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AN EMPIRICAL ANALYSIS OF BACKLOG, INVENTORY, PRODUCTION, AND PRICE ADJUSTMENTS: AN APPLICATION OF RECURSIVE SYSTEMS OF LOG-LINEAR MODELS

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ABSTRACT

This paper presents an empirical analysis of firms' order backlog, inventory, production, and price adjustments to unanticipated demand shocks. The data are obtained from quarterly INSEE Business Survey Tests on firm's realizations, expectations, and appraisals of some various economic variables. The analysis is based on the formulation and the estimation of a recursive system of conditional log-linear probability models.

AN EMPIRICAL ANALYSIS OF BACKLOG, INVENTORY, PRODUCTION, AND PRICE ADJUSTMENTS: AN APPLICATION OF RECURSIVE SYSTEMS OF LOG-LINEAR MODELS [1]

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For many years, some countries like France and Germany have collected through periodic surveys data on firms' expectations, plans, appraisals, and realizations of some various economic variables. Because data on some usually unobservable variables such as expectations are available, these surveys constitute a unique source for the study of firms' behavior at the individual level. Indeed in earlier empirical studies such as studies on production, price, and inventory behavior (see e.g. G. A. Hay (1970), L. J. Maccini (1976), E. S. Mills (1962) among others) hypotheses on the formation of expectations are put forward in order to relate expectations to observable variables. These hypotheses are then used to derive relations that are suitable for empirical investigation. Since data on expectations and appraisals are available in the survey, this information can be used to directly evaluate and test the role played by expectations and appraisals in models of firms' behavior.

Another particularity of the survey which is of great importance for the statistical analysis is that most of the questions are qualitative. While similar survey data have been analyzed by many researchers (for an earlier study see H. Theil (1955)) most empirical analyses used aggregated data or required that the microdata be aggregated into so-called "balances". Only recently the qualitative nature of these microdata was fully incorporated in the statistical analysis (see S. Kawasaki (1979), H. König, M. Nerlove, and G. Oudiz (1979, 1981), S. Kawasaki, J. McMillan, and K. Zimmermann (1981)).

In these latter works, the analysis of the relationships among the variables was based on the formulation and the estimation of joint log-linear probability models (for theoretical references, e.g., Y. M. M. Bishop, S. E. Fienberg, and P. W. Holland (1975), L. A. Goodman (1978), S. J. Haberman (1974a)). The variables were thus treated as mutually dependent, and no distinction was made between endogenous and exogenous variables. Since conditional probability distributions were in fact of interest, their estimates were then derived from estimated joint probability distributions.

As pointed out in Q. H. Vuong (1982), joint estimation and conditional estimation are not, however, necessarily equivalent. Hence, the estimates of the conditional probability distributions derived there might be (and in fact are) substantially different from the estimates that are obtained from the direct estimation of the conditional probability distributions. Second, since the dependencies among all the variables of interest must be simultaneously specified in a joint probability approach, the formulation of a model becomes quite complex as compared to a formulation in which the dependencies among the variables are successively considered. Moreover, because

the joint approach treats all the variables as mutually related, one cannot interpret the estimated associations as dependencies of some variables on other variables.

In this paper, we apply the framework presented in Q. H. Vuong (1982) to the analysis of the French Business Survey Data. Specifically, our analysis is based on the formulation and the estimation of a recursive system of conditional log-linear probability (CLLP) models. As we shall see, the use of such a recursive system allows us to include in the analysis a large number of variables that are available in the French survey. The main purpose of our empirical investigation is the study of the various adjustments made by firms that experience unanticipated demand shocks. We shall also study the formation of production and demand expectations.

The paper is organized as follows. In Section 1, the data are presented. Then, in Section 2, a fixed-price model of firms' adjustments is introduced. A particular attention is given to the signs of the effects of the explanatory variables on the dependent variables. The estimation results are presented and discussed in Section 3. Then, we summarize our empirical findings in Section 4.

1. The Data

Since the beginning of the 50's, the Institut National de la Statistique et des Etudes Economiques (INSEE) has collected a wide body of data from individual firms through periodic surveys. These surveys are often referred to as Business Survey Tests. We shall be interested here in one of these surveys: the "Enquête quadrimestrielle sur la situation et les perspectives dans l'industrie".

