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FIRMS' MARKET BEHAVIOR UNDER IMPERFECT INFORMATION AND ECONOMIC NATURAL SELECTION

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The economic natural selection argument claims superior survival performance for profit-maximizing firms. This assertion is investigated in a factorial simulation study assuming imperfect information. Three alternative models of firms' behavior are tested with respect to their ability to adapt to the observed realizations of non-stationary demand processes. Findings show that, in such a scenario, it is the difference in implicit learning and adaption capabilities rather than that in motivation or goals which affects survivability. Consequently, differential bankruptcy and disengagement rates vary with the peculiarities of the market environment. The tested assertion cannot generally be confirmed.

1. Introduction

Early studies of Cyert and March (1963), Baumol and Quandt (1964), Day and Tinney (1968) showed that business performance depends critically not only on characteristics of the environment, but on the information about them that agents acquire and on the specific rules of adaptation employed in responding to that information. Using a similar experimental modeling approach it is investigated here how three specific decision-making algorithms perform with special emphasis on the survival of firms over time. A situation is examined in which firms enter a market initially unknown to them. In order to keep the investigations manageable, the history of only one such venture per firm is followed up. That means that aspects of product differentiation, innovation, R&D, are neglected. Instead an examination is made of the way firms try to adapt capacity, output, and prices, in accordance with different decision-making algorithms, to the observed realizations of a non-stationary stochastic demand process.

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The three algorithms are first, the O-model involving features of optimization in that demand is re-estimated in each period and an expected profit function is maximized; second, the S-model in which prices are chosen according to an adaptive target return criterion (satisficing) augmented by a mark down pricing rule in the face of excess supply; third, the C-model in which a simple learning strategy is used based on 'operant' conditioning. The first of these decision-making algorithms, though in its simple regression procedure set up for a different context, shares a feature with the model discussed by Kirman (1975). He showed that firms which had an imperfect knowledge of the environment could construct an incorrect picture of the world but one in which their behavior would appear to them to be optimal. The second model is a variant of adaptive goal adjustment behavior described by March and Simon (1958) and applied by Cyert and March (1963) in their model of department store decisions. The third is similar to the Day–Tinney model which was also based on behavioral economics principles. In the present model a specific recourse is made, however, to the operant conditioning theory of Skinner. The latter has recently been elaborated in an economics context by Alhadeff (1982).

The results bear on the 'natural selection' argument (NSA) [Alchian (1950), Friedman (1953)] which, briefly stated, asserts that only firms which maximize profits, or behave as if they do, will survive in the long run, because only they can prosper and acquire the resources with which to expand. In two seminal articles Sidney Winter (1964, 1975) established a number of reasons why the 'as if' premise of the NSA is valid only under extremely limited conditions, conditions violated in the real world. The present results support Winter's conclusion that the ruling place of optimization models 'at the foundations of the theory of the firm is undeserved' (1975, p. 99). It turns out that none of the algorithms dominate under all conditions and that, as in the earlier studies, performance hinges critically on the initial conditions and the exogenously given (random) shocks in the environment. In particular, the explicit optimizing does not dominate the alternative behavioral adjustment and learning strategies.

The discussion proceeds as follows. The specific market scenario assumed in the study is described in section 2 together with potential causes of deficient survival performance, given this scenario. Because of the complexity, the survival performance of the decision-making algorithms is investigated by conducting computer simulations. Section 3 presents the main features of the three models of decision-making behavior each of which is then tested in isolation under identical conditions and, as well, in confrontation with the others in several contests. The experimental design of the factorial Monte Carlo simulation study is summarized in section 4. The results, backed by an analysis of variance, are discussed in sections 5 and 6. The last section presents some tentative conclusions.

2. Potential causes of deficient survival performance and the simulated scenario

Since we are interested in the impact of imperfect information, searching, and learning on the firm's survivability, the following assumptions are introduced. The only way a firm can learn about its initially unknown true demand situation is by observing the realizations of its own sales and demand over time. Sales as well as demand are assumed to be subject to random disturbances and systematic shifts. More specifically, two alternative market scenarios are chosen.

The first is the monopoly-scenario. The firm enters (or establishes) a market and, for price $p(t)$ posted in period t, observes a quantity demanded $x(t)$ as given by

$$x(t)=u-vp(t)+\varepsilon(p(t)), \tag{1}$$

where u and v are positive constants and $\varepsilon(p(t))$ is a hypergeometrically distributed random term. The latter has expectation $\mathrm{E}(\varepsilon(p(t)))=0$ and variance δ_ε dependent on $p(t)$ in such a way that when price increases δ_ε decreases and vice versa (heteroskedasticity). Since, for convenience, only integer price variations are permitted (1) implies that the firm actually samples from a finite number of demand distributions which vary conditional on the chosen $p(t)$. As usual the range of $p(t)$ in (1) is bounded by an upper price p^- such that for any $p(t)>p^-$ the demand distribution degenerates to $x(t)=0$. Furthermore, a lower price p_- is given below which the demand distribution becomes invariant, i.e., $x=u-vp_-+\varepsilon(p_-)$ for $p(t)\leqq p_-$.

The second scenario is more complex and can best be explained by first having a look at what the consumers on the demand side of the market are assumed to do in the simulations. Consider a consumer entering and searching in the market in t. Imagine a reservation price r so that the consumer quits searching and buys one unit of the market good the first time he finds a price offer $p\leqq r$ or else leaves the market after having inspected all offers in t without a purchase. As long as there is only one offer – the monopoly scenario – it is easy to see what follows. If a randomly determined number of consumers, with r being randomly distributed in the range $p^-\geqq r\geqq p_-$ enter the market in t, the monopolist posting $p(t)$ will meet the demand of all the consumers whose reservation price is not less than $p(t)$ – hence the hypergeometrically distributed random term $\varepsilon(p(t))$, the variance of which varies with $p(t)$.

Now, in the second scenario, used in the contest version, imagine m firms entering a market at the same time with a homogenous product without knowledge of each other. Thus, there is no strategic interaction among the firms. It will be assumed that the total number of consumers in the market in t now is m times as large as in the case of monopoly. Nevertheless, even if consumers behave as sketched just now, the expected demand per firm under this assumption is the same as in the first scenario only if two additional conditions are satisfied: all firms must post the same price and none of the firms' quantities supplied in t may run short of demand. If this is not so demand spill-overs between the firms can be induced: Consumers who, because of a reservation price $r<p(t)$, would have left the monopoly market now go on searching among the other firms and perhaps succeed in finding an acceptable offer (firms with comparatively low price have a chance of gaining additional demand); consumers who find stores sold out go on searching among the other firms and may even accept a higher price than the sold-out firms were charging, provided $p \leqq r$ (firms not sold out can gain additional demand).

Thus, for each single firm j the demand function is

$$x_j(t)=u-vp_j(t)+\xi(p'(t),y'(t)). \tag{2}$$

Everything except the random term $\xi(\cdot)$ is unchanged. The latter now depends on the vector of supplies and prices posted in the market. According to the reasoning above, the expectation for the random term, $\mathrm{E}(\xi(p'(t),y'(t)\,|\,(p_j(t)=\pi)) \geqq \mathrm{E}(\varepsilon(p(t)=\pi))$ under otherwise unchanged conditions in the two scenarios. The variance of the random shifts, δ_ξ, now also depends on $p'(t)$ and $y'(t)$ and is in any case greater than δ_ε in the first scenario, the same price being posted.

Eq. (2) indicates that, in the second scenario, the price and supply policy chosen by one firm indirectly affects all other firms; yet, room for monopolistic price variation is retained. Thus, the market regime in the second scenario is a peculiar form of monopolistic competition caused by imperfectly informed, searching agents on both sides of the market.[1] In both scenarios it is assumed that the (stochastic) demand is not stationary but changes over time in a way which is subject to experimental variation according to the factorial design of the study, see section 4.

