



Marketing and production capacity strategy for non-differentiated products: Winning and losing at the capacity cycle game

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Abstract

Customer satisfaction and supplier loyalty in markets where products are mainly undifferentiated are heavily affected by assurance of supply. Marketers manage production capacity in such markets to assure supply, but the resulting capacity competition leads to cycles of over-capacity followed by capacity deletions, which lead to under-capacity. We investigate some of the possible causes of this form of industry behavior in two ways. First, we report on an exploratory empirical investigation, motivated by in-depth interviews with industry executives, and develop a set of structural principles. We formalize those principles in a set of statistical models. Next, we review some related theory and identify a number of possible reasons that may combine to cause this phenomenon. We develop some simple, game theoretic models that focus on the issues of strategic interaction with demand uncertainty and different values of capacity change. We use the theory results to illustrate how over- and under-capacity situations arise. We compare our theoretical and empirical results and find an encouraging degree of convergence. We discuss the implications of these findings for individual firm strategies. © 1999 Elsevier Science B.V. All rights reserved.

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1. Introduction

Marketing is the study of exchange relationships and marketers traditionally attempt to create products and services that provide more value than their competitors to the customers that they choose to serve. Marketers typically perform this task by differentiat-

ing their product-features or prices from those of competitive products. However, in markets for many chemical products, agricultural products, oil, paper and the like—i.e., raw or graded materials—physical product differentiation is marginal, prices are typically set by the supply–demand balance in the marketplace and marketers seek other ways to compete.

In such markets, assurance of supply is critical to buyers. Lehmann and O’Shaughnessy (1974) cite

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reliability of delivery (along with price) as most important when buyers are dealing with routine order goods. In a later study Lehmann and O'Shaughnessy (1982) identify five key dimensions that drive supplier selection more generally: performance, economic, integrative, adaptive and legalistic. The third and fourth of these dimensions—commitment to meeting or exceeding buyer expectations and ability to produce and deliver to expectations—mean assurance of supply in the markets with which we are concerned. Wilson (1994) shows that assurance of delivery and service have increased in importance as vendor selection criteria to buyers in the years since these earlier studies. Indeed, Dion et al. (1991) report a 40% chance of change of suppliers following a missed delivery! And Cooper et al. (1991) point out that on-time and consistent delivery is nearly always one of the top three drivers (along with quality and price) when selecting and retaining vendors.

Jackson (1995) underscores one of the implications of the current focus on viewing customer retention and capture from a long-term perspective: "...the seller can justify heavy up-front investment in trying to win new commitment from such [large] customers" (p. 123). And one of the key determinants of buyer–seller trust (Ganesan, 1994) is evidence of such transaction-specific investment. From the buyer's perspective, assurance of supply is sufficiently critical in many industries that, in the face of clear trends and pressures to reduce the supplier base and increase quality through focusing on this smaller supplier base, many buyers still maintain multiple supply sources (Doney and Cannon, 1997). Hence, in markets where product and price differentiation is negligible, assurance of supply becomes the paramount supplier-differentiator, and the way such marketers compete. And the key variable under the control of the marketer is the level (and location) of production capacity.

Up-front investment has strategic risks, of course. Underbuilding capacity is an invitation for competitors to enter the market as Brandenburger and Nalebuff (1996) (p. 121) note: "Overbuild a little and every customer is as powerful as you are. Underbuild a little, and each customer has little value added."

The purpose of this paper is to explore the market and economic consequences of the seemingly ratio-

nal and natural desire of producers in such industries to capture and retain customers: capacity competition and capacity cycles. We provide a marketer's perspective on this problem, viewing the capacity decision as a means of capturing and retaining customers. But other factors, particularly financial and risk considerations, are likely to drive those decisions (particularly the capacity deletion decisions) as well. Hence, we view the capacity problem as a business decision with a strong marketing flavor and address the following questions:

Question Q1. Are capacity cycles a problem and, if so, what do managers believe cause them?

Question Q2. Can we build credible, empirical models that describe and predict these cycles?

Question Q3. Can we develop some formal theoretical explanations for these phenomena?

Question Q4. Can we provide guidance for managers operating in industries characterized by such cycles?

We will require different approaches to deal with these different, but closely related questions. In Section 2, we report on the results of industry interviews that address the first question. Those interviews help us specify empirical models that we have tested with data in two industries, one of which we report here and addressing Q2 in the section that follows. These models predict capacity addition and deletion decisions in the cases that we observe surprisingly well. However, they fall short of providing a formal explanation for the phenomena, as we are unable to observe the strategic drivers of the actions in this market. Hence, we build formal theoretical models in Section 2 to address Q3. We find that even simple models exhibit phenomena such as the winner's and loser's curse, strategic preemption and coordination problems, all of which lead to capacity cycles. And a careful examination of our empirical findings provides evidence that all of these phenomena are present in practice. We conclude with suggestions for managers operating in such industries (Q4).

2. Market competition leads to capacity cycles: A qualitative analysis

The dynamics in many high capital investment markets produce cycles of various sorts:

In the familiar boom–bust pattern of the not-too-distant past, managers added production capacity, allowed overhead to swell, and stockpiled inventories in anticipation of rising demand during expansions. When the economy tanked, they shut factories, laid off workers, iced new-product development, and purged excess inventories at distress prices. (*Fortune*, August 7, 1995, pp. 59–60)

Firms, driven by the desire to capture new customers and to satisfy and retain existing customers (by promising assurance of supply), invest in production capacity (often excessively). When market demand fails to match production capacity (meaning low capacity utilization), costs rise, prices fall and firms may selectively delete capacity. So, all competing firms simultaneously balance two objectives: they weigh their desire to capture market share through assurance of supply by building (and appropriately locating) production capacity against their desire to keep capacity utilization high (and unit production costs low) by not building or even divesting production capacity. Although in a monopoly a firm might tune its production capacity to track demand cycles optimally, such coordination cannot occur naturally in an oligopoly when firms make decisions independently.

Fig. 1 illustrates the results of this capacity competition in the iron and steel industry, showing clear and persistent cycles in capacity utilization over the past several decades in the US, varying from 40% to

110%! Are these just natural business cycles that promote a healthy marketplace? We think not: "... the structure of an industry may be so dysfunctional to the results of competition that collective action is appropriate to fix it. In such an instance the workings of the market produce neither efficiency nor profit" (Bower, 1986, p. 14). And customers, who see widely varying levels of supply assurance and prices, report lower satisfaction and change suppliers more frequently than they would like to.

To find out what causes these cycles, we first conducted 23 exploratory personal interviews with product, marketing and purchasing managers at five firms in the chemicals, glass and fabricated materials industries. Each open ended interview lasted about an hour and addressed a number of issues, the most important of which for us here are: What do you think causes capacity cycles? How do you decide to add or delete production capacity? What is the relationship between capacity decisions and other marketing decisions?

A typical story that emerged from these interviews went something like this: "A capacity decision is a long-run planning decision based on cost and demand projections. Prices can be changed quite rapidly. In the short run, if we have excess capacity (and with our very low marginal production costs) we respond by increasing our discounts from list price (temporarily lowering price). As we move toward full capacity utilization, our marginal production costs increase, our discounts decline or disappear and list prices may even increase. We increase capacity to retain old customers (assuring them of our ability to meet their needs) and to try to capture new customers."

