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THE LEARNING CURVE, TECHNOLOGY BARRIERS TO ENTRY, AND COMPETITIVE SURVIVAL IN THE CHEMICAL PROCESSING INDUSTRIES

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This paper evaluates entry and survival rates in a sample of 39 chemical product industries. The analysis focuses on learning-based cost advantages potentially held by incumbent firms. A logit model of entry gives no evidence that entry decisions were sensitive to the cumulative production lead held by incumbents. Entry was facilitated by the fact that for most products, technology was available from a range of sources. A hazard function model reveals that entrant survival rates were unrelated to order of entry or source of process technology. However, survival was adversely affected when the leading incumbent held a large cumulative output advantage or when entrants built plants of sub-optimal scale. Thus, a large incumbent lead in production experience did not deter new entry but did reduce the entrant's probability of survival.

INTRODUCTION

The 'learning curve' (or 'experience curve') is a central concept in strategic planning. It provides a rationale for pursuit of market share as well as the conceptual basis for portfolio planning techniques such as those introduced by the Boston Consulting Group in the 1970s.[1] Most of these strategic planning models presume that the firm with greatest cumulative production experience will enjoy a cost advantage over rivals and may be able to deter entry by new producers.

Numerous studies have documented the existence of learning curves in a wide range of industries. (See Dutton and Thomas, 1984, for a review.) However, few researchers have tried to empirically assess the magnitude of competitive advantages derived from the learning curve. Shaw and Shaw (1984) tracked market shares for European producers of three synthetic fibers—acrylic, nylon, and polyester. They concluded that 'early entrants who established major market shares early in the growth phase of the product life cycle were able to maintain that leadership nearly twenty years later . . . not only did almost all of the late entrants fail to achieve significant market shares, but in the difficult market conditions between 1974 and 1981 they provided seven out of nine market withdrawals'. In the disposable diaper industry, Porter (1984) noted that learning-related cost advantages reinforced industry dominance by the first-mover firm, and contributed to the exit of several rival producers. Similarly, Ghemawat (1984) exained DuPont's efforts to exploit learning-based cost advantages in the production of titanium dioxide.

The argument that greater production experience confers a cost advantage depends critically on the assumption that learning can be kept proprietary. There is, however, considerable

[1] The BCG planning procedure prescribes that firms with an initial lead should invest resources to maintain or increase market share during the early growth phase of the market. Later, when growth slows, less experienced rivals and new entrants will be unable to catch up to the accumulated output, and hence costs, of the dominant firm. See Boston Consulting Group (1972).

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evidence that process technology diffuses rapidly. Based on a survey of firms in 10 major industries, Mansfield (1985) concluded that 'information concerning the detailed nature and operation of a new product or process generally leaks out within a year'. Of the 10 industries in Mansfield's sample, chemicals was the one where process developments could be kept most proprietary: 90 percent of the respondents reported that process developments could be kept secret for more than 18 months. But even in chemicals, substantial leakage ultimately occurs. In a study of nine petrochemical industries, Stobaugh (1984, 1988) found licensing to be a common source of technology transfer that facilitated entry.

Theoretical models of market structure in industries characterized by learning illustrate the effects of such technological 'leakage' on market concentration and profitability. Spence (1981), Gilbert and Harris (1981), and Lieberman (1987b) show that when learning remains proprietary, only a few firms can coexist in equilibrium, and barriers to late entry can be exceedingly high.[2] Gilbert (1989), however, shows that an incumbent monopolist with a significant learning-based cost advantage might find it more profitable to set a high price and allow entry by fringe producers, rather than set a price sufficiently low to deter entry.

In environments with rapid technology diffusion there are no learning-based advantages to a first-mover position or to greater market share. Ghemawat and Spence (1985), Lieberman (1987b) and Stokey (1986) show that diffusion erodes entry barriers and causes prices to decline roughly in parallel with costs, as is commonly observed in most industries. Learning is observed at the industry level, but firms have similar costs.

Processes of random search by firms within a fixed population of technological possibilities can also yield cost behavior consistent with the learning curves commonly observed in practice (Muth, 1986). If incumbents hold little advantage over potential entrants in searching for improved manufacturing processes, production experience may carry negligible value even though industry costs are observed to decline with cumulative output. Stochastic models of industry evolution in this spirit include Nelson and Winter (1982), Lippman and Rumelt (1982) and Jovanovic (1982). In many industries, outsiders have been the source of dramatic technical breakthroughs that have nullified the accumulated learning of existing producers.

This paper assesses the importance of the learning curve as a barrier to entry and as a determinant of the success or failure of firms. The analysis is based on observed rates of entry and exit in 39 chemical product industries over roughly two decades. The sample is limited to homogenous products, where production costs are the primary measure of an entrant's success or failure. As documented in Lieberman (1984, 1987c), the learning curve has been a significant factor at the industry level in this chemical products sample.

The paper also assesses the importance of technology licensing as a factor affecting entry and exit. Process technologies developed through learning or R&D activity may diffuse to new entrants through licensing arrangements. When licenses are not available, entrants must develop their own technology in-house; this might be expected to reduce the rate of entry or the survival rate of firms that do enter. These hypotheses, and factors affecting license availability, are examined using data on process technology sources.

The remainder of this paper is in five sections. Following a brief description of the chemical products sample, the discussion focuses first on entry, and then on exit. The connection between the learning curve and entry is examined using a logit model. This model expresses the probability of entry as a function of a series of explanatory variables. Included among these variables are two alternative measures of entrant's expected cost disadvantage, assuming a proprietary learning curve. The next section documents the specific sources of process technology used by entrants, focusing on the frequency of technology licensing versus internal development. The technology source and learning curve measures are then tested in a hazard function model of entrant mortality. A final section concludes with a summary of findings and a discussion of strategic management implications.

[2] In these models with proprietary learning, competition is intense early in the evolution of the market, as firms price aggressively to gain greater cumulative experience. Margins increase over time, so that firms earn high profits as the industry matures. This resembles the logic of the BCG planning framework.

DATA SAMPLE

The data sample covers the 39 chemical products listed in Table 1.[3] There are approximately 20 years of coverage for each product. For most products coverage begins in the late 1950s or early 1960s; coverage ends uniformly in 1982.[4] The data are for plants built and operated in the United States.

The sample products share a number of common characteristics. All are homogeneous, undifferentiated chemicals, synthetic fibers, or metals.[5] They are essentially commodity products—speciality chemicals are excluded, given lack of public data. Profitability and competitive success are primarily determined by manufacturing costs; consumer brand loyalty, advertising, and other marketing-based factors are unimportant in these producer goods industries.