The period of the survey is primarily four months. However, because of a low number of respondents due to a drop of activity during summer vacation, June was preferred to July. The survey is therefore taken each year in March, June, and November. About 3000 firms are surveyed. However, some firms do not answer all the questions of the survey. Thus, due to missing observations on some variables of the model, the sample is in fact much smaller.

Three specific features of the survey are worth mentioning. (As a matter of fact, these features are common to other Business Survey Tests.) First, the survey provides information which is usually not available, such as information on firms' expectations and/or appraisals of some variables. Second, the information is not on absolute levels, but rather on variations of variables or on levels relative to some "normal" levels. For instance, firms are asked to answer by "increase", "stability", or "decrease" to questions on variations (e.g., expected variation of demand), and by "above normal", "normal", or "below normal" to questions on appraisals (e.g., appraisal of inventory). Finally, an important feature of the

questionnaire, especially for statistical analysis, is that most of the variables are qualitative. The log-linear framework therefore provides a convenient tool for specifying the relationships between the variables, and hence for formulating and testing a model of firm behavior.

Table 1 lists the definition of the variables and the notation used in our empirical analysis. Table 2 reports the corresponding questions of the survey. (The questions have been translated from French.) The questionnaire actually contains additional questions on capacity utilization, production bottlenecks, employment plans, etc. This latter information is, however, not used in the model studied below.

As Table 2 shows, all the variables are trichotomous except for the two variables related to price, dP_t and dP_t^*. Hence, in principle, the variables dP_t and dP_t^* should be treated as continuous variables. The continuity of price expectations that are reported on surveys is, however, questionable (see J. A. Carlson (1975)). Indeed, individuals tend to round off their answers to the nearest integer. In other words, the percentages reported on the survey have already been somewhat categorized. We have then transformed the price variation and the expected price variation into trichotomous variables. The transformation used is: if x denotes the reported percentage (of realized or expected price variation), then "$x \geq 5$", "$0 < x \leq 5$", and "$x \leq 0$" define the three categories which are respectively interpreted as "substantial increase", "slight increase",

TABLE 1: List of variables

dQ_t : Production variation from time t - 1 to time t.

dQ^*_t : Production variation from time t to time t + 1 expected at time t.

dD_t : Demand variation from time t - 1 to time t.

dD^*_t : Demand variation from time t to time t + 1 expected at time t.

O^a_t : Appraisal of backlog of orders at time t.

I^a_t : Appraisal of inventory of finished goods at time t.

dP_t : Price variation from time t - 1 to time t.

dP^*_t : Price variation from time t to time t + 1 expected at time t.

dQG^*_t : General production variation from time t to time t + 1 expected at time t.

dPG^*_t : General price variation from time t to time t + 1 expected at time t.

TABLE 2: Questions

dQ_t : Change in your production--trend in the past period: increase, stability, decrease.

dQ^*_t : Change in your production--probable trend in the next period: increase, stability, decrease.

dD_t : Change in demand--trend in the past period: increase, stability, decrease.

dD^*_t : Change in demand--probable trend in the next period: increase, stability, decrease.

O^a_t : Do you consider, taking into account the season, that at the present time your backlog of orders is: too large, normal, too small.

I^a_t : Do you consider, taking into account the season, that your present inventory of finished products is: greater than normal, normal, less than normal.

dP_t : Would you indicate the variation of your sales prices (net of tax) since the last survey:
+ ... %, =, - ... %.

dP^*_t : What will be the probable variation of your sales prices (net of tax) until the next survey:
+ ... %, =, - ... %.

dQG^*_t : What will be the most probable variation of the industrial production in the next period: increase, stability, decrease.

dPG^*_t : What will be the most probable variation of the general price level of industrial goods in the next period: increase, stability, decrease.

and "stability". The choice of the thresholds was motivated by a steady rate of inflation from 1974 to 1978. Thus the number of respondents reporting a decrease in prices is very low. The natural choice "$x \leq x_1$", "$x_1 < x < x_2$", "$x_2 \leq x$" with x_1 negative and x_2 positive, which corresponds to "decrease", "stability", and "increase", then leads to a cell "decrease" that is often empty. As is well known, this raises some problems of identification and/or existence of M. L. estimates. On the other hand, about one third of the firms report that their prices have not changed or will not change. (We shall return to this point later.) Hence the threshold "0" seems appropriate. The other threshold "5" is chosen on the ground that the category "$0 \leq x \leq 5$" then corresponds approximately to a price stability in real terms, that is, after having taken into account the rate of inflation.