More formal content analysis of these interviews paints the following picture.

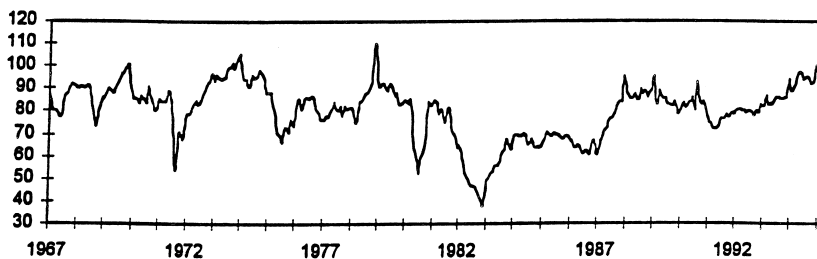


Fig. 1. Capacity utilization for iron and steel, 1967–1995.

- (1) Total industry demand depends on general economic conditions and (possibly) product price. Price affects demand in the short run if there are immediate substitutes and in the long run through production process modifications.
- (2) Total industry capacity changes (reflecting individual firms' capacity addition/deletion decisions) are driven by capacity utilization and current or projected profitability.
- (3) Price changes are closely linked to industry capacity utilization.
- (4) Production cost is determined by plant size, technology, and level of capacity utilization.
- (5) Market share is determined by the firm's competitive strength in production and marketing (closely linked to capacity share), and the carry-over effect of its current market position (driven by long-term buyer–seller relationships).
- (6) Capacity addition and deletion decisions are driven by profit margin, growth rate of market demand, and the firm's strategic objectives.

These observations are generally consistent with those of Lieberman (1989), except for (6), where we include profit margin and the firm's strategic objectives.

3. Exploratory empirical modeling

3.1. Data needed

To model these phenomena, one needs data for at least six types of analyses. For some of these analyses we had to rely on data supplied to us by companies in the industry.

- (1) *Market demand analyses.* We found all necessary data publicly available, although we do not know what forecasts the companies actually used.
- (2) *Pricing analysis.* Industry newsletters and price sheets only give posted prices. Discounts from posted price (known by industry insiders) can commonly be 40% or more, so we had to rely on company-supplied data.
- (3) *Cost analyses.* In the chemicals and other process-manufacturing industries, relative cost information is often available as 'general engineering knowledge'. Knowledge of the type of equipment used and the capacity utilization of

the facility allows for reasonable estimates of relative costs.

- (4) *Market share analyses.* Most of the industries of the type we are concerned with here sell direct to customers. Therefore, market share data are only available as estimates by 'industry experts', or through proprietary studies by members of the industry.
- (5) *Capacity additions and deletions.* Such additions and deletions are generally public knowledge as firms must apply for building permits and the like well in advance of adding such capacity.
- (6) *Company strategies.* Such strategies are normally proprietary information. For example, one firm in the titanium dioxide industry, NL Industries, had a long-term plan to leave the industry, which could not have been known by its competitors *ex ante*.

We applied these ideas to two industries, titanium dioxide and zircon (disguised name), although we report only the titanium dioxide analysis here. (Zircon results are very similar.) In the next subsections we review the results of those analyses, particularly those that are specific to capacity decisions.

3.2. Titanium dioxide case background and data

Titanium dioxide (TiO₂) is a commodity chemical used as a whitening and opacifying agent for paint, paper, plastics, rubber, and other products. It has no significant rivals in its principal uses. Customers of TiO₂ are concentrated in the coatings (paint, varnish, and lacquer), paper and paperboard, and plastics industries. Buying firms in those industries typically purchase from multiple sellers for security of supply, with technical qualifications, assurance of supply and good service being keys in the buying decision.

Annual domestic consumption of TiO₂ has grown in the long run, with a downward shift of the growth rate over 1974–75, the oil-shock period. As an ingredient product with no close substitutes, total TiO₂ demand is sensitive to the output of its consuming industries, reflected through relationships between its sales and measures of general economic conditions. For the same reason, TiO₂ shows low short-term price–demand elasticities, although long-term shifts might occur in reaction to TiO₂ price trends. The price of TiO₂ has been set primarily by the lowest

cost producer. The nominal list price of TiO_2 has increased over the last three decades but its real price has declined, mainly due to production cost reductions.

In 1979, the United States Federal Trade Commission (FTC) documents (Docket 9108, 1979) charged E.I. DuPont de Nemours with an ‘unfair method of competition’ in an attempt to dominate the titanium pigment market in the U.S. (Federal Trade Commission, 1979). Because of this case (won by DuPont), a rich set of data on price margins, costs, market shares, etc. are available through the FTC discovery process. A Harvard Business School (1986) case focused on capacity decisions and the marketing strategy of the market leader in the TiO_2 industry. Ghemawat (1984) also analyzed these decisions in a more limited framework than the one we apply here.

We supplemented the data in FTC documents, which covers the history of TiO_2 industry up to 1977, with information from the *Chemical Economic Handbook*, published by the Stanford Research Institute and from industry periodicals including *Chemical Week* and *Chemical Purchasing*. For more details on the industry, the data sources, variable definitions and analysis background, see Dearden et al. (1997).

3.3. Empirical analysis

Our goal in this section is to demonstrate that we can both explain and predict capacity decisions (and the related utilization cycles) with the ideas and data that emerged from our industry interviews. Our models are simple and exploratory, as we have neither extensive theory (beyond our firm-interviews) to guide us nor extensive data sets to support a complex modeling exercise. Using the principle of parsimony, our simple regression models are either linear or log-linear forms, model forms most suitable in such restrictive circumstances.

We estimated aggregate market and firm-level capacity models using annual data; for details on the price, industry demand, cost and market share models, see Dearden et al. (1997). The results of those models can be summarized as:

(1) Industry demand is driven by market price, general economic conditions and specific economic shocks (oil crisis, for example).

- (2) Market price is driven by capacity utilization (demand and capacity) and specific economic shocks.
- (3) Manufacturing costs are driven by production technology and capacity (economies of scale).
- (4) Market share is closely linked to (lagged) capacity share.

The above models are either linear or log-linear in form and the resulting R^2 's range from 0.68 to 0.86.

3.3.1. Capacity utilization cycles at the industry level

Fig. 2 provides a graphical analysis of TiO_2 industry data, suggesting that capacity utilization appears to fluctuate with a cycle length of 4–8 years. Our regression model in Table 1 suggests that capacity utilization appears less important than price in explaining the changes of industry capacity, a result that may be due to high multicollinearity between price and capacity utilization. To recognize and model the interactive nature of industry demand and industry capacity with market price, we also developed a simultaneous estimation system for industry demand and industry capacity using two stage least squares (Dearden et al., 1997) whose results are generally consistent with those reported here.

3.3.2. Capacity additions and deletions at the firm / plant level

We pooled our data across time, plant and firm and used dummy variables to assess firm-specific effects. By such pooling, we implicitly assume that capacity decision rules have been stable over time.