To what extent do differences in the firms' patterns of searching and learning under such conditions lead to a significantly differing survivability? Obviously, if there are differences, they must be caused by some kind of maladjustment or insufficient provisions against unfavorably cumulating

[1]The assumed consumer search behavior has an important implication under the monopolistic competition market regime. The expected number of contacts with a supplier which a consumer has is one if and only if all firms post a price $p(t) \leqq r$ and no shortage occurs. In all other cases the number is greater so that firms overestimate demand if they use the number of consumers dropping in as an estimate of potential demand. If, e.g., there is a substantial excess demand in the market in the beginning causing several consumers to visit several firms and if all firms with a time lag for realization expand capacity simultaneously on the basis of the excess demand they individually observed, it is very likely that they will run into excess capacity. For the details of simulating the intricate interactions between consumers and firms in the search market see Witt and Perske (1982, ch. 4).

random fluctuations. But, of course, if imperfect information prevails and if the environment is subject to non-stationary random disturbances the task to be solved by the firm is not only highly complex but also beset with ambiguity. A firm's venture in a more or less unknown, changing market can be explained, where risk-spreading motives do not apply, as a decision to search for an extra yield on capital exceeding the best known alternative yields. Because of the lack of information, the firm, whether trying to optimize or not, always has to convince itself to what extent its conjecture on yields (still) holds.

For the outcome of this permanent 'testing the market' there are three possibilities with respect to the firm's market persistence. The firm either goes bankrupt or it stops experimenting and transfers the remaining net wealth to some alternative use outside the market because it assesses further yield prospects in the market as non-promising ('exit'), or the firm stays in the market. In any case, the first of the possible events indicates inferior behavior. The evaluation of the other two outcomes of the firm's experimentation behavior is conditional on the unknown actual state of the market.

Two types of error must be avoided: exit when potential yields exceed the opportunity yield as well as *no* exit when the reverse is true. To be equally good at avoiding both errors seems difficult. Therefore, it is quite possible, per se, that wrong inferences will be drawn from the information obtained and that voluntary exit will occur even though the actual state of the market is favorable (as is assumed throughout the present study). Thus, erroneous exit comes in as an additional source of deficient survival performance and it is not the goal underlying the firm's decision-making algorithm that is decisive here, but the cognitive power associated with it which more or less allows the firm to discriminate against the two different types of error.

3. Three prototype models of firms' behavior

In order to investigate the relation between a firm's decision-making algorithm, profitability and survivability, three different models of firms' behavior have been tested in the numerical simulations. To avoid increasing complexity further, the internal conditions of production, costs and financial relations are in all three cases modeled identically in a simple deterministic fashion. (For the numerical specification of the parameters see the appendix.) Capacity $c(t)$ is assumed to be a linear lagged function of invested capital K, $c(t)=1/k \cdot K(t-1)$, $k>0$. Price $p(t)$ and current output $q(t)$ must be determined ex ante in each t with $q(t) \leqq c(t)$. But, since output can be stored with a fixed inventory unit cost h, effective supply $y(t)$ may exceed $q(t)$ by the inventory $I(t-1)$ taken over from the previous period. Sales $s(t)$ are determined as $s(t)=\min[y(t), x(t)]$. The total costs $C(t)$ of the firm are given by the function $C(t)=f \cdot c(t)+g \cdot q(t)+h \cdot I(t)$, where $f \cdot c(t)$ is the fixed costs component (assumed to include depreciation expenses), $g \cdot q(t)$ is the variable cost component, and $h \cdot I(t)$ are the inventory costs, the coefficients $f>0, g>0, h>0$.

A positive interest rate i is taken to be the best alternative yield on capital known to a firm. Accumulated profits and losses of a firm make up its liquid funds $L(t)$ on which i is paid. They are allowed to take negative values indicating net-liabilities on which i has to be paid. Investment is financed by a transfer from $L(t)$ to $K(t)$. On the latter yields must be earned by the market activity. Disinvestment appears as a transfer the other way round so that withdrawn capital is assumed to earn the interest rate i. If net-liabilities exceed a certain multiple of $K(t)$, the firm goes bankrupt. As a measure of a firm's success a profitability index for a given period t can be used. It is defined as

$$W(t)=(K(t)+L(t))/K(1), \tag{3}$$

i.e., expresses current wealth as a multiple of initial wealth. All numerical specifications are chosen such that, for a firm in any period t, one and only one price $p^*(t)$ exists for which expected profits reach a maximum. If $p^*(t)$ is posted and capacity is sufficiently adapted to $E(x(t) \mid p^*(t))$ expected profits are substantially greater than the opportunity yield.

The differences between the three models are with a set of rules, or routines in the sense of Winter (1975), compounded so as to adopt characteristic behavioral and motivational features of the notions of optimizing, satisficing, and operant behavior in the present context of searching and learning. These routines carry out price experimentation together with output and capacity adjustment. As well, a judgement of the present market state with respect to yields is generated and exit is initiated if the result does not agree with the motivational features assumed for the different models. The nature of these routines and their interactions, of course, determine what can be labeled the 'cognitive power' of the respective models. Note, that all models are realized with basically the same, realistic, prerequisites concerning computational capability in problem solving and availability of information. Thus, all of them imply some myopic form of information processing and storage, current data quickly falling into oblivion. The details of the models can be gathered from the complete FORTRAN program lists reprinted in Witt and Perske (1982, pp. 139–146, 120–128, 109–119 respectively).

The O-model. The first model involves explicit optimization with the consequence that, under stationary conditions, the price–quantity solution which maximizes expected profits for given t, is quickly approximated and is maintained with a very high frequency. Under non-stationary conditions this result is also achieved with a high frequency in the longer run, provided the firm survives.[2] The core routine is an elementary statistical optimization procedure to which the *pricing and quantity adjustment rules* are made subject: (i) take a fixed sequence of demand observations at two different prices, (ii) carry out a simple regression, i.e., estimate a linear expected demand curve, (iii) on this basis calculate Cournot's solution according to an elementary certainty equivalence optimization hypothesis and adjust $p(t)$, $q(t)$ and $c(t)$ to the estimated optimal values, (iv) up-date the estimates using subsequent observations and simultaneously apply a simple demand shift test.[3] If the test is positive, reinitiate sampling and estimating, otherwise adjust $p(t)$, $q(t)$ and $c(t)$ further if necessary. *Exit decision routine.* If average yield earned at the estimated optimal values is not greater than i, reduce capacity. That means, transfer $K(t)/2$ to the alternative use, i.e., to $L(t)$ (according to the logic underlying this model, an unfavorable state of the market has been indicated). Leave the market after capacity has been successively brought down to the lower bound $c(t)=1$.

The S-model. This is a satisficing model.[4] In contrast to the idea of searching for the expected profit maximizing solution, satisficing here means settling on a price p_α at which the current aspiration level with respect to yields $\alpha(t)$ is satisfied. Correspondingly, the *pricing rule* is (i) calculate price by a mark-up on total unit costs, (ii) determine mark-up so as to yield the current target return on capital, assuming sufficient capacity utilization, (iii) in the case of a strong reduction in demand apply a mark-down rule to counter excess supply with a one-period bargain. The *quantity adjustment rule* is set out so as to eliminate previously observed excess-demand for given $p(t)$. *Exit decision routine.* After quantities have been adjusted according to the previous rule control profitability. If the realized return $\rho(t)$ continually falls short of current target return $\alpha(t)$ and the loss frequency increases, transfer $K(t)/2$ to $L(t)$ and if these phenomena persist, go on doing so until exit at $c(t)=1$. *Aspiration level adaptation* is experience dependent according to a simple

[2]There is, of course, a more inclusive concept of solving, in an optimal way, a dual control problem, that is the problem of determining the optimal amount of experimentation simultaneously with approximating the optimal price–quantity combination so that expected profits are maximized over a finite time horizon, see, e.g., Chong and Cheng (1975). However, this concept has no basis here since it is assumed that relevant prior information is missing and, moreover, that the environment changes in an unknown way.