The other price variable in the questionnaire, which is the expected general price variation dPG^*_t, is originally trichotomous. Given the implausibility of the answer "decrease" to the corresponding question, for the analyzed period, we have merged this answer to the answer "stability". In what follows, the variable dPG^*_t is then dichotomous.

Finally, an important issue is how firms understand the question on demand, and hence how one should use the information provided by this question. Two interpretations come readily to mind. First we can consider that dD_t (or dD^*_t) indicates the direction of the actual (or expected) shift of the demand curve. Alternatively, we can

consider that dD_t indicates the variation in demand <u>received</u> by the firm for its product. The fundamental difference between these two interpretations come from the fact that, according to the second interpretation, the change in demand also depends on the change in prices. While the first interpretation agrees with the one given in any economic textbook, the second interpretation is, because of its simplicity, the one most likely given by firms to the question on demand. Consider, for instance, firms that produce to orders. Then, according to the second definition, demand simply corresponds to the flow of incoming orders during a given period, and its variation to the change in this flow from period to period. On the other hand, if the first definition is used, a firm would have to take into account the change in its prices in order to adjust (and this in an appropriate manner!) the change in the flow of incoming orders when assessing the corresponding change in demand. In what follows, we shall therefore retain the second interpretation and hence consider demand as simply the flow of incoming orders.

2. A Fixed-Price Model

The study of production, price, and inventory behavior has been the source of numerous theoretical and empirical works. To cite a few, one has the earlier contributions of G. A. Hay (1970), E. S. Mills (1962), and more recently the contributions of A. S. Blinder (1982), J. P. Gould (1980), L. J. Maccini (1976). Similarly, the role of backlogs of unfilled orders have been abundantly studied (see e.g.

J. P. Gould (1980), V. Zarnowitz (1962) among others). Two remarks on these works are worth mentioning.

First, in most of these works, firms are assumed either to carry inventories of finished products, or to keep backlogs of unfilled orders. When both inventories and unfilled orders were allowed in a theoretical model, then inventories were usually considered as the negative of the backlog so that the simultaneous existence of unfilled orders and inventories of finished products was automatically ruled out. Our survey, however, shows that there is an important number of single-product firm that have both inventories of finished product and backlogs of unfilled orders in the same period. While the purpose of our model and of our empirical investigation is not to explain why firms may simultaneously have inventories of finished products and a backlog of unfilled orders, many possible explanations of this phenomenon can be given. For instance, this may be due to the necessary heterogeneity of a product even though our sample was initially reduced to single-product firms. Alternatively, one can elaborate a theoretical model in which delivery period and the smoothing of the production process can explain this phenomenon.

Second, as mentioned earlier, in the previous empirical studies of firms' behavior, hypotheses on the formation of expectations and on the determination of optimal levels are made in order to derive relations that are suitable for empirical investigation. As the previous section shows, our survey directly provides data on expectations and appraisals of some variables. As a

consequence one can use these data to study models of expectations formation. For instance, using the same data set or similar data on German firms collected by the Institut für Wirtschaftsforschung in Munich, S. Kawasaki (1979), and H. König, M. Nerlove, and G. Oudiz (1979, 1981) have studied the joint or separate formation of production and price expectations. Another possible use of data on expectations is to determine directly the role played by expectations in firms' behavior. Specifically, one can construct a model of the firm and use the data on expectations (and appraisals) in order to evaluate the model empirically.

The main purpose of the present model is to analyze the different adjustments made by a firm facing an unexpected shock in demand, i.e., a discrepancy between realized demand and expected demand. We shall also study the formation of production expectations and demand expectations.

At the outset, we can distinguish four types of adjustments: inventory of finished products, backlog of orders, production, and price adjustments. For instance, when the realized demand exceeds the corresponding expected demand, the firm can (i) increase its price (ii) increase its production to meet the unanticipated increase in sales, (iii) let its backlog of unfilled orders grow and become greater than the planned number of unfilled orders, (iv) decrease its inventory relative to the planned level of inventory. The firm can also choose a combination of the above four possible adjustments.