All products in the sample demonstrated positive net growth in industry output from the earliest years of coverage through the mid-1970s. Thus, the sample represents products with growing demand, although some products declined after 1975. Growth attracted considerable entry; entry occurred for all but five of the sample products. There are a total of 258 entrants in the sample.

Entrants often failed to survive, but their mortality rates were not substantially different from those of incumbent firms in existence at the start of sample coverage. On average, 66 percent of entrants survived through the end of the sample period, compared with 60 percent of the incumbent firms.

While entry occurred for nearly all products, incumbent producer concentration varied greatly. Table 1 shows that the number of producers ranged from one to more than 60.

Vertical integration is common in the chemical industry, and many entrants in the sample were pursuing policies of forward or backward integration. Despite the presence of integration, all products in the sample had well-defined output markets, with at least 25 percent of industry output sold through arms-length channels.

Reports published in the trade press often indicated the primary source of process technology used by entrants.[6] As shown in Table 1, such information was obtained for 114 of the entrants in the sample. The incompleteness of coverage results from gaps in the author's files, and the fact that the source of technology was not always announced. Excluded are all products with more than 20 producers, and nearly all firms that entered after 1973.

The rate of process improvement was gradual for most products in the sample. However, for several products there were important discontinuities in process technology.[7] These breakthrough processes were often introduced by outside sources (e.g. European producers, engineering contractors, or new entrant firms) and were often followed by significant entry and exit. In a few cases it is clear that such technological shocks eliminated all experience-based advantages held by incumbents. For example, the development and licensing of a new, low-cost refinery-based process for cyclohexane induced the pioneering producer (DuPont) to exit.

ANALYSIS OF ENTRY

Logit model

A logit model was used to test the significance of the learning curve as an entry barrier. This logit model is an elaboration of the basic entry model developed in Lieberman (1987a). The logit model estimates the probability of new entry during each observation year as a linear function

[3] The dataset is described in greater detail in Lieberman (1987a). Data on production capacity at the plant level are primarily from annual issues of the *Directory of Chemical Producers*, published by SRI International. Industry-level output data are from U.S. International Trade Commission and Census Bureau publications. Additional data on the fixed investment cost of new plants in the 1970s (FIXED) are from the chemical engineering literature.

[4] Entry is recorded through 1978 only, given that 5 years of post-entry data are required for the logit and survival analysis.

[5] A few products in the sample, such as the synthetic fibers and polyethylene, are slightly differentiated across producers.

[6] Robert Stobaugh kindly provided his data on technology licenses, which supplemented the trade press reports for six products in the sample.

[7] Specific examples include the adoption of centrifugal compressor technology in ammonia and methanol manufacture, development of processes to exploit low-cost feedstocks for phthalic anhydride, maleic anhydride and vinyl acetate, and a breakthrough in catalyst technology for acrylonitrile.

Table 1. Products included in data sample

Product name	Coverage period	Number of firms at start of coverage period	Number of entrants during coverage period*	Fraction of entrants surviving through 1983	Number of entrants for which technology information available
Organic chemicals					
Acrylonitrile	1956–82	4	2	1.00	2
Aniline	1961–82	5	3	1.00	2
Bisphenol A	1959–82	3	2	1.00	1
Caprolactam	1962–82	2	3	0.67	3
Carbon disulfide	1963–82	5	0	—	0
Cyclohexane	1956–82	2	14	0.50	12
Ethanolamines	1955–82	3	2	0.50	0
Ethylene	1960–82	20	10	0.90	0
Ethylene glycol	1960–82	9	6	0.83	4
Formaldehyde	1962–82	15	5	0.80	1
Isopropyl alcohol	1964–82	3	1	1.00	0
Maleic anhydride	1958–82	3	7	0.57	1
Methanol	1957–82	8	6	0.67	6
Methyl methacrylate	1966–82	4	0	—	0
Neoprene rubber	1960–82	1	1	1.00	1
Pentaerythritol	1952–82	5	4	0.50	1
Phenol	1959–82	8	7	0.86	6
Phthalic anhydride	1955–82	8	9	0.22	8
Polyethylene-LD	1957–82	9	7	0.71	6
Polyethylene-HD	1957–82	2	13	0.85	13
Sorbitol	1955–82	2	2	0.50	2
Styrene	1958–82	7	7	0.86	4
1,1,1-Trichloroethane	1966–82	3	1	1.00	1
Urea	1960–82	12	29	0.83	0
Vinyl acetate	1960–82	4	5	0.20	3
Vinyl chloride	1962–82	12	6	0.67	4
Inorganic chemicals					
Ammonia	1960–82	40	32	0.56	0
Carbon black	1964–82	9	0	—	0
Chlorine	1961–82	34	15	0.67	0
Hydrofluoric acid	1962–82	10	0	—	0
Phosphoric sulfide	1965–82	4	0	—	0
Sodium	1957–82	3	0	—	0
Sodium chlorate	1956–82	3	8	0.63	3
Sodium hydrosulfite	1964–82	6	1	1.00	1
Titanium dioxide	1964–82	5	1	1.00	1
Synthetic fibers					
Acrylic fibers	1953–82	3	3	1.00	3
Nylon fibers	1960–82	5	19	0.47	7
Polyester fibers	1954–82	1	18	0.44	14
Metals					
Aluminum	1956–82	4	8	1.00	0
Magnesium	1954–82	2	4	0.25	4

* Includes entrants through 1978 only, as computation of CDR requires 5 years of data subsequent to entry.

of a series of explanatory variables.[8] Explanatory variables considered in Lieberman (1987a) include measures of industry growth, capacity utilization, and the 'lumpiness' of new plant investment. The present study adds two proxies for the anticipated cost disadvantage of entrants, under the assumption that learning by incumbents could be kept proprietary.[9]

In the logit analysis the data are arranged so that there is one observation for each product and year in the sample. The dependent variable is binary, equal to one if entry into the product occurred during the observation year and zero if entry did not occur.

Explanatory variables

The explanatory variables are defined as follows:

$GROW_{i,t}$, the average annual growth rate of industry output for product i over a 5-year period, starting 1 year prior to the observation year t and extending through year $t+4$.[10]

$CU_{i,t-2}$, industry capacity utilization for product i, recorded 2 years prior to the observation year. The 2-year lag reflects the period typically required for construction of a new chemical plant.

$NPLTS_{i,t}$, the total number of plants producing product i at the start of the observation year. NPLTS serves as a control for differences in new plant 'lumpiness' and the rate of replacement investment. With a larger number of plants in an industry, individual plants account for a smaller fraction of total output. Plants must therefore be built more frequently as output grows over time. The frequency of replacement investment is also roughly proportional to NPLTS. Most replacement investment is by incumbents, but entrants may displace incumbents, e.g. when incumbents choose to exit rather than replace their plant.[11]

$FIXED_i$, total fixed investment cost of a typical plant to produce product i, built in the mid-1970s, in millions of dollars.