[3]This test uses the variance of demand, estimated in another sampling interval once the previously calculated optimal price p'^* has been realized. If the two-period moving average of observed demand deviates from the estimated mean demand given p'^* by more than a certain multiple of the estimated variance a systematic change in demand is inferred and the test decided positively.

[4]For a more detailed discussion on satisficing behavior and the psychological theory of aspiration levels cf. Simon (1967). The present S-model, though it is more abstract, in some features resembles the 'Retail department store model of pricing and output decisions' developed by Cyert and March (1963, pp. 128–148).

averaging procedure given by the function

$$\alpha(t)=\max\left[\left(\alpha(1)+\frac{1}{t-1}\sum_{\tau=1}^{t-1}\rho(\tau)\right)\Big/2, i\right].$$

Since the average realized return stabilizes quickly, $\alpha(t)$ and thus mark-up span and $p(t)$ become somewhat sticky with growing t under stationary conditions. Furthermore, due to the term $\alpha(1)$, i.e., the return aspired to when the market is entered, price trajectories generated by the model strongly depend on the arbitrary choice of the initial values. $p^*(t)$ is thus only met with accidentally (even in a stationary environment).

The C-model. This model borrows its main ideas from the theory of operant behavior, see Skinner (1953, ch. 5–9). According to this theory an observed behavior can be explained by its contingency on a sequence of reinforcements or rewards – hence contingency model. If the response to a stimulus is accompanied by a satisfactory state of affairs, a positive reinforcement, the probability of that response behavior recurring is increased; if it is accompanied by an unsatisfactory state of affairs, a negative reinforcement, the probability is decreased.[5] This idea is applied here to modeling the *pricing routine*: (i) post some price for which an initially expected yield can be supposed to be earned, (ii) if currently realized yields fall short of expected yields increase the probability of a price change,[6] (iii) if price is to be changed for the first time follow a random device to determine in which direction price is to be varied by one unit, otherwise use previous experience: if the preceding price change has on average been reinforced by a profit increase preserve the direction, if not, reverse it, (iv) terminate price variation immediately after reversing the direction of price change the second time, (v) if sales break down altogether because $x(t)=0$, reduce price immediately by one unit and start price experimentation scheme from the beginning. The *quantity adjustment rule* follows the same excess-demand eliminating device that was applied in the S-model; the average profit change due to a price variation is not estimated before capacity has been adjusted. Note that the measure for currently expected yields is adaptive (and could again be

[5]Thus, reinforcement is viewed as having the function of an incentive and response behavior becomes an 'operant' with respect to the acquisition or avoidance of reinforcement stimuli. This behavior is contingent upon the previously experienced reinforcement history. The strength of a reinforcement stimulus is usually seen as a relative magnitude which depends on the degree of deprivation an individual is currently exposed to. For extensive discussions of the concepts in an economic context see Alhadeff (1982) and Hursch (1984).

[6]This is assumed to be a situation of deprivation. The more persistently realized yields turn down, compared to the currently expected yields, the greater the degree of deprivation and, correspondingly, the greater the probability of a price change, particularly in response to a loss made in $t-1$.

interpreted as an aspiration level). The *expectation adaptation rule* is such that, with growing t, expected yields converge from the initially (exogenously) given value at the time point of market entry to the average realized return or to i, whichever is greater. *Exit decision routine.* In this model, it is only reasonable for price experimentation to be abandoned altogether if rewards are continually unsatisfactory and if an alternative is available which does not cause deprivation. Correspondingly, the rule is: transfer $K(t)/2$ to $L(t)$ – possibly until the disengagement bound $c(t)=1$ is reached – if the measure of yields aspired to (to which the degree of deprivation is related) has fallen to the opportunity yield and realizable yields still do not satisfy the measure. The reinforcement scheme actually constitutes a myopic groping procedure by which $p^*(t)$ can be found. However, an initially low or strongly downgraded value of expected yields tends to slow down price change frequency the more closely the optimal price is approximated afterwards, i.e., the more the realizable yields increase. Thus, although the model is oriented towards finding an optimal solution and therefore differs in principle from the S-model, it may take an extremely long time – depending on the choice of the initial values – until the optimal solution is in fact realized.

4. The experimental design

The exploration of the profitability and the disengagement and bankruptcy performance of decision-making algorithms as complex as those described in the previous section requires systematic numerical experimentation. Thus, a sequence of 16 simulation experiments has been designed in which five assumptions or, more formally, factors have been varied in order to get more general results. The factors a–e and their alternative levels are:

the way in which demand changes,
(a1) the demand functions (1) and (2) are 'rotated' in the deterministic part into $x=(u-vp)/2$, maintaining the interval $[p_-,p^-]$ and p^*. δ_ε and ξ_ε are reduced appropriately,
(a2) both (1) and (2) are translated in the deterministic part into $x=(u-v(p+z))/2$ so that a new interval $\{p_- - z, p^- - z]$, z a positive integer ($<p$), and a new p^{**} result, and δ_ε and ξ_ε are reduced appropriately,

the time profile of the trend of decreasing demand,
(b1) gradual rotation or shift of (1), (2) starts from the beginning,
(b2) both start after a stationary phase of 24 periods,

the market regime or scenario (see section 2),
(c1) monopoly scenario,
(c2) monopolistic competition scenario (contest version),

the data source used for the numerical specifications,
(d1) data from domestic electrical appliance retailing,
(d2) data from the prefabricated housing industry,

the initial conditions,
(e1) firms enter the market with a price $p(1)=p^*(1)$ (although not being aware of this),
(e2) firms enter the market with $p(1)\neq p^*(1)$.

Factor a has been included in order to investigate two kinds of environmental change representing challenges of different magnitude to the firm's identification and/or adaptation potential. Clearly, level a2 is much harder to cope with than level a1. Factor b is considered in order to find out whether demand alterations that interfere with the initial phase of orientation of the models have a disturbing effect on 'testing of the market', by the models. To compare the different selection environments implied by the alternative simulation scenarios their effect must be made explicit by including a factor c. The aspect motivating factor d to be investigated is the major difference in the ratio between $K(t)$ and total unit costs at full capacity utilization, $c(t)\cdot(f+g)$, in both cases; under d1: $K(t)/[c(t)\cdot(f+g)]\sim 1$, under d2: $K(t)/[c(t)\cdot(f+g)]\sim 0.1$. Since the current bankruptcy bound is a function of $K(t)$, a firm bears a much greater risk of going bankrupt due to a wrongly recognized or unfavorable demand fluctuation under d2 than under d1. Factor e has been admitted because the price and quantity trajectories generated by the satisficing model and, at least partly, those generated by the conditioning model are known to be influenced by the choice of the initial conditions. For the numerical details in the specification of the various factor levels see the appendix. The composition of the factor levels in the 16 simulation experiments is denoted in table 1.

By combining appropriately the single simulation experiments, factorial experiments or experimental blocks can be constructed. They allow the compound effects of the five factors on survivability to be at least partially estimated.[7] The following factorial experiments were made:

Block A Experiments 1–8. Represents a full factorial design for the three systematic factors a, b, c.

Block B Experiments 2, 4, 6, 8, 9–12. Focusses on the effects of a changed numerical specification; variation of the factors a, c, d is nested under factor level b1 because of the neglectable effect which factor b had in block A.