However, models including an equation for contemporaneous price adjustments were not satisfactory for our data. Specifically, any variable that was tried turned out to be insignificant in a model explaining the actual price variation dP_t whenever the expected/planned price variation dP^*_t was also introduced. The reason was that the association between the expected/planned price change was so strong that any additional explanatory variable became unnecessary. This suggests that firms that face unanticipated demand shocks do not instantaneously adjust their prices relative to their expected/planned prices. These empirical results are in fact consistent with earlier findings reported by S. Kawasaki, J. McMillan, and K. Zimmermann (1981), H. König, M. Nerlove, and G. Oudiz (1981) stating that firms are less responsive to (current) market conditions in setting prices than in setting quantities.

We are thus led to consider a fixed-price model, i.e., a model where the sales of a firm for the period (t, t + 1) between two surveys are made at the price announced at the beginning of the period, and hence at time t. This does not, however, imply that prices never adjust, but only that they do not adjust to contemporaneous demand shocks. The choice of a fixed-price model is all the more justified as the period between two surveys is short, about four months. Hence the model only assumes that firms do not revise their prices for periods shorter than four months. Then, given that prices are fixed within each period, there are only three types of adjustments left: inventory of finished products, backlog of orders, and production adjustments.

Our fixed-price model is defined by a recursive system of five conditional L.L.P. models with six endogenous variables. (The model representing the simultaneous adjustments of the inventory of finished products and the backlog of orders has two endogenous variables.) The endogenous variables are the price adjustment dP_t, which takes into account the price adjustment prior to the period (t,t+1) the two expectations dQ^*_t and dD^*_t, and the three adjustment variables O^a_{t+1}, I^a_{t+1} and dQ_{t+1}. The natural variables for the backlog and inventory adjustments are the variation in backlog of orders dO_{t+1} and the variation of inventory dI_{t+1}. However, dO_{t+1} is not directly observed whereas O^a_{t+1} is. We then use O^a_{t+1} and I^a_{t+1}: this keeps the symmetry between backlog and inventory.

We suppose that each firm sets its price P_t at the beginning of the period (t,t + 1) and that this price remains constant throughout the period. Given this price, the firm anticipates at time t the demand it will receive during the period (t,t + 1). Let D^*_t denote the expected demand at time t. Then the firm determines its expected/planned production Q^*_t for the period (t,t + 1). The demand D_{t+1} for the period (t,t + 1) materializes. Given the discrepancy between realized demand D_{t+1} and expected demand D^*_t, the firm first absorbs the surplus or shortage of demand simultaneously on its backlog of orders and its inventory of finished products. Then it adjusts its production relative to its expected/planned production.

The behavior described in the preceding paragraph can be represented by a recursive system. As predetermined variables, we use some lagged endogenous variables and the expected variations dPG^*_t and dQG^*_t of the price level and production level for the French economy. These prospects are evaluated differently by the surveyed firms. We can consider that the variety in firms' amswers to questions on general trends is the result of differences between specific effects of macroeconomic variables on individuals. We can also consider that a firm weighs relatively more the price trend in its sector when it answers the question on the expected trend of the general price level.

We now discuss the choice of the explanatory variables in each conditional L.L.P. model of the recursive system. With the exception of the price-adjustment model, we shall use a quantitative formulation of the relations between "level" variables. Then we shall derive some equations relating variations. These equations will then allow us to justify the choice of the explanatory variables as well as the expected signs of the effects of the explanatory variables on the endogenous variable(s). It is, however, important to note that the statistical model that we shall estimate do not exactly correspond to the simple model of firm's behavior presented thereafter. Actually, our statistical model is more flexible with respect to the specification of the dependencies that a stochastic version of the simple model.

2.1. Price Adjustment

$$\text{Model 1:}\quad Pr(dP_t \mid \underset{+}{O^a_t}, \underset{?}{dP_{t-1}}, \underset{+}{dP_{t-3}}, \underset{+}{dPG^*_{t-1}})$$

It is assumed that firms set their prices at time t, and that these prices remain constant throughout the period (t,t + 1). Hence prices do not instantaneously adjust to disequilibria appearing during the period (t,t + 1). However, prices do not have to remain constant through time. Indeed, they can adjust to past disequilibria. To explain the variation $dP_t = P_t - P_{t-1}$ of a firm's price, we can distinguish two types of variables: variables that are specific to the firm and variables that represent macroeconomic conditions.