$TIME_t$, a time trend, measured as the last two digits of the observation year. This time trend should prove negative if entry followed a diffusion process, with the queue of potential entrants becoming depleted over time.

Consistent with most prior studies, learning is assumed to be a function of cumulative output. Lieberman (1984) shows that, for products in the data sample, price (and by implication cost) reductions at the industry level were strongly correlated with growth in industry cumulative output. Thus, cumulative output serves as a reasonable proxy for learning at the industry level. Much of the strategic planning literature assumes that cumulative output also serves as a good proxy for relative cost and learning at the firm level. This holds true if learning is an incremental process, firms learn at similar rates, and the accumulated knowledge is kept proprietary.[12]

The measures of learning-based advantage evaluated here incorporate these assumptions about firm-level learning. The learning curve entry barrier hypothesis was tested using two measures of the expected cost differential between entrants and incumbents, given the observed 'head-start' of incumbents in cumulative production. When included in the logit equations a significant negative coefficient for either or both of these measures suggests the existence of learning curve-based barriers to entry.

The first measure is $CDR1_{i,t}$, the expected unit cost of the entrant, relative to the cost of the

[8] The logit model relates the probability of entry to a series of explanatory variables through the functional form:

$$P_{i,t} = \frac{e^{\beta X_{i,t}}}{1+e^{\beta X_{i,t}}}$$

where $p_{i,t}$ is the probability of entry into product i during year t, $X_{i,t}$ is the vector of explanatory variables, and β is the vector of logit coefficients. Lieberman (1987a) gives a motivation for this model in the context of entry.

[9] In Lieberman (1987a), entrants and incumbents are assumed to have identical costs: entry and incumbent new plant investment are equivalent except for the fact that entry increases the number of producers. With a proprietary learning curve, asymmetries arise between entrants and incumbents which favor expansion by the latter, thus constituting a barrier to entry.

[10] This computation assumes that entrants were capable of forecasting market growth beyond the entry year. The time period from $t - 1$ through $t + 4$ overlaps the period used for the CDR measures, so that the logit tests distinguish potential cost disadvantages from the effects of market growth. Similar results were obtained using historical market growth, as in Lieberman (1987a).

[11] The logit results are quite similar when the reciprocal of NPLTS is used to control for lumpiness and NPLTS for replacement investment, as in Lieberman (1987a).

[12] See Bohn (1988) and Dutton and Thomas (1984) for evidence that the process is more irregular when viewed at the disaggregate firm or plant level.

most experienced incumbent, 5 years after entry. Computation of CDR1 assumes that the entrant attains an average market share immediately following entry and maintains this share over time. With proprietary learning and a conventional 'log-linear' learning curve, each producer *j*'s marginal unit cost at any time *t* can be represented as

$$C(X_{i,j,t}) = c_0(X_{i,j,t})^{-b} \tag{1}$$

where $X_{i,j,t}$ is the cumulative output of the firm through the start of year t,[13] b is the 'elasticity' of the learning curve, and c_0 is a constant, corresponding to the cost of the first unit. With proprietary learning, an entrant's initial cost is always extremely high; we therefore allow the entrant a 5-year start-up period.[14] Let x_{t+5} represent the expected cumulative output of the entrant over the first 5 years of production; and let $\tilde{X}_{t+5}$ represent the expected cumulative output of the most experienced producer measured through the start of year $t+5$. CDR1 can then be expressed as

$$\mathrm{CDR1}_{i,t} = \left[\frac{x_{t+5}}{\tilde{X}_{t+5}}\right]^{-b} \tag{2}$$

To compute this expression, values for x_{t+5}, $\tilde{X}_{t+5}$ and b are required. The mean learning elasticity of 0.36 reported in Lieberman (1984) was used for b. The actual cumulative output of the 'most experienced' firm, observed 5 years after the observation year, was used for $\tilde{X}_{t+5}$.[15] The cumulative output anticipated by a potential new entrant, x_{t+5}, was estimated as follows. Immediately after entry, the entrant was assumed to gain an average market share of $1/(n+1)$, where n represents the number of producers prior to entry. Cumulative output was then computed by assigning to the entrant this share of actual industry output over the period from year t through year $t+4$.[16]

The second cost ratio, $\mathrm{CDR2}_{i,t}$, compares the entrant with an 'average' incumbent firm. CDR2 was computed from the formula in (2) with the denominator redefined as follows. The cumulative output of an 'average' incumbent, at the start of observation year *t*, was calculated by taking total industry cumulative output at the start of year *t* and dividing by the number of producers. This base level of cumulative output was added to x_{t+5} to give the cumulative output of an average incumbent at the start of year $t+5$. In this computation the entrant differs from an average incumbent in that the entrant begins production in year *t* with a zero base level of cumulative output.

CDR1 and CDR2 are both designed to predict an entrant's relative costs under the assumption that learning is completely proprietary. While this assumption is extreme, the CDR measures should capture relative cost differences even if there was some diffusion of learning.[17]

Table 2 gives summary statistics and a correlation matrix for the explanatory variables. Across the sample, market growth averaged 6.7 percent per year, and capacity utilization averaged 82 percent. The number of plants ranged from one to 98, and the capital investment cost of a new plant ranged from one million to 60 million dollars. The cost disadvantage ratios, CDR1 and CDR2, ranged from slightly above unity to 4.1 and 2.7 respectively.

Logit estimation results

Table 3 reports results of the logit analysis of entry. Equations 1, 2 and 3 are based on the full data sample. Equations 4 and 5 are limited to concentrated product markets with five or fewer producers at the start of the observation year. If

[13] Firm-level cumulative output was computed as follows. An estimate of industry cumulative output prior to the initial year of sample coverage was made using historical output data, plus extrapolation where necessary. This cumulative output was allocated among incumbent producers in the initial year of sample coverage in proportion to their capacity shares in that year. Cumulative output was then updated annually by allocating total industry output to firms in proportion to their observed capacity shares.

[14] While this 5-year period is arbitrary, the resulting CDR values are highly correlated with those obtained using longer or shorter start-up periods.

[15] The 'most experienced' firm is the producer with the largest cumulative output at the start of year $t + 5$.

[16] This procedure assumes that entrants were able to anticipate industry output and expected to capture an average market share. The assumption of an average market share simplifies the calculation but is overly optimistic for most entrants. However, alternative share assumptions give similar values. The CDR measures were also computed based on an extrapolation of historical (rather than actual) market growth, with similar results.

[17] Diffusion drives the cost ratios closer to unity, but if diffusion rates were similar across products, the cost penalties would have remained roughly proportional to CDR1 and CDR2.