3.3.2.1. Capacity addition model. As the economics of addition and deletion decisions vary by plant location, the plant is the appropriate unit of analysis. Table 2 reports discriminant analyses of capacity additions by individual plants. We estimated two-way ($\text{ADD} = 1$ for addition and $\text{ADD} = 0$ for no addition) canonical discriminant functions for data for all the plants and then for each respective subset of the data, leaving out one plant for predictive validation in a rotating manner (not shown here). Based on the results of our interviews and preliminary correlation analysis, we selected the following variables as potential discriminators: four *industry-level* variables including capacity utilization (both one-year and

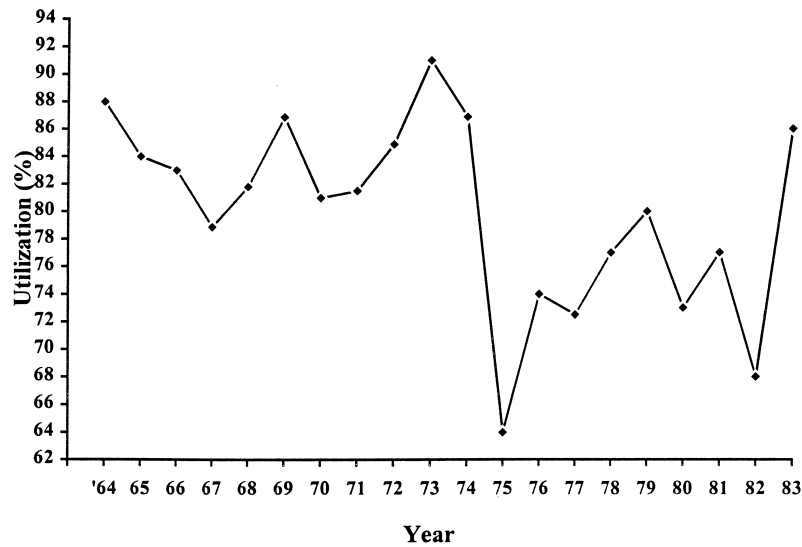


Fig. 2. Cyclical nature of industry capacity utilization.

two-year lags, IUTIL(1) and IUTIL(2)), market price in real terms (one-year lag, PRICE(1)), total capacity change (during the previous and current years (CAPCHG(0,1))); two *plant-level* variables including, manufacturing cost (one-year lag, COST(1)) and market share (one-year lag, SHARE(1)); and dummy *firm* indicators (FIRM-B, FIRM-C, and FIRM-D). The model also included a dummy variable, OILD, to represent the structural changes around the 1974–1975 World Oil Crisis.

The standardized canonical discriminant function coefficients suggest that a plant's decision for capacity addition is sensitive (or responsive) to other

firms' capacity additions (CAPCHG), to its comparative production cost (dis)advantage (COST) and to its market share position (SHARE), although the relative importance of these variables vary. Market price (PRICE) is not very important, reflecting the existence of a price leader. Industry's capacity utilization (IUTIL) is important, but somewhat less significant than other variables, perhaps due to its correlation with CAPCHG. Relatively large FIRM-B and FIRM-C behave somewhat differently from the market leader (FIRM-A), while (relatively small) FIRM-D's capacity decisions usually go along with the market leader's decision. In addition, following

Table 1
Regression analysis of TiO₂ industry capacity (ICAP)^a

Constant	Explanatory variables ^b			Model fit (R ²)	Number of observations (N)
	IUTIL	PRICE	OILD		
906.67 ** (6.08)	261.44 * (2.38)	-22.60 ** (-3.94)	90.29 ** (3.54)	0.856	20

^aDependent variable: ICAP = Industry capacity.

^bIUTIL = Industry capacity utilization; PRICE = Market price of the product (real, deflated with industrial producer's price index); OILD = Dummy variable for the World Oil Crisis, i.e., OILD = 0, if year ≤ 1974, 1, if year ≥ 1975.

() includes *t*-statistic for each estimate.

* indicates that the estimate is significant at 0.05 level.

** indicates that the estimate is significant at 0.01 level.

the World Oil Crisis, firms became less aggressive in adding capacity.

Our (linear discriminant) models performed surprisingly well (and quite a bit better than with a logit specification). We correctly classify 83% (81%) of the capacity addition (no-addition) cases (retrospectively) by the discriminant function (estimated from the all-plants data), while we are able to predict 67% to 83% of individual plant cases correctly as capacity

addition or no addition (calculated from the hold-out sample). The same measures of model fit and prediction for zircon data (not shown here) are 83% to 91% in retrospective classification and 79% to 82% in predictive classification.

3.3.2.2. Capacity deletion model. We built similar capacity deletion models, also shown in Table 2, and found that capacity deletion decisions can mainly be explained by the firm's comparative cost (dis)advantage, market share position at each plant, the product's market price and industry capacity utilization at the industry level. These models also performed well, classifying 89% of deletion and 78% of no-deletion cases correctly.

Table 2
Discriminant analysis^a of capacity addition and deletion

	Capacity addition	Capacity deletion
<i>Standardized canonical discriminant function coefficients</i>		
IUTIL(<i>t</i>)	0.230	-0.475
IUTIL(<i>t</i> - 1)	0.009	-0.483
PRICE(<i>t</i>)	0.645	-0.532
CAPCHG(<i>t</i> - 1, <i>t</i>)	0.573	0.262
COST(<i>t</i>)	0.766	0.579
SHARE(<i>t</i>)	0.540	0.577
OILDM	0.737	0.028
Firm-B (Plant 2)	0.347	-0.039
Firm-C (Plant 3)	0.223	0.687
Firm-D (Plants 4, 5, 6)	-0.091	-0.144
<i>Unstandardized canonical discriminant function coefficients</i>		
IUTIL(<i>t</i>)	2.811	-5.783
IUTIL(<i>t</i> - 1)	0.123	-6.306
PRICE(<i>t</i>)	0.543	-0.425
CAPCHG(<i>t</i> - 1, <i>t</i>)	0.008	0.004
COST(<i>t</i>)	0.225	0.169
SHARE(<i>t</i>)	3.791	4.116
OILDM	1.745	0.065
Firm-B (Plant 2)	0.921	-0.105
Firm-C (Plant 3)	0.607	2.109
Firm-D (Plants 4, 5, 6)	-0.243	-0.386
(Constant)	-21.412	15.165
<i>Canonical discriminant functions estimated at group means (Group centroids)</i>		
No Change of Capacity	0.485	1.893
Change of Capacity	-0.970	-0.270
<i>Statistics for testing equality of the discriminant function means</i>		
Canonical correlation	0.571	0.587
Wilks' lambda	0.674	0.655
Chi-square	25.64	27.50
Sig (Chi-square)	0.004	0.002
<i># of cases correctly classified / # of cases used for estimation[*]</i>		
No change of capacity	39/48 (81.3%)	56/63 (88.9%)
Change of capacity	20/24 (83.3%)	7/9 (77.8%)

3.4. Predicting cycles

The capacity trends we described in Section 3.3.1. essentially aggregate the behavior of individual firm actions in Section 3.3.2. But understanding capacity utilization requires that we blend these seller actions (building capacity) with the actions of the buyers (market demand). Our goal in this subsection is to show that even very simple models using ONLY the variables that are in the public domain (gross capacity decisions and changes in industrial production indices) can help predict the onset of a cycle. (While we build relatively simple regression models, note that the variables in those models include capacity and capacity utilization which, in turn, include key

Notes to Table 2:

^a Grouping variable: ADD $j(t) = 1$ (DEL $j(t) = 1$), if plant j added (deleted) its capacity during year t , and ADD $j(t) = 0$ (DEL $j(t) = 0$), if it did not, where $j = 1, \dots, 6$.