As firm specific variables, we use the firm's appraisals at time t of its backlog of orders O^a_t and of its inventory of finished products I^a_t. These appraisals are thought of as summarizing the disequilibria previous to time t. It is clear that these appraisals influence the firm's price behavior. For instance, a firm that has a backlog of orders greater than normal and an inventory less than normal, will be more likely to increase its price than a firm that has a backlog of orders less than normal and an inventory greater than normal. Thus, we expect a positive effect of O^a_t on dP_t and a negative effect of I^a_t on dP_t. (However, the appraisal of inventory I^a_t turned out to be insignificant for all the periods whenever the appraisal of backlog was introduced.)

As macroeconomic variables we may want to use the expected variation of the general price level: indeed firms take into account the expected general inflation rate, when deciding upon their own price increases. Since prices are fixed at the beginning of the period in our model, the relevant variable is the realized variation of the general price level from t − 1 to t, i.e.:

$$dPG_t = PG_t - PG_{t-1}.$$

However, the survey does not provide data on dPG_t. We use instead the variation of the general price level expected at time t − 1:

$$dPG^*_{t-1} = PG^*_{t-1} - PG_{t-1}.$$

The sign of dPG^*_{t-1} on dP_t is positive since it reflects the adjustments of individual prices on the general price trend.

In addition to the two aforementioned variables O^a_t and dPG^*_{t-1}, we consider the individual price variations dP_{t-1} and dP_{t-3} which correspond to changes during the last period and one year earlier. Indeed, a brief look at the variations of prices charged by firms over the 13 periods suggests that there are two types of firms: firms that gradually revise their prices, and firms that adjust their prices only annually. For the second type of firms, the categorization of the variable dP_t discussed earlier and a continuous inflation between 1974 to 1978 lead to a positive effect of dP_{t-3} on dP_t. In addition, the existence of such firms makes the sign of the effect of dP_{t-1} on dP_t

ambiguous. We shall return to this point in Section 3.

2.2. Expected demand

Model 2: $\Pr(dD^*_t \mid \underset{+}{dD_t}, \underset{-}{dP_t}, \underset{+}{dQG^*_t}, \underset{+}{dPG^*_t})$

To simplify the discussion, we suppose that demand is linearly related to the price set by the firm at the beginning of the period. Since prices are fixed throughout the period, we have:

$$D_{t+1} = a_{t+1} - bP_t \text{ , } b > 0, \tag{1}$$

where D_{t+1} is the demand for the period (t, t + 1), and P_t is the price at the beginning of the period. Since prices are known, the expected demand D^*_t is:

$$D^*_t = a^*_t - b\ P_t. \tag{2}$$

The expected constant term a^*_t is not observed. However, macroeconomic conditions shift the demand curve faced by each firm. Thus the constant term a_{t+1} depends on some macroeconomic variables. By aggregation, we have:

$$QG_{t+1} = A_{t+1} - B\ PG_t,$$

and

$$a_{t+1} = c\ A_{t+1}, \tag{3}$$

where QG_{t+1} and PG_t are respectively general production and general price levels for period (t, t + 1), and c is some constant.[2] Hence:

$$a^*_t = c(QG^*_t + B\ PG_t). \tag{4}$$

On the other hand, we have:

$$D^*_t - D_t = (a^*_t - a_t) - b(P_t - P_{t-1}).$$

Hence, from (1) - (4), we get:

$$dD^*_t = \underset{+}{c\ dQG^*_t} + \underset{+}{cB\ dPG_t} - \underset{-}{b\ dP_t} \tag{5}$$

The signs of the effects are easily understood: for instance, ceteris paribus, an increase in the general price level leads to an expected increase in firm's demand, because such an increase in the general price level implies a relative decrease in the firm's price.

Since the survey does not provide information on the general price variation dPG_t as perceived by the firm, we use instead the general price variation dPG^*_t expected at time t. (This latter variable turns out to be more significant than the general price variation dPG^*_{t-1} expected at time t - 1.)