Table 2. Summary statistics of variables used in the logit analysis of entry

	Variable	Mean	Minimum	Maximum
1.	$ENTRY_{i,t}$	0.229	0	1.00
2.	$TIME_t$	69.2	54.0	78.0
3.	$GROW_{i,t}$	0.069	−0.123	0.489
4.	$CU_{i,t-2}$	0.821	0.268	1.18
5.	$NPLTS_{i,t}$	15.7	1.00	98.0
6.	$FIXED_i$	13.4	1.00	60.0
7.	$CDR1_{i,t}$	2.24	1.33	4.08
8.	$CDR2_{i,t}$	1.55	1.06	2.71

Correlation matrix

	1	2	3	4	5	6	7	8
1	1.00							
2	−0.15	1.00						
3	0.24	−0.53	1.00					
4	0.10	0.13	−0.17	1.00				
5	0.27	0.15	−0.08	0.14	1.00			
6	0.06	−0.05	0.06	0.14	0.05	1.00		
7	0.03	0.29	−0.51	0.05	0.50	0.11	1.00	
8	−0.24	0.33	−0.67	−0.04	−0.15	0.02	0.53	1.00

process technology diffuses more slowly when there are only a few competitors, the learning curve may limit entry in concentrated markets but not in markets with many producers.

The coefficient values in Table 3 represent partial derivatives of the probability of entry during a typical observation year. These derivatives were computed at the sample mean, where the probability of entry was 23 percent.[18]

The coefficients for GROW, CU, NPLTS and TIME all appear consistent with the predictions of the entry model in Lieberman (1987a). Entry was stimulated by high capacity utilization and rapid market growth.[19] Entry was more frequent for products with a large number of plants, reflecting opportunities for replacement investment and less 'lumpiness' of plant relative to industry output. The negative time trend suggests that entry followed a diffusion process, where the queue of potential entrants diminished over time as entry occurred. FIXED appears uniformly insignificant in Table 3, indicating that investment capital requirements were not a major entry barrier.

The CDR1 and CDR2 coefficients give no evidence that entry was retarded when incumbent firms held a large cumulative output advantage. The CDR1 and CDR2 coefficients are insignificant in all of the entry equations. Indeed, considerable entry occurred for many products in the sample despite large relative cost penalties implied by the CDR measures.[20]

[18] Table 2 reports the mean values of the variables.

[19] The coefficients can be interpreted as follows. The CU coefficient of 0.447 in equation 1 indicates that an increase of 0.1 in the rate of capacity utilization (e.g. from 80 to 90 percent) raised the probability of entry during the year by about 4.5 percent. Similarly, an increase of 0.1 in the growth rate (e.g., from 10 to 20 percent per year) raised the probability of entry by about 15 percent.

[20] In addition to the CDR ratios, I tested several patent count measures in the logit entry equations. (Lieberman (1987c) describes the data on manufacturing process patents, obtained for 23 products in the sample.) Conceivably, patents by incumbent U.S. producers might retard entry, while patents by foreign firms and U.S. non-producers might facilitate entry. In the entry equations, I tested (1) the number of patent applications by each group during the 5-year period prior to each observation year, and (2) cumulative historical counts of patents. None of these measures proved statistically significant. Thus, there appears to have been no general relationship between patent activity and rates of entry.

Table 3. Logit analysis of entry[a]

Sample:	1 All observations	2 All observations	3 All observations	4 Five or fewer producers[b]	5 Five or fewer producers[b]
constant	−0.284 (−1.0)	−0.405 (−1.3)	−0.017 (−0.0)	0.519 (1.4)	0.373 (1.0)
$TIME_t$	−0.0079* (−2.1)	−0.0080* (−2.1)	−0.0078* (−2.0)	−0.0156** (−3.3)	−0.0160** (−3.4)
$GROW_{i,t}$	1.49** (5.4)	1.63** (5.1)	1.18** (3.3)	0.410 (1.1)	0.583 (1.5)
$CU_{i,t-2}$	0.447** (3.2)	0.468** (3.3)	0.414** (2.9)	0.510** (2.9)	0.565** (3.3)
$NPLTS_{i,t}$	0.0066** (7.0)	0.0060** (5.2)	0.0063** (6.6)	0.0088 (0.7)	0.0075 (0.6)
$FIXED_i$	0.0003 (0.2)	0.0000 (0.0)	0.0005 (0.4)	0.0003 (0.1)	0.0000 (0.0)
$CDR1_{i,t}$		0.050 (0.9)		−0.094 (−1.2)	
$CDR2_{i,t}$			−0.149 (−1.3)		−0.042 (−0.4)
Log likelihood	−317.96	−317.55	−317.04	−90.99	−91.68
Mean of dependent variable	0.229	0.229	0.229	0.146	0.146
No. of observations	695	695	695	267	267

[a] Dependent variable equals 1 if one or more firms entered product i during year t; dependent variable equals zero if entry did not occur. Numbers in parentheses are asymptotic t-statistics.
[b] Sample limited to observations with five or fewer producers at the start of the observation year.
* Significant at the 0.05 level, one-tailed test.
** Significant at the 0.01 level, one-tailed test.

The insignificance of the CDR measures and the frequent observations of late entry are consistent with a number of possible explanations, including the following: (1) there was sufficient diffusion of technology that late entrants did not suffer major cost disadvantages; (2) incumbents had lower costs but chose to set a high price and allow entry; (3) the industry learning process was analogous to a succession of 'random draws' from a population of potential process technologies, with entrants sampling on roughly equal terms with incumbents. Unfortunately, without data on firm-level costs it is impossible to distinguish among these explanations empirically.

Market growth and entry

The logit results in Table 3 suggest that market growth served as the primary long run stimulus for entry. Figure 1 plots entry for each product as a function of output growth over the sample period. The vertical axis gives the increase in producers, measured as the initial number of incumbents plus the total number of entrants, divided by the number of incumbents (i.e. the sum of columns 3 and 4 in Table 1, divided by column 3).[21] The horizontal axis gives the growth in total output, measured as the ratio of output in 1982 to that observed at the start of sample coverage. Both axes are in logarithms.

Figure 1 shows that output growth and entry were highly correlated (r=0.69). A linear regression trend line is included in the figure. Products below this line experienced less than average entry, given the magnitude of market growth. Of the five products that experienced no entry, four had negative or negligible output growth over the sample period. Only in the case of methyl methacrylate was there a lack of entry for a product with significant growth.[22] Several other products—e.g. acrylic fibers, acrylonitrile,

[21] The numerator represents the number of producers that would have been in existence at the end of the sample period if mortality rates were zero.
[22] Entry into methyl methacrylate did occur shortly before the start of sample coverage.