Predictor variables: IUTIL(t) or IUTIL($t - 1$) = industry's overall capacity utilization (%) in year t or $t - 1$, PRICE(t) = market price in real terms in year t , CAPCHG($t - 1, t$) = industry's capacity change during years $t - 1$ and t , COST(t) = individual plant's manufacturing cost in year t , SHARE(t) = individual plant's market share in year t , OILDM = dummy variable representing the structural shift around the 1974–75 World Oil Crisis, and FIRM- i = dummy firm indicators, $i = B, C,$ and D in comparison with A .

^{*} Predictive validity results are 83% (67%) for add (don't add) decisions; we had insufficient data to do this analysis for deletion decisions.

drivers such as price, changes in price and macroeconomic indicators, e.g., pre/post World Oil Crisis.) Our reference point or benchmark will be time series models. We apply this analysis to data on TiO_2 from 1984–1993, a period for which we do not have access to the FTC related detailed data that we used for our analyses in Section 3.3.

Table 3 presents predictions of Aggregate Demand, Capacity, and Capacity Utilization in the TiO_2 industry for that period. The predictions are based on a year-by-year estimation of relevant nested linear

regression and time series models on a data base updated for each year; e.g., the 1984 prediction was based on 1964–1983 data, 1985 was on 1964–1984 data, 1986 was on 1964–1985 data, etc. We use a cubic form for the time series models to permit flexibility in capturing both trends and cycles.

3.4.1. Industry demand (D)

We estimated regression-based demand, D_{reg} , using a regression model (as per our earlier discussion

Table 3
Predictions of industry demand, capacity, and capacity utilization **

Year	Demand (D)			Capacity (C)			Capacity Utilization (U)			
	D_{act}	D_{reg}	D_{ts}	C_{act}	C_{reg}	C_{ts}	U_{act}	U_{reg}	U_{ts}	U_{ts}^*
1964	475			529			89.8			
1965	505			573			88.1			
1966	526			599			87.8			
1967	514			625			82.2			
1968	559			634			88.2			
1969	581			635			91.5			
1970	576			674			85.3			
1971	603			690			87.4			
1972	660			682			96.8			
1973	710			705			100.7			
1974	617			756			81.6			
1975	549			788			69.7			
1976	634			864			73.4			
1977	625			838			74.6			
1978	636			787			80.8			
1979	673			771			87.3			
1980	660			783			84.3			
1981	691			785			88.0			
1982	598			791			75.6			
1983	690			796			86.7			
1984	757	808	676	789	812	752	95.9	99.5	89.9	89.2
1985	783	798	749	827	814	751	94.7	98.0	99.7	98.5
1986	844	798	808	855	853	780	98.7	93.6	103.6	102.7
1987	879	856	882	864	886	818	101.7	96.6	107.8	107.3
1988	927	880	945	914	895	848	101.4	98.3	111.4	111.4
1989	1007	903	1008	965	948	898	104.4	95.3	112.2	113.1
1990	979	924	1090	1026	1005	1091	95.4	91.9	99.9	115.1
1991	992	918	1117	1199	1056	1035	82.7	86.9	107.9	110.4
1992	1137	948	1133	1329	1212	1180	85.6	78.2	96.0	99.2
1993	1162	1011	1215	1330	1353	1344	87.4	74.7	90.4	92.7
MSE		8552	4012		3694	7725		41.4	105.6	165.1

D_{act} , C_{act} , and U_{act} are actuals, D_{reg} and C_{reg} are regression-based predictions, $U_{reg} = D_{reg}/C_{reg}$, $U_{ts} = D_{ts}/C_{ts}$, U_{ts}^* = direct time series forecast, and D_{ts} , C_{ts} and U_{ts} are time series-based predictions. MSE are Mean Squared Errors of prediction values computed against actual values.

** The causal model both predicts better and picks up the beginning of the cycles better than a time series model does.

about posted prices not reflecting real transaction prices, we eliminate that variable in this model):

$$D_{\text{reg}}(t) = a_1 + a_2 \text{IPRI}(t) + a_3 \text{OILDUM}, \quad (1)$$

where:

IPRI = industrial production index (1987 = 100),
 OILDUM = 1, if year, t , is 1974 – 1983,
 OILDUM = 0, otherwise,
 a_1 , a_2 , and a_3 are regression coefficients.

We estimated the time series-based demand, D_{ts} , using a cubic time series model:

$$D_{\text{ts}}(t) = a_1 + a_2 T + a_3 T^2 + a_4 T^3, \quad (2)$$

where:

$$T = t(\text{year}) - 1963.$$

A comparison of predictive performance between the two models in Table 3 shows that the time series model was better than the regression model using the criterion of predicted Mean Square Error (MSE = 4012 vs. MSE = 8552, more than halving MSE) for 1984–1993.

3.4.2. Industry capacity (C)

We estimated regression-based capacity, C_{reg} , using a definitional equation:

$$C_{\text{reg}}(t) = C_{\text{act}}(t - 1) + cC_{\text{reg}}(t), \quad (3)$$

where:

C_{act} = actual industry capacity,
 cC_{reg} = incremental change in industry capacity;
 and a regression model:

$$cC_{\text{reg}}(t) = a_1 + a_2 \text{UTIL}(t - 1), \quad (4)$$

where:

$$\text{UTIL} = (\text{actual}) \text{ capacity utilization.}$$

(We eliminate price from this model for the same reason as in the demand model.)

Again we estimated a time series-based industry capacity, C_{ts} , using a cubic time series model:

$$C_{\text{ts}}(t) = a_1 + a_2 T + a_3 T^2 + a_4 T^3. \quad (5)$$

A comparison of predictive performance between the two models in Table 3 shows that here, unlike for demand, the regression model is considerably supe-

rior to the time series model in terms of predicted Mean Square Error (3694 vs. 7725, with the regression model here more than halving the MSE of the time series model).

3.4.3. Industry capacity utilization (U)

We calculate regression-based capacity utilization from regression-based Demand and Capacity as:

$$U_{\text{reg}}(t) = D_{\text{reg}}(t) / C_{\text{reg}}(t); \quad (6)$$

while we similarly calculate time series-based capacity utilization, U_{ts} , from time series-based Demand and Capacity as:

$$U_{\text{ts}}(t) = D_{\text{ts}}(t) / C_{\text{ts}}(t). \quad (7)$$

As a third benchmark, we estimated another (time series) prediction, U_{ts}^* , directly from historical capacity utilization data, using a cubic time series model:

$$U_{\text{ts}}^*(t) = a_1 + a_2 T + a_3 T^2 + a_4 T^3. \quad (8)$$

A comparison of the predictive performance between these three models in Table 3 shows that the regression model was far better than either of the two time series models in terms of predicted Mean Square Error (MSE) vs. the actual values for 1984–1993 (i.e., 41.4 vs. 105.6 and 165.1 respectively). In addition, and more importantly, the regression model picks up the beginning of the decline in capacity utilization in 1990 while both the time series models project increasing capacity utilization for two additional years. In sum, our basic model structure, even at the aggregate level (and only including publicly available data) appears to pick up the cycle phenomenon, and does so much better than a time series benchmark.