[7]The significance of the estimated main and interaction effects can be explored by an analysis of variance. Using a linear hypothesis for the estimations, the statistical background is standard, see, e.g., Winer (1971, ch. 5).

Table 1

Factor level combinations in the simulation experiments.[a]

	Systematic factors						Specification factors			
	Kind of change		Timing of change		Market organization		Numerical specification		Initial conditions	
Experiment	(a1)	(a2)	(b1)	(b2)	(c1)	(c2)	(d1)	(d2)	(e1)	(e2)
1	+	−	−	+	+	−	+	−	+	−
2	+	−	+	−	+	−	+	−	+	−
3	+	−	−	+	−	+	+	−	+	−
4	+	−	+	−	−	+	+	−	+	−
5	−	+	−	+	+	−	+	−	+	−
6	−	+	+	−	+	−	+	−	+	−
7	−	+	−	+	−	+	+	−	+	−
8	−	+	+	−	−	+	+	−	+	−
9	+	−	+	−	+	−	−	+	+	−
10	+	−	+	−	−	+	−	+	+	−
11	−	+	+	−	+	−	−	+	+	−
12	−	+	+	−	−	+	−	+	+	−
13	+	−	+	−	+	−	−	+	−	+
14	+	−	+	−	−	+	−	+	−	+
15	−	+	+	−	+	−	−	+	−	+
16	−	+	+	−	−	+	−	+	−	+

[a]Experiments 1, 2, 5, 6, 9, 11, 13, 15 consist of three Monte Carlo runs with 50 replications each, one for each model of firms' behavior, the other experiments consist of one contest Monte Carlo run with 50 replications.

Block C Experiments 9–16. Explores the effect of changing the initial conditions; variation of factors a, c, e is nested under the factor levels b1 and d2.

For each single simulation experiment, survival and bankruptcy probabilities, θ_j and ψ_j, are estimated for each model $j=$O, S, C as follows. A random varaible $X_j(t)$ is defined taking value 1 if period t is survived and value 0 otherwise. Then $\mathrm{E}(X_j(t))=\theta_j(t)$, the probability of surviving period t. Similarly, the probability $\psi_j(t)$ of going bankrupt up to period t can be defined as the expected value of a random variable $Y_j(t)$, taking value 1 if bankruptcy occurs up to period t and value 0 otherwise. Since each of the 16 simulation experiments consists of 50 replicated runs (n the index of replication) with identical conditions but changing random number seed, the statistic generated in each experiment are the maximum likelihood estimators

$$S_j(t)=\frac{1}{50}\sum_{n=1}^{50} X_{jn}(t), \quad \text{the survival rate, and} \tag{4}$$

$$B_j(t)=\frac{1}{50}\sum_{n=1}^{50} Y_{jn}(t),\quad \text{the bankruptcy rate.} \tag{5}$$

Where the time index is suppressed those values resulting at the end of the simulation time interval ($t=200$) are given. Further, if according to (3), W_{jn} is the profitability index realized by model j after surviving 200 periods in run n, the mean profitability index in a simulation experiment can be estimated by

$$R_j=\frac{1}{s_j}\sum_{n=1}^{50} W_{jn}, \tag{6}$$

where $s_j=\sum_{n=1}^{50} X_{jn}(200)$ and $W_{jn}=0$ if $X_{jn}(200)=0$.

5. The results: optimizing and survivability

The NSA claims, in brief, that only firms which maximize profits, or behave as if they do, will survive in the long run, because only they can prosper and acquire the resources with which to expand.[8] In this section we will be concerned with the question of whether the O-model which involves explicit optimizing indeed entails a superior survival performance as asserted where it does allow for superior profits to be made. The prerequisite is met in the experiments 1–8, see table 2, where in the last two columns the estimated profitability indices R_S and R_C are expressed as a fraction of R_O. However, the asserted superiority with respect to survival cannot be confirmed for these experiments. In a simple difference test on the corresponding S_j-values in table 2 it turns out that, on a 10% error level, θ_O can be said to be greater than θ_S and θ_C in only 3 cases (in experiment 2, $\theta_O \sim \theta_S > \theta_C$ on that level). The ordering $\theta_C > \theta_O > \theta_S$, in constrast, is significant on a 2.5% level in 4 cases.

Result 1. The hypothesis that the optimizing firm has a higher probability of survival in a market than any of the other firms can, despite the fact that its average profitability is significantly higher in all of them, be rejected at a high level of significance in half of the experiments 1–8. None of the tested

[8]See Friedman (1953). For a detailed discussion of the NSA the reader is referred to Winter (1964) and (1975). Note that the argument is not based on assuming profit maximization constrained by *additional* subgoals as, e.g., safety-first or some probability-of-bankruptcy-minimizing strategies. As Day, Aigner, and Smith (1971) have shown those strategies would lead to price and/or output behavior different from the ordinary profit maximizing one.

Table 2

Survival, bankruptcy, and profitability.

Experiment	S_O	B_O	S_S	B_S	S_C	B_C	R_S/R_O	R_C/R_O
1	1.0	–	0.96	–	0.72	–	0.78	0.59
2	1.0	–	0.98	–	0.8	–	0.59	0.46
3	0.96	–	0.7	–	0.48	–	0.84	0.7
4	1.0	–	0.68	–	0.64	–	0.79	0.58
5	0.76	–	0.08	–	1.0	–	0.66	0.31
6	0.7	–	0.04	–	0.86	–	0.61	0.09
7	0.44	–	0.04	–	1.0	–	0.67	0.65
8	0.42	–	0.12	–	0.68	–	0.77	0.63
9	0.98	–	0.38	0.12	0.94	–	0.2	0.91
10	0.74	0.22	0.8	0.2	0.64	0.22	0.27	1.08
11	0.7	–	0.86	0.14	0.92	–	0.24	0.99
12	0.6	0.22	0.8	0.2	0.72	0.22	0.31	1.07
13	1.0	–	0.7	0.02	0.72	–	0.45	0.98
14	0.96	0.04	0.84	0.16	0.7	0.06	0.51	1.11
15	0.58	–	0.42	0.02	0.96	–	0.62	1.21
16	0.64	0.04	0.32	0.16	0.76	0.06	0.62	1.23

models of firms' behavior dominated the others with respect to survival performance in all the experiments.[9]

This result is due exclusively to erroneous voluntary exit. The data display differences, which are connected to cognitive features, yet the latter seem to affect survivability in a quite complicated manner dependent on several factors. A thorough statistical analysis of the experiments 1–8, which make up block A of the factorial design, verifies this. The main and first order interaction effects on survival probabilities estimated for the factor levels aα, bβ, cγ, where α, β, $\gamma = 1, 2$, and the corresponding F-statistic calculated for each model of behavior separately are contained in table 3.[10]

Factors a and c affect significantly the ability of all the models to avoid erroneous exit. Furthermore, there is a significant compound effect of the factors a and c (O-model, S-model) and of the factors a and b (C-model) if they are varied simultaneously. The main effect of factor a differs strongly

[9]The last part of Result 1 also holds with respect to the contest experiments 3, 4, 7, 8, 10, 12, 14 and 16 in table 2. That means, in these simulation experiments, where all three different firms enter the market at the same time and indirectly compete with each other as explained in section 2, none of the different firm types always dominates the scene at the end. Rather each of the firms succeeds to dominate in some of the experiments while falling back in others.