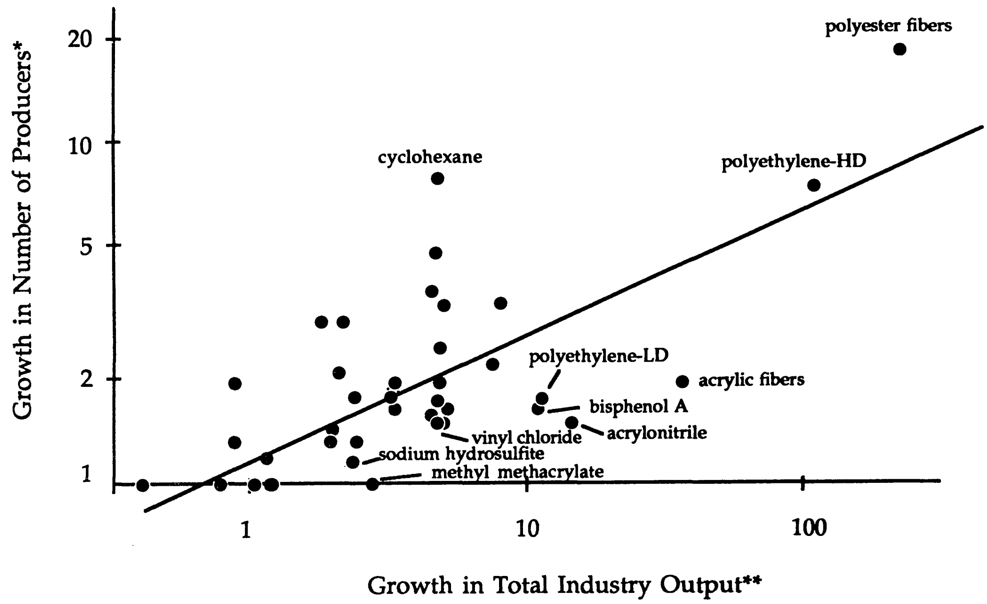

Figure 1. Plot of entry vs market growth. * Ratio of: (a) initial number of producers plus number of entrants, to (b) initial number of producers. ** Ratio of; (a) industry output in 1982, to (b) industry output at start of sample coverage

bisphenol A and low-density polyethelyne—experienced less entry than might be expected given the rate of market growth. These products are examined further in the following section, which considers the availability of process technology licenses.

SOURCES OF TECHNOLOGY USED BY ENTRANTS

One explanation for the absence of a link between the learning curve measures and entry is that there was substantial diffusion of process technology from incumbents to potential entrants. Such diffusion could occur through various channels. These include inter-firm mobility of personnel, networks of informal communication among engineers, technology licensed from domestic or foreign producers, and know-how purchased from capital goods suppliers and contractors.

Stobaugh (1984, 1988) documented channels of technology diffusion for nine petrochemical products. He defined three stages of the 'product life cycle' and examined the relative importance of various diffusion mechanisms within each of these stages. Stobaugh found licensing to be an important technology transfer mechanism that increased in importance over time: 27 per cent of plants were built using licensed technology in stage 1, increasing to 73 percent by stage 3. Foreign licensing was more common than domestic licensing. His results suggest that once several firms have developed commercial processes, each firm has an incentive to grant licenses before rivals do the same. This incentive is particularly strong in the case of foreign licenses, since the new entrants will not compete directly in the home market of the licensing firm.

Table 4 documents the major sources of process technology used by the 114 entrants in the present study for which technology source data were obtained. The table distinguishes six channels for technology acquisition. Technology could be licensed or purchased from: (a) a U.S. producer of the product in question, (b) a U.S. firm that was not a producer (e.g. a chemical plant contractor), or (c) a foreign firm (either producer or non-producer). Foreign producers could also enter directly into the U.S. market, either alone or in partnership with a domestic firm. Finally,

Table 4. Sources of process technology used by new entrants*[a]

Primary source of technology used by entrant	All observations	Products with five or fewer producers prior to entry date	Products with largest negative residuals in Figure 1[b]	Synthetic fibers	Major chemical companies[c]	Petroleum companies[d]	Exiting firms[e]
Developed internally by entrant (new process or significant variation on existing process)	34%	51%	65%	29%	31%	27%	39%
Licensed from existing U.S. producer	21	12	29	17	19	31	16
Licensed from U.S. non-producer	16	10	—	4	3	27	16
Licensed from foreign firm	18	15	6	13	31	8	18
Entrant was foreign producer	3	2	—	8	—	—	—
Entrant was joint venture between foreign producer and U.S. firm	10	10	—	29	16	8	11
	100%*	100%	100%	100%	100%	100%	100%
Number of entry observations in subsample:	114	41	17	24	32	26	44

[a] Based on sample of entrants indicated in Table 1.
[b] Acrylic fibers, acrylonitrile, bisphenol A, low-density polyethylene, sodium hydrosulfite and vinyl chloride.
[c] Entrant was in SIC category 2801.
[d] Entrant was in SIC category 2912 or 2913.
[e] Entrants that subsequently exited.
* Columns may not sum to 100 percent due to rounding.

a U.S. firm without prior production experience for the product could enter by developing its own manufacturing process.[23]

The first column of Table 4 covers the full 114 entrant sample. About one-third of these firms developed their own technology. Licensing was also prevalent: 21 percent of the entrants obtained technology licenses from domestic producers, 18 percent obtained licenses from foreign firms (primarily producers), and 16 percent licensed or purchased technology from U.S. non-producers. Foreign producers accounted for 13 percent of the entrants, typically in the form of a joint-venture arrangement with a U.S. firm.

Entrants were more likely to develop their own technology when the existing number of producers was small. The second column of the table reveals that the majority of entrants into concentrated markets (having five or fewer U.S. producers) developed their own technology. By comparison, in markets with more than five producers, only 24 percent of entrants developed their own technology. Licenses, when obtainable in concentrated markets, rarely came from domestic producers. These observations imply that direct access to incumbent technology was more difficult when the number of existing producers was small.

The next column of Table 4 gives the distribution of technology sources used by entrants into products with a smaller than expected amount of entry, as indicated by large negative deviation from the trend line in Figure 1. About two-thirds of these entrants developed their own technology, as compared with one-third of the entrants in the sample overall. Thus, entry appears to have been diminished when technology licenses were difficult or impossible to obtain.

The next three columns give the distribution of technology sources for other sub-samples of entrants. Column 3 reports the distribution for entrants into the three synthetic fiber industries. Here, joint ventures were prevalent, but otherwise the breakdown resembles that shown for the overall sample. Columns 4 and 5 distinguish two specific categories of entrants: major chemical companies (SIC 2801) and oil companies (SIC 2912 and 2913). The distribution of technology sources used by the major chemical companies is similar to that shown for the sample as a whole. However, the oil companies appear to have relied disproportionately on licensing from other domestic U.S. firms.