3.5. Summary of empirical analysis

Our findings, which generally support the insights from our executive interviews, are that over-capacity and under-capacity cycles are likely to occur because firms, acting on demand forecasts, current prices, their current capacity and their manufacturing costs, simultaneously add (perhaps too much) capacity in good times, and delete (perhaps too much) capacity in poor times.

The empirical models fit and predict aggregate industry dynamics and individual firm decisions well. The sensitivity of a firm's capacity addition and deletion decisions to other firms' capacity changes and industry capacity utilization across the models (Table 2) suggests simultaneous, competitive firm behavior. But what are the goals of the firms in these markets? Do they or can they anticipate the actions of their competitors? How do their beliefs (and the possible errors in those beliefs) about the evolution of demand affect their actions? Our empirical models do not include the structure, nor do we have the data, to address these questions, raised in our qualitative interviews. Hence, we develop some theoretical models to address these other issues.

4. Why do these cycles occur? An economic/theoretical perspective

Thus far we have seen that capacity cycles appear to occur and our empirical results suggest some predictors. In this section we look to economic theory for additional insight. We must consider the interaction of marketing interests (sufficient capacity to guarantee supply assurance and to capture new customers) and financial/production interests (limiting production to keep prices high and average production costs low) in this process. We first review some related literature. Then we model a duopolistic, homogenous product industry and examine three possible explanations—strategic preemption, the coordination problem, and the winner's (and loser's) curse—for suboptimal industry capacity decisions.

4.1. Theoretical background

Shepherd (1979), recognizing that coordination ameliorates cycles, indicates that cycles are reduced when (a) there is a dominant firm, (b) costs are similar, (c) fixed costs are low, (d) demand is stable (or more easily forecast), and (e) uncertainty is lower amongst sellers, i.e., more information based on independent forecasts is shared. But what happens when the conditions that Shephard identifies are not satisfied? We investigate those conditions in our models.

4.1.1. Strategic preemption

The literature on oligopoly theory related to our research has primarily considered strategic preemption in capacity expansion decisions (Friedman, 1983, Chapter 7; Gilbert, 1986; Fudenberg and Tirole, 1986). The central theme in this literature is that if investment is irreversible (i.e., costly to change recent additions or deletions), then the first-mover adds excess capacity to prevent the other firm from either entering the industry or from adding additional capacity. This strategic preemption increases the first-mover's profit but lowers overall industry profit through this excess industry capacity.

In the absence of 'natural' market leaders, the presence of dominant firms cannot be assumed but must be endogenous to the analysis. The Reinganum (1981a,b), Gilbert and Harris (1984), Harris and Vickers (1985), and Fudenberg and Tirole (1985) analyses do this, examining preemption games in which firms simultaneously decide at each point in time whether to build a new plant. The capacity decision in these models is lumpy and the market is big enough to support only one such addition. One interesting result of these (full information) models is that in equilibrium, firms may each add capacity resulting in over-capacity with positive probability.

4.1.2. Coordination problems

With simultaneous moves, lumpy capacity, and a market big enough to support only one additional unit of capacity, firms face a coordination problem: to maximize joint profit, only one firm should add capacity. However, with simultaneous decisions, if both firms add capacity with positive probability, there is positive probability of over-capacity; and if both firms do not add capacity with positive probability, there is positive probability of under-capacity. Gal-Or (1994) considers product differentiation in a capacity addition game and demonstrates that the competition for customers (in particular, the customers without a strong preference for one firm's product) induces investment in excess capacity.

4.1.3. Imperfect forecasts and the winner's/loser's curse

Suppose the firms' true needs for capacity changes are positively correlated, as for example, when an

increase in market demand benefits all firms. In the extreme case the firms have the same true value (V), that is a common value, for adding capacity. However, when the capacity decision is made, the firms are uncertain about the true future needs for capacity changes and have access to different forecast information. Hence, the firms have imprecise demand forecasts and the forecasts may be different. The firms with higher forecasts add capacity. This is known as the winner's curse. Analogously, a firm will add capacity too infrequently when its forecast is too low, what we call the loser's curse. (See Milgrom, 1985, 1989, for more on the winner's curse.) The possibility of a winner's curse may cause suboptimal waiting; firms wait to see what other firms are going to do before they are willing to make a commitment to a capacity investment decision (Gale, 1996).

Thus, the literature suggests that there are at least three possible explanations for the types of capacity cycles we explore here. We formalize our thinking here with some simple models, below.

4.2. Modeling capacity decisions¹

To illustrate how easy it is for a market to induce the winner's/loser's curse, preemption and coordination problems, we sketch out some simple, game-theoretic models that are stylized representations of our empirical models. Our empirical models showed that individual firm capacity decisions are mainly driven by prices, costs, capacity utilization (at the industry level) and recent capacity changes in the industry. Suppose we use a single indicator of market conditions, ρ , to represent the market conditions for a specific firm. Thus a high value of ρ (good market conditions) would occur when prices for the firm were high, costs were low, capacity utilization were high and when the industry was adding capacity: thus ρ for a particular firm is like a conditional profit forecast—if a firm were to know ρ and also know what competitors were doing, it would know its profit. What drives our analysis is the fact that a firm's profit depends not only on what it knows

about its market and its customers, but also depends on what competitors know and how they behave as well.

To keep our analysis as simple as possible, we consider two firms only, two levels of capacity (high or low) and two periods of competition, where firms must decide whether or not to add capacity. Firms each have a forecast ρ of market conditions.

Firm i ($i = 1, 2$) begins with capacity $Q_i^0 \in \{Q_i, \bar{Q}_i\}$, where $\bar{Q}_i > Q_i$. We look at a two-period model to account for the dynamics of possible cycles.

In period 1, firm i chooses $Q_i^1 \in \{Q_i, \bar{Q}_i\}$. In our model, investment may be either reversible (capacity deletions followed by additions or vice versa) or irreversible (where we consider either capacity additions or deletions only). In period 2 (when firms observe each others' actions), if investment is irreversible and if capacity is changed in period 1, then it cannot be further changed.

After period 2, the firms see their profits, which are functions of their capacities and of true market conditions. When making capacity decisions, both firms may be uncertain about future market conditions and at the onset, each firm receives a forecast of future market conditions. We let P denote the set of possible market conditions, and $\rho_i \in P$ denote a specific market condition for firm i . For each capacity pair (Q_i, Q_j) , firm i 's profit is a probability distribution on P of possible profit, $\pi_i(Q_i, Q_j; \rho_i)$.