[10]The sum of squares required in the preparation of F-ratios can be reconstructed from the observed survival rates $S_{j\alpha\beta\gamma}$ under factor levels α, β, γ, in table 2. In particular, if S'_j is the observed grand mean in the block, the sum of squares due to experimental error can be found by summing $\sum_\alpha \sum_\beta \sum_\gamma \sum_n (X_{j\alpha\beta\gamma n} - S'_j)^2$, where $\sum_n (\cdot)^2 = 50 \times S_{j\alpha\beta\gamma} \times (1 - S_{j\alpha\beta\gamma})$ by definition.

Table 3

Main and interaction effects on the estimated survival probabilities in block A.[a]

Statistic	O-model	S-model	C-model
Grand mean			
S'_j	0.785	0.45	0.7725
Main effects of factor level[b]			
a1	+0.205	+0.38	−0.1125
	(143.1)[d]	(610.6)[d]	(33.6)[d]
b1	−0.005	+0.005	−0.025
	(0.1)	(0.1)	(2.0)
c1	+0.08	0.065	+0.0725
	(21.8)[d]	(17.9)[d]	(14.0)[d]
Interaction effects of factor levels[c]			
ab$\alpha\beta$	+0.015	−0.005	+0.0875
	(0.8)	(0.1)	(20.4)[d]
ac$\alpha\gamma$	−0.07	+0.075	+0.0275
	(16.7)[d]	(23.8)[d]	(2.0)
bc$\beta\gamma$	−0.01	−0.01	+0.0125
	(0.3)	(0.4)	(0.4)
abc$\alpha\beta\gamma$	0	0.02	−0.0325
	(–)	(1.7)	(2.8)

[a]The bracketed figures are the observed F-ratios.

[b]Main effects of the alternative factor levels have the opposite sign.

[c]Results given for equal values of the indices; interaction effects for unequal values of the indices have the opposite sign.

[d]Significant at 0.1% level ($F_{0.999}(1,392)\simeq 11.1$).

between the models in magnitude and sign and explains most of the changing rank order with respect to survivability, i.e., the avoidance of exit. In the transition from level a1 to level a2 a mean reduction of the survival rate by 0.41 occurs in the case of the O-model. A closer look at the conditions governing the processes under the two levels can show why.

The three models have in common the fact that exit is a consequence of *successive* capacity diminution. Hence, the greater the capacity of a firm the better it can perform a buffer function with respect to erroneous exit if unfavorable fluctuations in demand and/or profitability mislead the corresponding routines regarding the true state of the market. Changes in demand will therefore be the more challenging to the cognitive power of a firm in discriminating between systematic and random variations the smaller demand becomes. Since $\Delta E(x\,|\,p)/\Delta p<0$, posting a low $p\in[p_{-},p^{-}]$ is, in this sense, less critical than posting a high p. This is even more valid if the price interval is shifted into $[p_{-}-z,p^{-}-z]$ as under factor level a2, hence the significant main effect of factor a in table 3. What remains to be explained is how the firms come to post a relatively high or low p and thus how the different signs of the main effects are brought about.

As already mentioned, $p^*(t)$ is, on average, posted rather quickly by the O-model. Under a2, p^* shifts from a medium position in the interval $[p_-, p^-]$ to the upper bound of $[p_- - z, p^- - z]$ when demand changes. Correspondingly, $E(x \mid p^*)$ is substantially smaller under a2 than it is under a1. When, after the demand change, $p^*(t)$ and $E(x \mid p^*(t))$ are closely approximated by the O-model the optimal capacity is therefore fairly small. The effect is illustrated in fig. 1, where mean and standard deviation functions estimated for the price-, effective-supply-, and profitability-index-processes and the exit-time-distribution in *one* of the respective experiments, experiment 5, are given.[11] In fact, capacity does not leave much room any longer for revising inaccurate evaluations of the true state of the market. The cognitive capabilities implied by the estimation and up-dating procedures of the O-model do not fully keep up with the challenge. The significant main effect of factor c and the significant interaction effect ac$\alpha\gamma$ are perfectly in line with this explanation of erroneous exit, since, because of demand spill-overs under the monopolistic competition regime, the variance of the random term in (2) can be much greater than the variance under monopoly, i.e., in (1).

Due to the choice of the initial conditions in block A, on average the price adjustment performed by the S-model happens to settle initially at a price $p(t)$, $p^- > p(t) > p^- - z$. Under level a1 this causes no probems. But, if under a2 the price interval shifts downward, demand falls to zero. Price is then adjusted to $p^- - z$ by intermittent mark-down pricing according to rule (iii) of the model. At the same time output and capacity are cut following the quantity adjustment rule so that the potential buffer effect of capacity is considerably weakened and exit is provoked with a high frequency. Again, this is well documented by the estimated functions in fig. 2 where the results for the same experiment as it underlies fig. 1 are given. Exits start once price has settled down and, in fact, many more exits occur than observed for the O-model, indicating that the cognitive capabilities implied by the S-model's routines are even more overcharged in this particular experiment.

[11]In experiment 5, $p^*(t) = p^- - z = 7$ for $t \geq 36$. For further details see table 1 and the appendix. The standard deviation functions are displayed by depicting estimated mean in $t \pm$ estimated standard deviation in t for $t = 1$ to 200. The estimated price process in fig. 1 shows that the mean price is indeed close to $p^*(t)$ until demand begins to change systematically in $t = 25$. [The sample size of the O-model's estimation routine is 4 observations per price here and the initial price happens to coincide with the unkown $p^*(1)$ in this experiment.] A strong disruption then takes place. The demand shift test induces new sampling and estimating so that supply and capacity are effectively brought down and the mean price again approximates $p^*(t)$ for $r > 36$, after systematic changes in demand have terminated. It is not before that time that exits begin to occur. For a more exhaustive discussion of the price and quantity processes generated by the O-model and the other models see Witt and Perske (1982, chs. 2 and 5).