Thus, the patterns in Table 4 corroborate and extend Stobaugh's findings. Licensing was a common mechanism for technology diffusion and was more prevalent for products having a large number of producers. When licensing was restricted the rate of entry was reduced (but typically not to zero). For most products, technology was available from a range of sources. The next section examines whether these technology sources differed in terms of risk—for example, one might expect internal development of a new production process to be riskier than licensing, but to carry a higher potential return if successful.

ANALYSIS OF ENTRANT SURVIVAL

Technology, risk, and survival

The absence of a significant link between the CDR measures and entry rates does not necessarily imply that entrants enjoyed cost parity with incumbents. If incumbents maintained a price umbrella, then the rate of entry might be high despite cost disadvantages suffered by entrants. And under certain conditions, incumbent cost advantages would be reflected in low survival rates of entrants, rather than in low rates of entry *per se*.

Consider the decision of a potential entrant, who elects to enter if anticipated profit exceeds zero. Anticipated profit depends on the firm's expectations regarding the future market price and the firm's own production cost, neither of which can be predicted perfectly in advance.[24] Entry normally involves payment of some fixed, non-recoverable entry cost; for example, the sunk cost of a manufacturing plant. Lippman and Rumelt (1982) have proposed an equilibrium model of entry and exit under such conditions.

[23] Presumably, some entry also occurred using standard production processes that were common industry knowledge and therefore not licensed or significantly modified by the entrant. Such entrants are omitted from Table 4, since technology information was not important enough to warrant announcement in the trade press. Multiple sources of technology were identified for ten entrants in Table 4; I selected what appeared to be the most important source.

[24] We ignore the entrant's uncertainty about incumbents' production costs; for a theoretical treatment of this issue, see Milgrom and Roberts (1982).

This section elaborates their basic approach to develop some simple propositions regarding the probability of exit.

Assume that the entrant's unit variable cost, C', is determined by a random draw from some probability distribution at the time of entry. Cost need not be static; for example, it may follow a proprietary learning curve as indicated by equation (1), where the firm draws an initial unit cost, c_0, and the cost of subsequent units declines at rate b. If learning occurs, C' represents the average discounted present value of the entrants' unit variable cost. Assume that the entrant remains in the market if C' proves to be less than the market price, P', and exits otherwise. Note that an entrant survives but earns negative profits if its margins are positive but insufficient to cover the fixed cost of entry.

Under these assumptions the probability of exit increases with the variance of the cost distribution from which the entrant draws. Consider the two alternative cost distributions shown as f_1 and f_2 in Figure 2, where f_2 has the larger variance. (For example, f_1 might correspond to the expected distribution of cost outcomes if the firm licenses a known technology, whereas f_2 might be the distribution if the firm pursues a riskier strategy of developing its own technology.) To enter, the firm must draw from one of the two distributions; the firm survives if the cost realization, C', falls to the left of P', and exits otherwise. If the firm is indifferent between the two distributions, then f_2 must have higher expected cost and higher probability of exit; this is counterbalanced by the fact that f_2 has a higher probability of achieving extremely low cost.

One empirically testable hypothesis is that alternative technology sources differ in risk in the manner described by f_1 and f_2. For example, internal development of technology may be riskier than licensing, with a higher variance of cost outcomes. If firms are indifferent between the two sources (as suggested by the fact that licensing and internal development are both observed for many products in the sample) then a higher rate of exit should be evidenced by firms that selected the internal development approach.

A second factor that should affect the probability of exit is the fixed cost of entry. Lippman and Rumelt (1982) show that, in equilibrium, an increase in fixed entry cost makes firms more conservative in their entry decisions, thereby increasing the rate of survival. In the context of

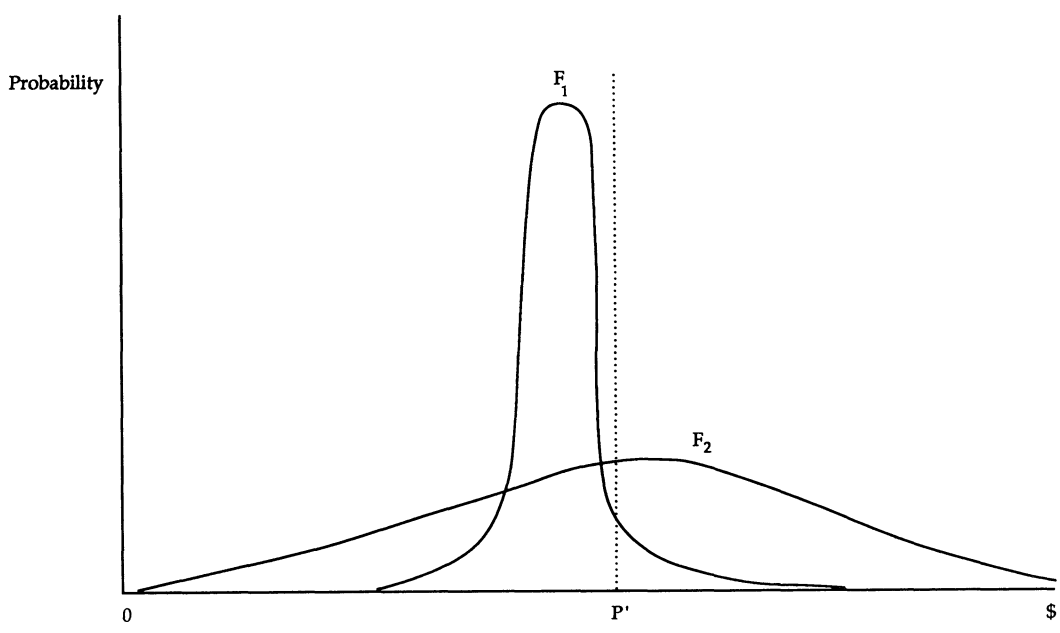

Figure 2. Probability distribution of entrant's cost under alternative risk assumptions

the chemical industry sample this implies a positive relation between survival and the initial fixed investment cost of plant.

A third set of factors affecting the likelihood of exit relates to expectations about P', the post-entry price, which is uncertain at the time of entry.[25] The probability of exit increases with the variance of P' as anticipated by the entrant.[26] Price expectations are impossible to measure directly; however, one reasonable hypothesis is that the variance of P' increases with the cost advantage held by the leading incumbent firm. With proprietary learning, entry will occur only when the incumbent maintains some price umbrella above its own cost; this umbrella may fall if a larger than anticipated fringe of entrants is attracted. The maximum extent of price-cutting (and hence variance of the price distribution) increases with the cost differential between the incumbent and the entrant. Thus, a larger value of CDR1, reflecting a larger cost differential between the entrant and the leading incumbent, should be linked to a higher probability of exit.