In the several cases we consider, we look at whether the true market values, ρ_1 and ρ_2 , are correlated or independent. (We consider two extreme scenarios: (1) ρ_1 and ρ_2 are independent; and (2) $\rho = \rho_1 = \rho_2$ are common values). Those forecasts can either be perfect (have no error) or include some error. And if these forecasts do have errors, those errors can be correlated (for example, when firms hire the same market research firm) or independent (when they do their forecasting internally). Finally, the firms can either have identical profit functions or different (privately known) profit functions. (The former is known as a common values case; the latter a private values case).

To illustrate the several possible drivers for cycles, we consider four cases. In Case 1 it is profitable for only one firm to add capacity and both firms have incentives to add capacity. In this case we

¹ Verification of the equilibria is available from the authors.

assume true market values are independent and each firm knows its profit function but is uncertain about the other firm's profit from adding capacity. That is, in period 0, firm i learns ρ_i , but is uncertain about ρ_j . Case 2 is similar to Case 1 in that the true market values and the forecasts are independent. However, in Case 2, at the onset of Stage 1, there is excess capacity. Joint industry profit is maximized if one unit of capacity is deleted. In this case, firms try to be the only firm that does not delete capacity. Cases 3 and 4 consider common market values, where both firms have identical profit functions and know that fact. In Case 3 we assume that each firm makes a forecast of market conditions (with some error) and those forecasts are independent. Case 4 is like case 3, but here we assume the forecasts are correlated. (We describe Case 1 fully here; for details on the analysis of the other cases see Dearden et al., 1997.)

4.2.1. Case 1. Independent values

Firms consider adding capacity. Hence, prior to the game, $Q_i^0 = \underline{Q}_i$. Investment is irreversible, each firm's forecast of the value of added capacity is perfect, and that forecast is private information. Therefore, each firm knows its own payoffs, but is uncertain about its competitor's value of adding capacity. The forecast ρ_i is distributed on $[-1, +1]$ according to the distribution function $G(\rho_i) = (\rho_i + 1)/2$. The payoffs from the various outcomes are:

$$\pi_i(\bar{Q}_i, \bar{Q}_j) = 1 + \rho_i,$$

$$\pi_i(\bar{Q}_i, \underline{Q}_j) = 8 + \rho_i,$$

$$\pi_i(\underline{Q}_i, \bar{Q}_j) = 4,$$

$$\pi_i(\underline{Q}_i, \underline{Q}_j) = 5$$

for $i = 1, 2$. This payoff structure, and those in the following examples, reflect the fact that a firm loses customers when it has too little capacity.

We examine perfect Bayesian equilibria, where the profile of strategies and beliefs is such that, at any stage of the game, strategies are optimal given beliefs, and the beliefs are obtained from the equilibrium strategies and observed actions using Bayes' rule.

In the symmetric perfect Bayesian equilibrium, firm i 's equilibrium strategy, $s_i(\rho_i)$, is

$$\sigma_i(Q_i) = \begin{cases} Q_i^1 = \bar{Q}_i, & \text{if } Q_i \geq -0.030; \\ Q_i^1 = \underline{Q}_i \text{ and } Q_i^2 = \bar{Q}_i, & \text{if } -0.30 > Q_i \geq -0.443; \\ Q_i^1 = Q_i^2 = \underline{Q}_i, & \text{if } -0.443 > Q_i. \end{cases}$$

This strategy is sequentially rational, given firm j ($j \neq i$) employs an identical strategy and given firm i 's probabilistic belief of ρ_j (which is updated by Bayes' rule at the end of stage). We depict the equilibrium strategy profile and outcome in Fig. 3. The joint profit, $\pi_1 + \pi_2$, is maximized if the firm and only that firm with the greater value of adding capacity (i.e., the greater value of ρ) actually adds capacity. The efficient industry strategy profile is depicted in Fig. 3 and the equilibrium strategy profile and outcomes are depicted in Fig. 4.

By examination of Figs. 3 and 4, we see that the equilibrium may result in either over-capacity (if ρ_1 and ρ_2 are large) or under-capacity (if ρ_1 and ρ_2 are small) compared to the capacity decision that maximizes joint profit. Moreover, for preemptive reasons, firms add capacity early—in period 1. If capacity is added before a correctly anticipated demand increase, then there is excess capacity before demand actually increases.

4.2.2. Case 2. Independent values and excess capacity

In this case firms consider deleting capacity, and prior to the game, $Q_i^0 = \bar{Q}_i$. Like Case 1, investment

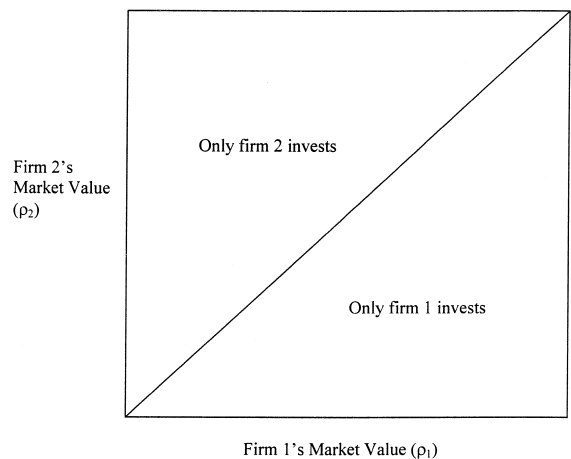


Fig. 3. The Case 1 strategy that maximizes total industry profit.

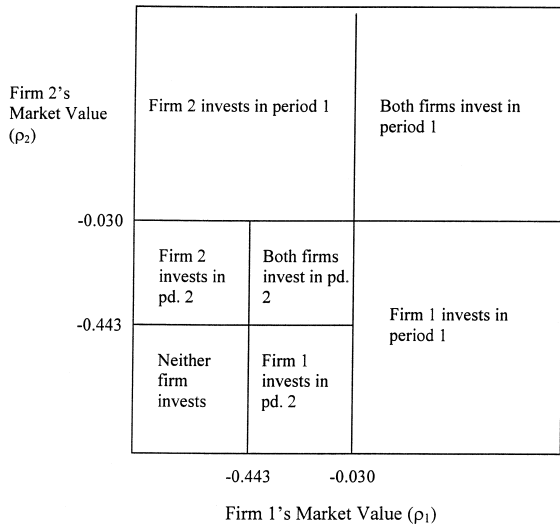


Fig. 4. The Case 1 strategy profile.

is irreversible, each firm's forecast of the value of deleting capacity is perfect (that is, there is no variance in the forecast), and that forecast is private information. Each firm knows its own payoffs precisely, but is uncertain about the competitor's value of deleting capacity. Analysis of the equilibrium strategy in this case reveals over-capacity (if ρ_1 and ρ_2 are small) or under-capacity (if ρ_1 and ρ_2 are large) compared to the capacity decision that maximizes joint profit. However, unlike Case 1, firms never delete capacity for preemptive reasons. Each firm has an incentive to be the one firm that does not delete capacity, and therefore does not delete capacity in the first period.

4.2.3. Case 3. Common values and independent forecasts

In this case the firms consider adding capacity. Hence, prior to the game, $Q_i^0 = Q_j$. Investment is either reversible or irreversible. Also, there are two possible states of the market: $P = \{\text{good market conditions, poor market conditions}\}$. The states are common to the firms (i.e., $\rho_1 = \rho_2 = \rho$, although the firms receive independent forecasts of the likelihood of those states occurring). The (identical, common value) payoffs depend on the true state of the market, ρ . There is a winner's curse in this case. If firm i receives the forecast that market conditions are good,

then it adds capacity in period 2. From our specification of the probability distribution for this specific case, both firms cannot make overly optimistic forecasts. Hence, firm i is the only firm that makes an overly optimistic forecast and the only firm that adds capacity. This is the winner's curse.