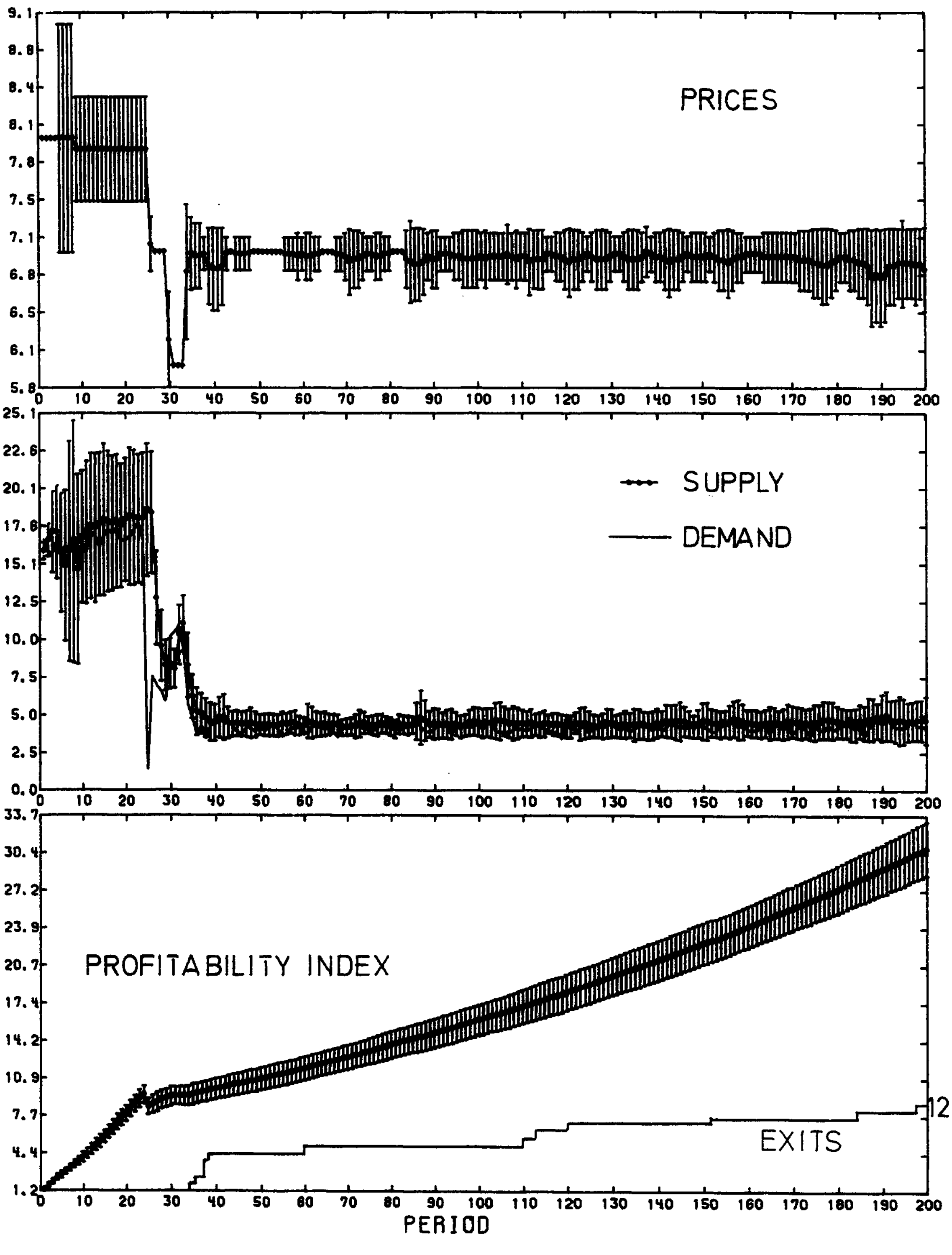

Fig. 1. Estimated mean and standard deviation functions for the O-model.

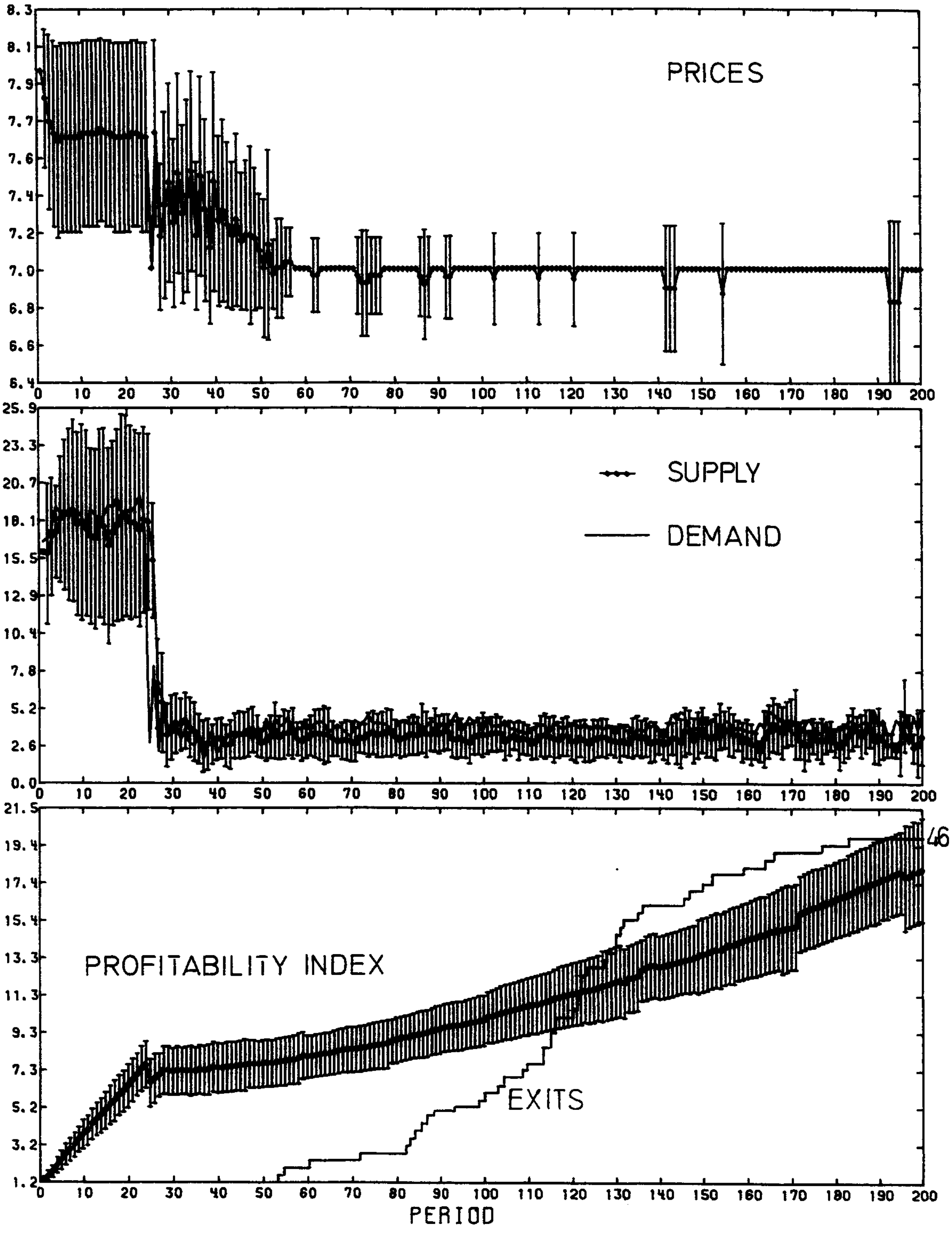

Fig. 2. Estimated mean and standard deviation functions for the S-model.

In contrast, the C-model on average tends to decrease price initially in its experimentation pattern under the initial conditions chosen for these experiments. After finding a price reduction non-rewarding the first time, price is raised again. If under level a1, $E(x|p)$ decreases for any $p \in [p_-, p^-]$, the interval being unchanged, this event can coincide with the price rising tendency and capacity then will be the smaller the more $p(t)$ approaches p^-. Accordingly, the number of exits increases. The later demand changes the more probable this becomes. However, if under level a2 $p(t) > p^- - z$ already, when $[p_-, p^-]$ is shifted into $[p_- - z, p^- - z]$, demand falls to zero. In this case, rule (v) of the model is applied and price experimentation starts all over again after cutting price. Since this is usually rewarding – profit increases again – price on average turns down further and capacity can take values sufficiently large to serve its buffer function properly. This downturn is again the more probable the later demand changes, hence the significant interaction effect ab$\alpha\beta$. The processes in fig. 3 display the described effect very clearly. No exit at all occurs in this experiment. But since this results from posting a suboptimal price the profitability index reached after 200 periods is significantly smaller than for the other two models.

Result 2. The findings in block A of the experimental design indicate that differences in survival performance emerge first of all from different reactions of the alternative models' pricing routines to the variation of the experimental factors a and c. Contingent upon the choice of the corresponding factor levels the differing pricing routines determine, by the diverging price processes they involve, whether quantity processes run into more critical ranges of the output/capacity space or not.

The problem with this kind of causation is that it allows the peculiarities of the initial and/or environmental conditions to become the dominant factor of survival performance.