Hazard function model

The survival hypotheses were tested using the Cox proportional hazards function model (Kalbfleisch and Prentice, 1980; Cox and Oakes, 1984) to evaluate the influence of the CDR and technology-type variables on the mortality of entrants. This model is commonly used in medical research to examine the effects of environmental and treatment factors on patient mortality. The Cox technique assumes that hazard (death) rates can be modeled as log-linear functions of the covariates (explanatory variables).[27]

The full sample for the survival analysis includes the 258 firms that entered during the sample coverage period. Thirty-four percent of these entrants failed to survive through the end of the coverage period. Incumbent producers in existence at the start of sample coverage had similar mortality rates. On average, 40 percent of incumbents exited over the course of the coverage period.[28]

Mortality was defined as exit of the firm via plant closure or sale to an unrelated firm. Excluded from this definition are exits via corporate merger, where an entire firm (or a major subset of its operations) was transferred to an independent party.

The hazard function results, as reported in Tables 5a and 5b, relate the probability of entrant mortality to a series of covariate measures. These include FIXED, CDR1 and CDR2 as defined previously for the logit analysis. The propositions derived from Lippman and Rumelt model suggest that the probability of exit should be negatively related to FIXED, which proxies for the fixed cost of entry. Similarly, entrant mortality would be positively related to CDR1 if incumbent learning was at least partly proprietary, so that the scope for possible price-cutting increased with the cumulative output lead of the most experienced firm. Mortality would increase with CDR2 if pricing risk depended on the output lead held by other incumbent firms.

To capture possible differences in technology risk, dummy variables were defined for each of the six technology source categories shown in Table 4. Table 5b includes one of these dummies, OWNTECH, which was set equal to one for entrants that developed their own process technology. If internal development carried greater risk than licensing, then OWNTECH should be linked to a higher probability of failure (counterbalanced by a larger but unobserved mean return for those internal development efforts that proved successful).

Two additional covariate measures were defined for the hazard function analysis:

ORDER, the relative order of entry of the firm. ORDER provides a measure of late entry that is independent of the cumulative output data used for CDR1 and CDR2. It was computed by first arranging all of the incumbents and

[25] Figure 2 ignores this source of uncertainty.

[26] The reasoning is analogous to that given above in the case of uncertain cost.

[27] More specifically, the Cox model has the form: $h(t,z) = h_0(t)e^{\beta z}$, where z is the vector of covariates, β is the vector of unknown regression coefficients, and h_0 is the unknown hazard function for an individual with covariate vector $z = 0$. I also tested some alternative hazard function models that assume specific parametric forms for the disturbances. These models were computationally more difficult, but gave similar results.

[28] The exit proportions for entrants and incumbents are not directly comparable, as incumbents are observed over a longer average time period than entrants. Incumbents must be excluded from the survival analysis given the lack of data on their entry dates and other information needed to compute the covariate measures.

Table 5a. Analysis of entrant mortality[a]

Sample:	1 All observations	2 All observations	3 All observations	4 Five or fewer producers[b]	5 Five or fewer producers[b]
FIXED	−0.006	−0.005	−0.005	−0.017	−0.015
	(−0.7)	(−0.6)	(−0.6)	(−1.0)	(−1.0)
SCALE	−0.487*	−0.505*	−0.505*	−1.92*	−1.94*
	(−2.4)	(−2.5)	(−2.5)	(−2.5)	(−2.6)
CDR1	0.479*			0.534	
	(2.3)			(0.7)	
CDR2		0.512			0.719
		(0.8)			(0.8)
ORDER			−0.039		
			(−0.1)		
Log likelihood	−450.67	−452.75	−453.05	−75.90	−75.85
No. of observations	258	258	258	59	59
Fraction exiting	0.34	0.34	0.34	0.37	0.37

[a] Based on Cox proportional hazard function model. Numbers in parentheses are *t*-statistics.
[b] Sample limited to observations with five or fewer producers at the start of the observation year.
* Significant at the 0.05 level.

Table 5b. Analysis of entrant mortality[a] (Subsample of entrants with information on source of technology)

Sample:	6 All observations	7 All observations	8 Five or fewer producers[b]	9 Five or fewer producers[b]
FIXED	0.064	0.061	−0.003	0.000
	(0.5)	(0.5)	(−0.1)	(0.0)
SCALE	−0.83*	−0.97*	−1.54	−1.53
	(−2.3)	(−2.6)	(−1.5)	(−1.5)
CDR1	1.23**		0.95	
	(2.8)		(1.2)	
CDR2		0.573		1.14
		(0.8)		(1.1)
OWNTECH	0.43	0.23	0.16	0.14
	(1.3)	(0.72)	(0.24)	(0.22)
Log likelihood	−181.31	−184.91	−41.13	−41.18
No. of observations	114	114	41	41
Fraction exiting	0.39	0.39	0.32	0.32

[a] Based on Cox proportional hazard function model. Numbers in parentheses are *t*-statistics.
[b] Sample limited to observations with five or fewer producers at the start of the observation year.
* Significant at the 0.05 level.
** Significant at the 0.01 level.

entrants for each product in historical sequence of entry. ORDER was then computed by dividing the entrant's position in the queue by the total number of firms. ORDER ranges from slightly above zero to a maximum of 1.0, where the latter value is assumed by the last observed entrant.

SCALE, the relative scale of the entrant's plant. SCALE was computed by dividing (a) the capacity of the initial plant built by the entrant, by (b) the average capacity of all plants producing the product at the start of the year in which entry occurred.

There are several reasons why larger plant scale might contribute to a higher probability of survival. First, a larger plant provides greater static economies of scale, which are important for most chemical products in the sample. Second, larger scale of plant implies more rapid growth of cumulative output by the firm, and hence more rapid movement down the learning curve, to the extent that learning is firm-specific.[29] Third, scale of entry may reflect technology risk; firms may enter on an initially-small scale when the commercial feasibility of their process technology is uncertain. Finally, firms that built small plants typically made fixed investments of less than the full magnitude indicated by FIXED, and hence might be more prone to exit.

Hazard function results

Tables 5a and 5b report the hazard function estimates. Table 5a includes observations for the full sample of 258 entrants, and a subsample of 59 entrants into concentrated product markets with five or fewer producers at the time of entry. Table 5b is limited to entrants with data on source of technology. In both tables a positive coefficient indicates that a larger value of the covariate measure was associated with a higher rate of entrant mortality.

