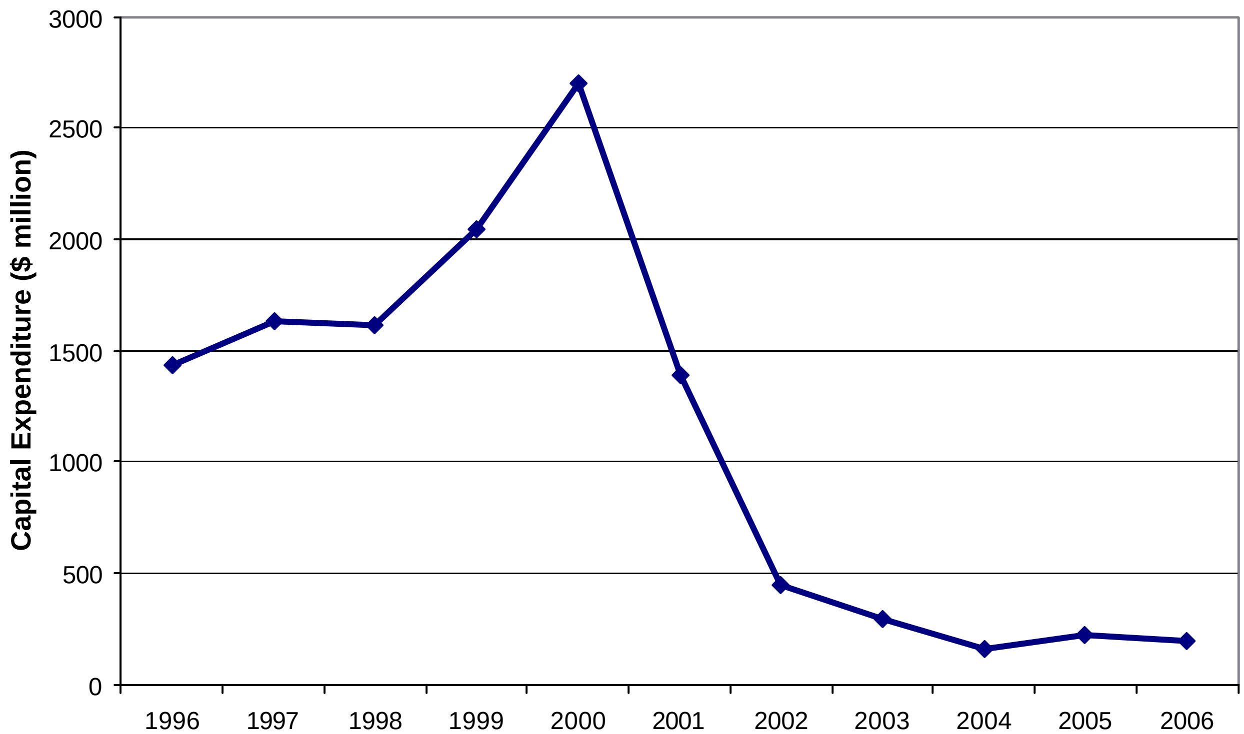

Table 1 Estimated Information Weights for Price and Target Capacity Decision Heuristics

Parameter	Mean reported by Paich & Sterman (1993)	Mean	Std Dev	Median p-value	% NS
Capacity Investment Decision Rule:					
Intercept (c)	8.414	3.8701	3.4409	0.0000	0.1318
Industry Demand (a_0)	0.383	0.0617	0.2994	0.0896	0.5698
Demand Growth Rate (a_1)	0.036	0.1286	0.2859	0.1388	0.5891
Backlog/Capacity (a_2)	0.318	0.2207	0.3828	0.0265	0.4574
Lag Target Capacity (ρ_{TC})	0.560	0.6532	0.2480	0.0000	0.0891
Adj. R^2	0.872	0.8340			
Pricing Decision Rule:					
Intercept (b_0)	3.125	-0.0790	0.7252	0.0498	0.4979
Unit Variable Cost (b_1)	0.259	0.3692	0.2919	0.0057	0.2675
Backlog/Capacity (b_2)	0.016	0.0053	0.0299	0.0809	0.5597
Lag Price (ρ_{Pr})	0.781	0.6750	0.1802	0.0000	0.0247
Adj. R^2	0.947	0.9511			

[1] The model estimated for the target capacity heuristic in both complexity conditions was:

$$\log(C_t^*) = c + a_0 \log(D_{t-1}) + a_1 \log(1 + g_{t-1}) + a_2 \log(B_{t-1} / C_{t-1}) + \rho_{TC} C_{t-1}^* + \varepsilon_1$$

[2] The model estimated for the price heuristic in both complexity conditions was:

$$\log(P_t) = b_0 + b_1 \log(UVC_{t-1}) + b_2 \log(B_{t-1} / C_{t-1}) + \rho_{\mathrm{Pr}} P_{t-1} + \varepsilon_2$$