6. Profitability and survival – The weak version of the NSA

The two results in section 5 contradict the NSA since the profit-maximizing solution is achieved very quickly by the O-model but nevertheless its comparative survival performance is not as asserted. Even if the algorithm itself is deemed to be a heuristic rather than a literally profit-maximizing strategy the conclusion is not invalidated. The model performs almost 'as if' it were profit-maximizing and thus conforms to the premise of the NSA. Abandoning the strong version of the NSA which is pinned down to the absolute criterion of the profit-maximizing solution, the weaker criterion of relative profitability might be considered decisive for survival performance. In effect, this represents the position held by Alchian (1950) in his seminal paper. It amounts to saying that the capacity to survive depends on the

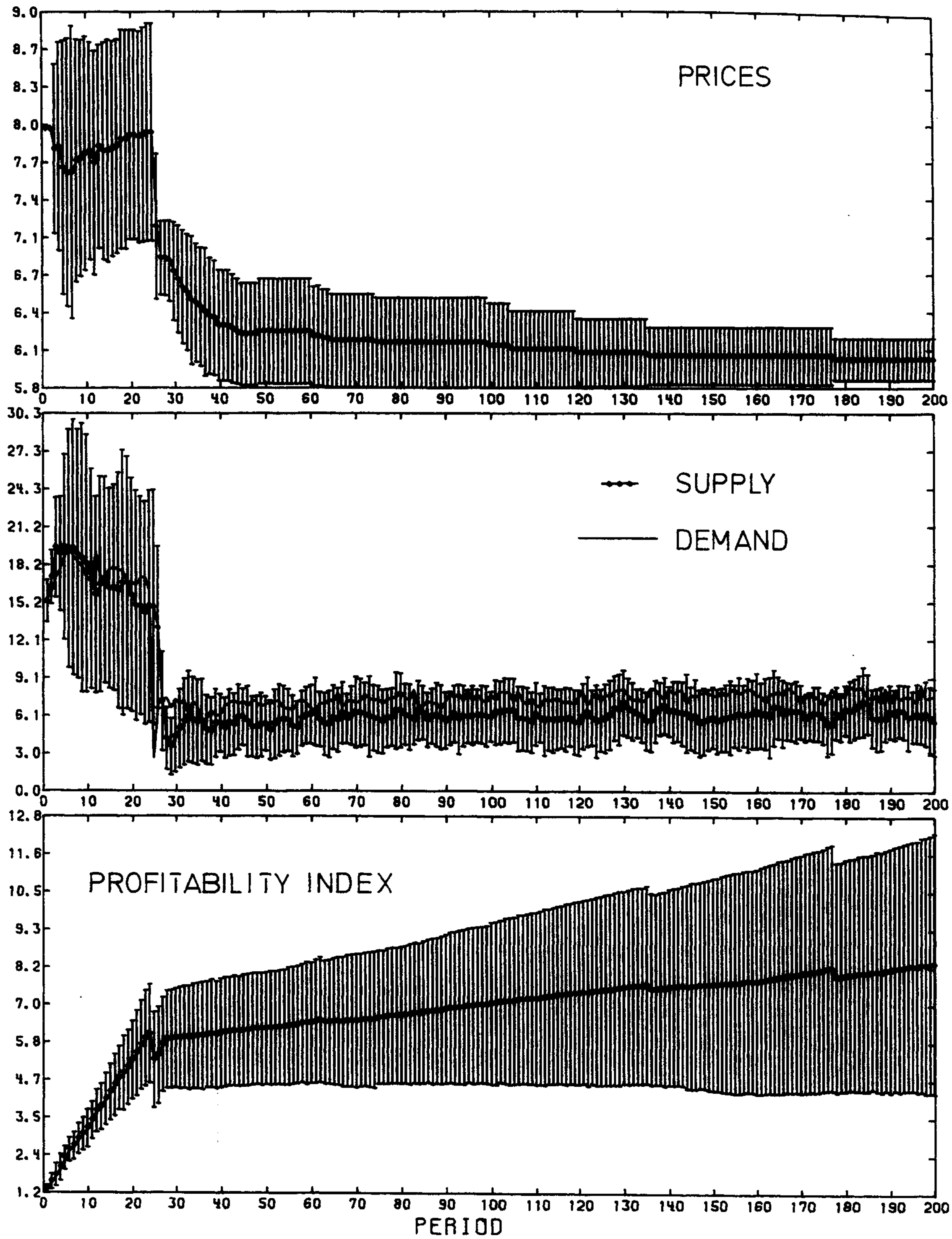

Fig. 3. Estimated mean and standard deviation functions for the C-model.

ability to realize better profits than others, whatever the motivation and the decision-making algorithm may be. That interpretation is called the weak version of the NSA here.[12]

Unfortunately, Result 1 is not in line with the weak version of the NSA either. Moreover, its validity is in principle questioned by Result 2. In order to reach a better assessment of these queries further experiments were conducted. In view of the profitability rates in the experiments 9–16 in table 2 the weak version of the NSA can be interpreted to mean that the S-model should have a significantly lower probability of survival than both the O-model and the C-model. However, on a 10% level, only in the experiments 9, 15 and 16 is a corresponding rank order significant.[13]

Result 3. The basic assertion underlying the weak version of the NSA is not supported. The hypothesis that the firm with the highest profits also has a significantly higher probability of survival than the other firms, can be rejected on a high level of significance in the experiments 5–8 and 10–14 i.e., more than half of all.

The investigation of the effects of factor level variation on survival performance in the additional factorial experiments of blocks B and C indicates that the survival performance is contingent upon the same reasons as those found in block A. The corresponding estimates of the main first order interaction effects on survival probabilities are contained in table 4.

The additional experiments also allow for a discussion of whether things change if bankruptcies become probable. The B_j-values in table 2 show that bankruptcy is indeed occuring where the data from the prefabricated housing industry are used for the specification of the parameters. The question now is whether profitability differences are decisive for bankruptcy or whether the

[12]The methodological implications of the two versions differ substantially. The strong version of the NSA is not only designed to counter the misgivings with respect to the realism of the optimizing hypothesis. In the broader perspective of economic theory the vindication of the optimization hypothesis (at least in its predictions on the observable outcome) also bears on the acceptance of the specific neoclassical synthesis which combines optimization calculus and the essentially static equilibrium approach. Approving the weak version of the NSA instead of the strong in effect means, therefore, to call in question this greatly simplifying synthesis. The necessity of investigating a host of alternative hypotheses on actual decision-making behavior and its implications emerges in order to determine which one is most profitable when. Moreover, the influence of situational and environmental factors such as the current composition of the competing population and the laws governing the changes of such frequencies has to be acknowledged. This, in turn, requires an elaborated dynamic theory in order to determine which kind of equilibrium eventually might result. These aspects become still more important, of course, if not even the weak version of the NSA can be upheld.

[13]If one looks at the firm realizing the highest profits in an experiment, this firm – whatever the motivation or goal – displays both significantly higher profitability and survival rates than the other firms on a 10% error level in only 5 of all 16 experiments, namely the experiments 1, 3, 4, 15 and 16.

Table 4

Main and interaction effects on the estimated survival probabilities in blocks B and C.