Both tables provide evidence that entrant mortality was greater when the most experienced firm held a substantial cumulative production advantage, as indicated by CDR1. CDR1 appears significant for the full sample of entrants. However, it is not significant when the sample is restricted to concentrated product markets having five or fewer firms. Neither CDR2 nor ORDER prove significant in any of the hazard function equations; thus, the entrant's position relative to all incumbents except the most experienced firm seems to have been irrelevant in affecting exit. Together, these results suggest that entrants were more likely to be 'shaken out' when the most experienced incumbent held a substantial production lead but had attracted a fairly large number of competing producers. This interpretation implies that some part of the incumbent's accumulated learning remained proprietary. Shakeout was not directly affected by concentration *per se*.[30]

The results also show that mortality was not directly influenced by FIXED, the dollar investment required to build a manufacturing plant of efficient scale. Mortality was, however, significantly linked to actual plant scale—entrants that built relatively larger-scale plants had lower rates of mortality, and vice-versa. This raises the question of why entrants frequently built plants of sub-optimal scale. One motive is suggested by the fact that SCALE and FIXED are negatively and significantly correlated—entrants into products with high fixed plant cost tended to build initially small-scale plants. This may reflect a desire to evaluate the process technology before commiting to investment in a larger-size plant. Thus higher FIXED investment cost made entrants more conservative, but in a different manner from that anticipated based on the Lippman and Rumelt framework.

Table 5b covers the subsample of entrants for which technology source information was available. The FIXED, SCALE, and CDR coefficients repeat their pattern from Table 5a. The OWNTECH coefficients appeared with a positive sign, indicating a higher failure rate for firms that developed their own technology, but the effect is not statistically significant. The other technology source dummies (not shown) also proved insignificant.[31] Moreover, a comparison of the first and last columns of Table 4 shows that the distribution of technology sources was

[29] The two CDR measures assume that the entrant captures an average market share; the extent to which this was actually the case is indicated by SCALE. Thus, the entrant's actual cumulative output, relative to incumbents, is reflected in both CDR and SCALE.

[30] To confirm that the significant CDR1 coefficient reflects cumulative production experience rather than market concentration or the size of the largest incumbent, I added several additional variables to the hazard function model. These included the Herfindahl index, the share of the largest incumbent, and the total number of incumbents at the time of entry. All three of these measures proved insignificant, and their inclusion had no effect on the significance of CDR1.

[31] I also tested dummies defined for major chemical companies and petroleum companies to determine whether these (large) firms might have lower mortality rates than other entrants in the sample product industries. No significant differences were detected. However, tests did show slightly lower mortality for firms that entered through either forward or backward integration. (Significant at 0.10 level.)

roughly the same for surviving and non-surviving firms. Thus, there is no evidence that internal technology development was a riskier entry strategy than licensing.[32]

CONCLUSIONS

The learning curve is a salient factor contributing to long-term cost and price reductions in many industries, including the sample of chemical products examined here. However, the results of this study suggest that the learning curve—based on cumulative output—had only a small impact on competition in these chemical product industries. In general, the empirical results give only weak support for some common assumptions made in the strategic planning literature.

Differences in the cumulative output lead of incumbent producers had little or no effect on rates of entry into the sample product industries. Technology appears to have diffused rapidly via licensing and other channels. This made entry feasible despite the fact that incumbents often held decades of prior manufacturing experience. Access to technology appears to have been more difficult in markets with few producers; this retarded entry but seldom reduced the entry rate to zero.

These findings are consistent with theoretical models of industry structure in environments where learning diffuses rapidly (e.g. Ghemawat and Spence, 1985; Lieberman, 1987b; Stokey, 1986). They are also consistent with models where learning occurs through processes of stochastic search (e.g. Muth, 1986; Nelson and Winter, 1982), assuming that entrants search on roughly equal terms with incumbents. Prior studies have shown cumulative output to be a good proxy for learning at the industry level; the findings here suggest that differences in cumulative output are a poor basis for making inter-firm cost comparisons. High rates of diffusion, variability in learning rates, and discontinuous technical change diminish the usefulness of the learning curve construct at the firm level.

The survival analysis provides stronger evidence that incumbents may have derived cost advantages from the learning curve. Entrant mortality was significantly greater in markets where the leading incumbent maintained a large cumulative output lead but had also attracted a sizeable number of competing firms. One explanation is that the dominant firm initially maintained a price umbrella, which was subsequently lowered when a larger than anticipated number of firms entered. Such 'shakeouts' appear to have been rare in concentrated product markets, where price stability is generally greater and the leading firm has less incentive to induce exit through price reductions. These results are broadly consistent with the previous findings of Shaw and Shaw (1984) and Porter (1984).

Such findings on competitive 'shakeout' can be rationalized in the context of the Lippman and Rumelt (1982) model, assuming that entrants perceived a link between incumbent cost advantage and post-entry pricing risk. However, two propositions derived from the Lippman and Rumelt model—that alternative technology sources differ in technical risk, and increases in fixed plant cost reduce the probability of exit—failed to be confirmed empirically.

Several important caveats are in order. The proprietary learning curve model evaluated here is the relation between cost and cumulative output popularized by the Boston Consulting Group in the 1970s, and now a standard topic in strategic management textbooks. The negative results do not imply that 'learning', more broadly or flexibly defined, failed to yield competitive advantages. The CDR measures used in the tests are relatively crude proxies based on a number of assumptions. The insignificant statistical results may reflect the failure of these assumptions rather than the absence of learning-based competitive advantages. Without disaggregate data on costs or profit rates, incumbent advantages must be inferred from observed rates of entry and exit.

The empirical results do show that numerous factors unrelated to the learning curve had major effects on entry and exit. Rapid market growth and high capacity utilization were strong inducements to entry. Entry was more frequent in markets where many plants were already in existence, so that an average new plant accounted for only a small proportion of total industry capacity. However, firms that entered with plants below efficient scale had a disproportionate rate

[32] One possibility is that the risk of internal technology development occurs entirely at the initial R&D stage, culminating in the construction of an (unobserved) pilot plant. Entrants that proceed further to construct a commercial plant represent a biased sample of technologically successful firms. Alternatively, entrants that developed their own technology may have been more technically capable than those who licensed, thus offsetting the difference in technical risk.

of failure. Entry seems to have followed a diffusion process, with entry rates falling over time as the 'queue' of likely entrants was depleted. Potential entrants appear to have had no difficulty raising sufficient capital to build manufacturing plant facilities. These observations are all consistent with the findings of prior empirical studies of entry.

The high diffusion rate of process technology implicitly documented here has important implications for competitive strategy. Rapid diffusion dulls the incentive to gain market share during the early growth phase of a market, as originally recommended by BCG and others. Indeed, if significant spillovers are anticipated, it can be desirable for firms to wait until late in the industry life-cycle before entering. Entrants should be sensitive to the availability of process licenses and to the timing of technological 'windows' that facilitate entry.

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