In addition to the previous explanatory variables, we consider the variation of firm's demand dD_t from period (t - 2, t - 1) to period (t - 1, t). This variable is introduced to take into account a possible association between dD_t and dD_{t+1} or a possible dependence of

the expected variation dD^*_t on the most recent realized variation dD_t. In general, we expect a positive sign for the effect of dD_t on dD^*_t.

2.3. Expected/planned production

Model 3: $\Pr(dQ^*_t \mid \underset{+}{dD^*_t}, \underset{-}{O^a_{t-1}}, \underset{+}{O^a_t}, \underset{-}{I^a_t})$

We have the following identity between stocks and flows:

$$Q_{t+1} + I_t + O_{t+1} = D_{t+1} + I_{t+1} + O_t, \tag{6}$$

where Q_{t+1} and D_{t+1} are respectively production and received demand during period (t, t + 1), and O_t and I_t are the backlog of orders and the inventory of finished products at time t. Thus, given expected demand D^*_t, planned backlog of orders O^*_t, and planned inventory I^*_t, we get for the planned production:

$$Q^*_t = D^*_t - (O^*_t - O_t) + (I^*_t - I_t). \tag{7}$$

Let us note that we implicitly suppose that firms first decide on their desired levels of backlog of orders and of inventory of finished products. These desired levels may take into account the capacity of production, the actual production, etc. Then, in order to reach the targets O^*_t and I^*_t, firms decide on their production plans Q^*_t. This recursive behavior is compatible with the behavior we shall postulate later when we analyze the adjustments made by firms that face unanticipated demand shocks. Specifically, the adjustments through backlog of orders, inventory of finished products, and production will have the same recursive structure as the present one has.

The variables O^*_t and I^*_t are, however, not observed. We observe instead firm's appraisals of backlog of orders and inventory. We postulate the following behavior:

$$\begin{aligned} O^*_t &= O_t + f_1(\bar{O} - O_t) + f_2(D^*_t - D_t), \\ I^*_t &= I_t + g_1(\bar{I} - I_t) - g_2(D^*_t - D_t), \end{aligned} \tag{8}$$

where $\bar{O}$ and $\bar{I}$ are respectively the "optimal" levels of the backlog of orders and the inventory, and where f_1, f_2, g_1, g_2 are all positive constants. Equations (8) are standard partial adjustment equations to which we have added a term that depends on the expected change of demand $(D^*_t - D_t)$. This last term is introduced to take into account the effect of an expected change in demand on the classical partial adjustments of backlogs of orders and inventories. Indeed, the greater the expected increase in demand, the greater will be the planned backlog of orders O^*_t relative to the planned level given by a standard partial adjustment equation.

Equations (8) can also be given another interpretation. For instance, the first equation can be rewritten as:

$$O^*_t = O_t + f_2(D^*_t - D_t) - f_1(O_t - \bar{O}).$$

Hence firms increase their backlogs of orders in proportion to the

expected increases in demand. In addition, the larger the backlog of orders relative to the optimal level, the smaller the proportional increase.

Appraisal variables are related to stock variables by:

$$\begin{aligned} O^a_t &= O_t - \bar{O}, \\ I^a_t &= I_t - \bar{I}. \end{aligned} \tag{9}$$

Then, it follows from Equations (7) - (9), that :

$$Q^*_t = D^*_t + f_1 O^a_t - g_1 I^a_t - (f_2 + g_2)(D^*_t - D_t).$$

Using the identity (6) written at time t and the previous equation, we get for the planned change in production:

$$\begin{aligned} dQ^*_t = {} & (1 - f_2 - g_2)dD^*_t - O^a_{t-1} + (1 + f_1)O^a_t \\ & - (1 + g_1)I^a_t + I^a_{t-1} \end{aligned} \tag{10}$$

Since, in general, a firm does not plan to fully absorb the expected change in demand through its backlog of orders and its inventory, we have:

$$f_2 + g_2 < 1.$$

Thus, the expected signs of the effects of the explanatory variables on the planned change in production are as indicated under Model 3.

The appraisal I^a_{t-1} of inventory at time t − 1 was, however, suppressed since it turned out to be insignificant for all the 12 periods.