Similarly, suppose firm i receives a forecast that market conditions are bad. There is a probability (0.1 in the specification that we used) that firm j adds capacity and firm i regrets its decision not to add capacity. Firm i then suffers what we call a 'loser's curse.'

4.2.4. Case 4. Common values and joint forecasts

Case 4 is identical to Case 3 with one exception: the firms receive only one forecast of market conditions. In this case, in our specification, the probability that both firms make an incorrect forecast and regret their capacity decisions is 0.1. In Case 3, however, the probability that both firms make incorrect forecasts and regret their decisions is 0!, i.e., in Case 3, if a mistake is made, it is made by only one firm. Thus, correlated forecasts increase the likelihood of all firms making the same mistake (or increase the likelihood of the winner's/loser's curse).

In these four cases, we examined strategic reasons why firms either over-invest or under-invest in capacity and hence why we observe capacity cycles. We identified two market problems in Case 1. When there is room for only one firm to add capacity and capacity decisions are made simultaneously, the firms have a coordination problem. The lack of coordination may result in either excess or insufficient industry capacity. Moreover, each firm has an incentive to be the only firm to add capacity, and thus may attempt to preempt the other firm and add capacity early. This preemption results in excess capacity prior to the improvement in market conditions. Case 2 also identifies a coordination problem when there is room for only one firm to profitably delete capacity. However, unlike Case 1, when firms are in a deletion game, there is no strategic preemption.

Cases 3 and 4 examine the winner's and loser's curse. In Case 3, when the true market values of capacity are common between the firms, either firm may be the one that makes an incorrect forecast, makes an incorrect capacity decision, and then be the

Table 4
Summary of theoretical results

Shocks to system	Capacity decisions	Cycles
A. Actual or forecasted demand change	1. Simultaneous capacity change decision causes coordination problem.	1. Coordination problem perpetuates cycles.
B. Cost structure change	2. Preemption. Capture forecasted demand increase before competitor does. Keep excess capacity to prevent competitor from entering market or adding capacity.	2. Preemption implies persistent excess capacity. Preemption can also prompt coordination problem.
C. New technology	3. Change capacity based on incorrect forecast (winner's and loser's curse).	3. Incorrect forecast by multiple firms can prompt coordination problem.
D. Competitive entry/change in competitive strategy	4. Wait and see (Herd behavior).	4. Wait and see can result in insufficient industry capacity, sparking over expansion followed by excess deletion.

These results show that there are a number of possible changes in the market that can affect capacity decision in ways that lead to under- and over-capacity cycles.

single firm that is cursed by its decision. Case 4 shows that the use of a joint forecast (for example, an industry association's forecast) may only compound the curse: both firms make the same mistake.

Note that a cycle may be initiated by any of the causes of over- or under-capacity. For example, preemption or the winner's curse may prompt a cycle, but cycles may be perpetuated by a coordination problem. When an industry has suboptimal capacity, each firm then vies either to be the firm that increases capacity (when there is insufficient industry capacity) or to be the firm that does not delete capacity (when there is excess industry capacity). The lack of coordination of the firms' capacity decisions compounds the capacity cycle (Dearden et al., 1997).

Table 4 summarizes what we have tried to demonstrate with these models. While the key drivers behind over-expansion and under-expansion differ—market preemption and customer satisfaction goals drive capacity expansion while financial concerns may primarily drive deletion decisions—the result is that there might be several causes of capacity cycles and it is unlikely that market data alone will enable us to identify the relative impact of these causes. Our models in this section were designed to illustrate that

fact; more complicated analytic models will only reinforce this observation.

5. Linking theory to observation

We have performed some exploratory empirical analyses and developed some simple theoretical models, all of which identify causes of capacity cycles. How do these results compare? We have seen that our empirical results provide substantial descriptive and predictive support for the existence of capacity cycles; our game theoretic analyses suggest some reasons why. An understanding of the why (or possible whys) will allow us to speculate on how to operate in such markets and to design mechanisms to improve the operations of such markets. Hence, we look for evidence of the phenomena identified in Table 4 in the marketplace.

Consider Table 5, which looks at capacity addition and deletion decisions in the titanium dioxide industry. That table suggests several behaviors that are consistent with our models.

Observation 1. Individual firms' *simultaneous* capacity additions and maintenance (e.g., 1973–1974 or 1982–1983) are all followed by their *simultane-*

Table 5
Capacity additions and deletions*

Year	Individual firm's capacity						Aggregate industry capacity	Capacity utilization**	
	A	B	C	D	E	F		1-year lag	2-year lag
1970	+	+	o	+	+	+	+	H	M
1971	o	o	o	–	o	+	+	M	H
1972	+	o	–	+	o	+	–	M	M
1973	+	o	–	+	o	+	+	H	M
1974	+	+	+	o	+	o	+	H	H
1975	o	o	o	o	+	o	+	M	H
1976	+	o	–	o	o	o	+	L	M
1977	o	o	–	o	+	o	–	L	L
1978	o	o	–	o	o	o	–	L	L
1979	+	o	o	–	o	o	–	M	L
1980	+	o	o	o	o	o	+	M	M
1981	–	o	–	–	+	+	+	M	M
1982	o	+	o	+	o	+	+	M	M
1983	o	+	+	+	+	+	+	L	M
1984	o	o	–	o	+	o	–	M	L
1985	o	o	o	o	o	o	+	H	M
<i>Individual firm's position</i>									
(a) Production cost****	L	L	H	H	M	M			
(b) Market share*****	H	L	H	M	M	L			

* +: addition, –: deletion, and o: no change.

** H: 90% or higher, M: 80–90%, and L: 80% or lower.

*** H: relatively high, M: medium, and L: relatively low.

**** H: relatively high, M: medium, and L: relatively low.

These results suggest coordination problems, lagged capacity driven cycles, preemption and non-deterministic actions.

ous capacity deletions or maintenance (e.g., 1976–1976 or 1984–1985). This suggests a coordination problem, an issue in all of our theoretical models (Cases 1 to 4).

Observation 2. Cycles (i.e., additions and deletions) of total industry capacity have occurred in parallel with the cycles (i.e., Highs and Lows) of *capacity utilization* with a typical lag of 1–2 years. In other words, lagged capacity utilization seems to drive cycles. But capacity utilization is common knowledge in the industry and is a key variable in all of our addition and deletion models. Assuming that capacity utilization signals demand (or changes in demand) then it serves as a joint forecast of future demand, suggesting the winner's and loser's curse situations as depicted in Case 4.

Observation 3. Low and medium *cost* firms (e.g., A or B) have typically responded to industry fluctuations by their capacity cycles of additions and main-

tenance, while *high* cost firms (e.g., C and D) have responded to industry fluctuations by their capacity cycles of additions, *deletions* and maintenance. This observation is consistent with preemption behavior (Cases 1 and 2).