Statistic	O-model	S-model	C-model
Block B			
Grand mean			
S'_j	0.7675	0.5825	0.775
Main effects of factor level[b]			
a1	+0.1625 (74.2)[d]	+0.1275 (48.2)[d]	−0.02 (1.0)
c1	+0.0775 (16.9)[d]	+0.0175 (0.9)	+0.105 (26.7)[d]
d1	+0.0125 (0.4)	−0.1275 (48.2)[d]	−0.03 (2.2)
Interaction effects of factor levels[c]			
$ac\alpha\gamma$	−0.0175 (0.9)	+0.0125 (0.5)	+0.05 (6.0)
$ad\alpha\delta$	+0.0575 (9.3)[e]	+0.2475 (181.7)[d]	−0.005 (0.1)
$cd\gamma\delta$	−0.0075 (0.2)	+0.0725 (15.6)[d]	+0.02 (1.0)
Block C			
Grand mean			
S'_j	0.775	0.64	0.795
Main effects of factor level[b]			
a1	+0.145 (59.4)[d]	+0.04 (3.4)	−0.045 (5.3)
c1	+0.04 (4.5)	−0.05 (5.3)	+0.09 (21.8)[d]
e1	−0.02 (1.1)	+0.07 (10.4)[e]	+0.01 (0.3)
Interaction effects of factor levels[c]			
$ac\alpha\gamma$	+0.03 (2.5)	−0.09 (17.1)[d]	−0.01 (0.3)
$ae\alpha\varepsilon$	−0.04 (4.5)	−0.16 (54.2)[d]	+0.03 (2.4)
$ce\gamma\varepsilon$	+0.045 (5.7)	−0.04 (3.4)	+0.035 (3.2)

For footnotes b, c and d see table 3.
[e]Significant at 1% level ($F_{0.99}(1{,}392)=6.7$).

responsibility is with the cognitive features. Furthermore, do the results indicate generic differences in bankruptcy avoidance between the alternative models? The data in table 2 show that for the O-model and the C-model, in contrast to the S-model, bankruptcy is a phenomenon restricted to the case of monopolistic competition and, moreover, is strongly dependent on the choice of the initial conditions. This observation leads to an answer to the two questions as follows.

According to the assumptions about the monopolistic competition scenario, all firms observe a demand for their products which is drastically inflated by demand spill-overs if there is a substantial excess demand as assumed in the experiments 10 and 12 (see footnote 1). In that case, all models apply their quantity adjustment routines before they are ready to change price. With all the firms adapting effective supply and capacity simultaneously to *individually* observed demand, aggregate market supply will exceed aggregate effective demand within the first 4 periods so that demand spill-overs fall to zero. If, at this moment, an unequal random allocation of the consumers over the firms occurs, the firms bearing most of the excess supply in the market may suffer a loss which exceeds the current value of the bankruptcy bound.

If bankruptcies are mainly brought about in this way, the B_j-values in the experiments 10 and 12 should exceed those in the experiments 14 and 16. Moreover, bankruptcies should be concentrated in the first four periods. Indeed, the time distribution of bankruptcies displayed in table 5 confirms this conjecture for the O-model and the C-model. Thus most of the bankruptcies of these models are a consequence of a wrongly perceived development, but since this result is mainly due to the arbitrarily chosen assumptions of synchronized market entry and identical initial offers it does not seem to indicate a more general deficiency. The S-model, in contrast, displays a different bankruptcy performance. The entries in table 5 show that for the S-model, in monopolistic competition, a major share of bankruptcies occurs after the fourth period. Moreover, bankruptcy also occurs in the monopoly scenario.

Table 5

Time distribution of bankruptcies.

Experiment	$B_O(4)$	$B_O(13)-B_O(4)$	$B_S(4)$	$B_S(13)-B_S(4)$	$B_C(4)$	$B_C(13)-B_C(4)$
9	–	–	–	0.12	–	–
10	0.22	–	0.08	0.12	0.22	–
11	–	–	–	0.14	–	–
12	0.22	–	0.08	0.12	0.22	–
13	–	–	–	0.02	–	–
14	0.04	–	0.02	0.14	0.06	–
15	–	–	–	0.02	–	–
16	0.04	–	0.02	0.14	0.06	–

Result 4. As compared with erroneous exit, bankruptcy is a relatively rare event. The bankruptcy rates observed in the experiments 9–16 indicate significant differences between the S-model and the other two in their capacity to avoid bankruptcy.

The reason for this deviant performance is a more excessive capacity expansion. i.e., a consequence of a cognitive feature of the model, rather than a difference in profitability. In fact, average profit differentials between the alternative models are fairly small in the first 13 periods. Price is more quickly cut by the S-model than by the others, when aspiration level and mark-up are strongly reduced because the first experiences are disappointing. As a response to the increasing demand, capacity and output are expanded rapidly since there are no delays associated with attempts to make estimates. But variance of demand also increases if price is lowered and therefore, a rash adaptation like this runs the risk of cumulative positive random fluctuation leading to a building up of damaging overcapacity. The persistent differences between the B_j-values for the S-model and for the other two seem to indicate that the rash price and capacity changes executed by the model are the source of the more generally deficient bankruptcy avoidance.

7. Conclusions

The present study has explored the comparative survival performance of three alternative models of firms' behavior in an unknown, changing market by conducting simulation experiments. Contrary to the NSA, the observed survival rates do not display any generally valid rank order with respect to survival. The significant differences in the probability of survival between at least some of the models in each of the 16 experiments show that each of the models performs differently under different conditions, none of them being superior under all conditions. The changes frequently observed in the rank order of the models' survival rates are caused by the crucial role of erroneous voluntary exit, bankruptcy turning out to be of minor importance. The changes can be explained by reference to the cognitive problems to be solved by the firms in the present scenario. The success in avoiding exit is for all three models strongly, but divergently, dependent on the specification of the initial and the environmental conditions. These peculiarities thus become most influential for the observed survival performance.

Clearly, the complexity introduced by the present scenario is essential if the cognitive problems are to be non-trivial and if their consequences, erroneous exit and bankruptcy, are to follow. These problems cannot be mimicked on the basis of the usual simplifying assumptions in the theory of behavior under uncertainty. More extended models of firms' behavior such as those discussed in this study must, of course, also be more specific and therefore invite the criticism that they do not represent the only possible prototype. Results might indeed change somewhat if one or another routine were modeled differently within the models. It can be conjectured, however, that, due to the assumption of a complex, initially unknown environment, dependency on the peculiarities of the initial conditions and of the environment is a rather invariable property of that class of models of firms' behavior which can cope with the tasks of adapting, searching or learning.

If this is true, the assessment given by Winter (1964, 1975) is supported: profit-maximization is neither a necessary nor a sufficient condition to increase the probability of survival for a firm in a changing market. Under the realistic assumption of imperfect information many environmental situations can be envisaged in which satisficing, operant behavior, or other prototypes of behavior display a superior survival performance. Under such conditions, the natural selection argument cannot serve as a generally valid device for dispensing with the vast variety of behavioral models of firms' decision-making and their possibly diverging implications. Which kind of behavior prevails at a certain place and time and why, must be decided by empirical investigations. They require a much more profound understanding of the large class of non-optimizing models of behavior than is currently available in economic theory.

Appendix: Numerical specifications in the experiments

In the simulations two data sets were used for the numerical specification of the parameters and initial values: data from domestic electrical appliance retailing and from the prefabricated housing industry. The data are based on personal communications with firms in the two industries. Since an empirical investigation is not intended, the material has been fitted to the structure in the present scenario without claiming statistical significance for this fit. For each of the two numerical examples the initial values and the time profile of the changes in the parameters of the demand function were varied (factors e and b respectively). The various specifications are listed below in a synoptical way for the two alternative data sources. In both cases the original values are found by multiplying the monetary terms by 1,000 in example 1 and 10,000 in example 2.

	Numerical examples	
	factor level d1	factor level d2
Parameters determining internal conditions		
k	5	1.43
f	1.525	2.857
g	4	10
h	1	1
i	0.005	0.05
Parameters of the demand function		
u	80	120
v	8	6
z	2	3
$[p_-, p^-]$	[6,9]	[16,19]
Time profile of demand changes		
initial decrease (factor level b1)	monotonous reduction between $t=1$ and $t=13$	non-monotonous reduction between $t=1$ and $t=22$
delayed decrease (factor level b2)	monotonous reduction between $t=25$ and $t=36$	—
Initial values		
$p(1)$, $y(1)$ (factor level e1)	8, 16	16, 11
$p(1)$, $y(1)$ (factor level e2)	9, 27	18, 11

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