To generate an additional observation we focus on firms A and C, the 'high' market share firms who mainly dictate the evolution of the market. If we assume that A and C are playing fixed strategies, then we would expect to see certain deterministic patterns of simultaneous moves dominate. (Both add, both delete, A adds, C doesn't, etc.) If we code the data as in Table 6 we have five possible 'deterministic strategy' patterns relating A's and C's capacity strategies. For a deterministic strategy to dominate, we should expect one of these patterns to prevail.

The numbers in the Frequency of Occurrence column show the frequency with which the noted pattern occurs in Table 5. Not surprisingly, the A – 1

Table 6

Case	Action	Frequency of occurrence
1	A + 2 = A adds, C deletes.	3
2	A + 1 = A adds, C no change; or A no change, C deletes.	6
3	A = A adds, C deletes; or A no change, C no change; or A deletes, C adds.	6
4	A - 1 = A no change, C adds; or A deletes, C no change.	1
5	A - 2 = A deletes, C adds.	0

and A - 2 patterns were virtually nonexistent (since A is the low cost firm). However, the high incidence of all three of the other patterns (3, 6 and 6) suggest capacity decisions that reflect probabilistic behavior, or:

Observation 4. Probabilistic behavior seems to be evident in the addition/deletion strategies. Non-deterministic action, results from independent values (Cases 1 and 2) or from independent forecasts with common values (Case 4).

Hence the titanium dioxide market *exhibits symptoms of all of the problems we have identified earlier.* (We have found similar observations from our work with zircon as well.)

So what is the marketer to do? As we have mentioned, these cycles cause problems for both buyers and sellers in these markets. Are these problems that firms simply must live with or are there cures? We discuss this issue below.

6. Discussion and implications

In their attempts to capture and retain customers, when there are positive changes in the marketplace (price or demand for example), marketers may be driven to add capacity in ways that lead to over-capacity. Financial or other objectives (such as the risk associated with increasing capacity) may call for decisions that result in under-capacity. Therefore, the

tension between marketing and other objectives may prompt capacity cycles. Our practitioner interviews helped provide insights into this tension and the resulting capacity cycles. We fleshed out these cycles in our empirical investigation of two industries and the dynamics of the titanium dioxide industry support our conceptual structure. The dynamics suggest in fact that as long as there are some changes in the marketplace, individual firm level decisions are likely to lead to capacity cycles. For example, our capacity addition model predicts an increase in 'add' probability if price goes up, capacity utilization goes up or cost goes down, and vice versa for our capacity deletion model. As this occurs for all firms, the model predicts cycles with any sustained change in market conditions. Our investigation of those markets also suggests that the cycles are predictable (using our regression models) and that firm behaviors are consistent with the results of the theoretical models. Our review of the literature suggests that there may be a number of causes, and, indeed our theoretical investigations suggest that those causes are likely to emerge in even the simplest of competitive markets. We identified three phenomena that emerge as possible culprits: the winner's/loser's curse, preemption, and coordination.

These cycles are inefficient, whatever their causes, disrupting buyers and sellers, and often leaving customers with higher prices or shortages or delayed supply of critical products. What can sellers do to address these issues? Bower (1986) (p. 221) suggests: "... it would be extremely helpful ... if industry associations were asked to produce long term forecasts of supply/demand balance." What Bower suggests is that reducing uncertainty about the nature of demand would help coordinate capacity planning efforts. But our models show that this will *increase* the likelihood of the winner's curse. Wind (1997) suggests preemptive strategies removing strategic options from the plates of competitors, but gives no compelling argument supporting the enforceability of those strategies.

Are there alternatives? In Japan, MITI helps coordinate the strategic plans of competitive companies. Firms give up some independence (legally in Japan, at least) in exchange for the benefits of coordination or consensus building. The stabilizing effects of such cartel-like coordination procedures reduce cyclical

behavior but may do so at the cost of keeping inefficient producers in the market (Shaw and Shaw, 1983), and may be partially to blame for the economic problems that several Asian nations are currently facing.

While these problems cannot (and perhaps should not) be eradicated, can their effects be reduced? We can do little about the independent/common values problem in general: indeed, proprietary production technology, a powerful competitive advantage in some industries, will perpetuate independent values, leading to preemption and coordination problems. However, *market research focusing on competitive intelligence* (“*Know your competitor as well as your customer*”) can help firms move toward common values, reducing that cause of cycles.

Note that under conditions of market demand uncertainty, independent forecasts lessen the winner’s/loser’s curse problem and may reduce the preemption problem as well. Firms who have downsized their forecasting departments, and have outsourced this function (to the same, ‘common,’ outside forecaster?) should rethink that decision. Hence, *increasing use of internal or independent data for market forecasting should reduce the preemption (and cycling) problem.*

While the winner’s curse and preemption may initiate a capacity cycle, coordination problems can perpetuate the cycle. If firms were able to credibly commit to capacity plans, could cycles be reduced? Prior to changing capacity, manufacturers often make public announcements of their plans. Those announcements could serve as signals to competitors, that some firms are planning to add capacity so competitors should not (Heil et al., 1997). With these announcements, the coordination problem could be reduced. The difficulty is that talk is cheap, a firm’s announced plans can often easily be changed (at least until plant construction begins) and those plans may indeed change based on announcements of other firms. (In the new product development area, Robertson et al., 1995, report that early new product announcements result in adverse competitive reactions more than half the time and advise against such action.) Note also, that an announcement does not involve a credible commitment and without such credible commitment, competitors can ignore the announcements (Dixit and Shapiro, 1986).

In the absence of the possibility of formal coordination in many countries, firms need to adopt other strategies. This paper serves as further support for the risks of operating in such markets: over-capacity/under-capacity cycles are almost destined to occur. Flexible manufacturing systems, sharing or reallocating production capacity with other, countercyclical (or uncorrelated, at least) products can help, though (Breshnahan and Ramey, 1993).

Marketers can take advantage of these situations. Our empirical analysis can be replicated in a particular marketer’s industry, resulting in better forecasts and plans. Better industry and competitive intelligence is likely to pay large dividends for firms operating in such markets, who can sign long-term supply contracts with customers during the onset of under-capacity, or by strategically timing capacity additions and deletions based on this superior intelligence. And better knowledge of the likely behavior of competitors in such markets will allow both buyers and sellers to employ hedging strategies to accommodate the more predictable demand and price cycles.

Our models, analyses and the above speculations have been exploratory. And because of the proprietary nature of some of the data needed for these analyses, the cooperation of industry actors may be necessary to replicate and expand the empirical work we report here. (This need for cooperation simply makes the research problem harder, but does not diminish its importance.)

We have investigated only a few theoretical cases here and one can envision other causes of the capacity cycle phenomenon. We do not believe that this phenomenon has a single cause or set of causes; rather we believe that it would be valuable, in future research, to see how general the phenomenon is and to generate and develop a taxonomy of causes and possible cures. It would also be valuable to perform simulations and laboratory experiments to determine experimentally if and when these phenomena are most likely to occur, the next phase of our research program.

We hope that we have shed some light on some of the possible causes of this phenomenon, and what marketers can do to prepare for and manage in such environments, and that further work will help deepen that understanding.

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