We also introduced the previous change in production dQ_t in order to take into account a possible smoothing of production plans. Given the inclusion of the above explanatory variables, the variable dQ_t was, however, insignificant for all the periods. Let us note that this latter result does not agree with a simple adaptive-expectations model or a simple extrapolative-expectations model of production. Indeed these simple models of expectations lead to distributions which are of the form $Pr(dQ^*_t | dQ_t, dQ^*_{t-1})$ or $Pr(dQ^*_t | dQ_t)$ (see H. König, G. Oudiz, and M. Nerlove (1981)).

2.4. Backlog of orders and inventory adjustments

Model 4: $Pr(O^a_{t+1}, I^a_{t+1} | dD_{t+1}, dD^*_t, O^a_t, I^a_t)$

$$\begin{array}{cccccc} & & + & ? & + & \\ & - & & & & \\ & & - & ? & & + \end{array}$$

(The first and second lines indicate the signs of the effect of the explanatory variables on O^a_{t+1} and I^a_{t+1} respectively.)

Given fixed prices, demand D_{t+1} materializes. When the realized demand D_{t+1} is equal to the expected demand D^*_t, the firm does not change its plans O^*_t and I^*_t concerning its backlog of orders and its inventory of finished products. However, when D_{t+1} substantially

differs from D^*_t, then we suppose that the firm first absorbs the discrepancy $(D_{t+1} - D^*_t)$ simultaneously through its backlog of orders and its inventory. Specifically, we assume that the adjustments are proportional to the surprise in demand. (As before, these adjustments may take into account possible production constraints, actual production, etc.) We have:

$$O_{t+1} = \begin{cases} O^*_t & \text{if } D_{t+1} = D^*_t \\ O^*_t + f_3(D_{t+1} - D^*_t) - f_4(O^*_t - \bar{O}) & \text{if } D_{t+1} \neq D^*_t \end{cases} \tag{11}$$

$$I_{t+1} = \begin{cases} I^*_t & \text{if } D_{t+1} = D^*_t \\ I^*_t - g_3(D_{t+1} - D^*_t) - g_4(I^*_t - \bar{I}) & \text{if } D_{t+1} \neq D^*_t \end{cases} \tag{12}$$

where f_3, f_4, g_3, and g_4 are all positive constants. The terms $f_4(O^*_t - \bar{O})$ and $g_4(I^*_t - \bar{I})$ are included in (11) − (12) for the same reasons as in Equation (8). We have not imposed the constraints:

$$f_2 = f_3 \ , \ f_1 = f_4 \ , \ f_2 = f_3 \ , g_1 = g_4 \ ,$$

so that we can take into account possible differences in ex ante and ex post adjustment costs.

From Equations (8) − (12), it follows that:

$$O^a_{t+1} = \begin{cases} (1-f_1)O^a_t + f_2 dD^*_t & \text{if } D_{t+1} = D^*_t \\ (1-f_4)(1-f_1)O^a_t + [(1-f_4)f_2 - f_3]dD^*_t + f_3 dD_{t+1} & \text{if } D_{t+1} \neq D^*_t \end{cases} \tag{13}$$

$$I^a_{t+1} = \begin{cases} (1-g_1)I^a_t - g_2 dD^*_t & \text{if } D_{t+1} = D^*_t \\ (1-g_4)(1-g_1)I^a_t - [(1-g_4)g_2 - g_3]dD^*_t - g_3 dD_{t+1} & \text{if } D_{t+1} \neq D^*_t \end{cases} \tag{14}$$

Thus the signs of the effects of the explanatory variables on the appraisals O^a_{t+1} and I^a_{t+1} are those indicated under Model 4. Let us note that the signs of the effects of the expected change in demand on both appraisals are ambiguous for firms that have not correctly anticipated the change in demand.[3] Let us also note that appraisals of inventory at time t do not affect appraisals of backlog at time t + 1. Similarly, appraisals of backlog at time t do not affect appraisals of inventory at time t + 1.

Since we assume that firms simultaneously determine their backlogs of orders and inventory held at time t + 1, Model 4 has two dependent variables. Moreover, since firms adjust their backlogs of orders and their inventories in opposite directions, we may expect a residual association between the two dependent variables that is negative, even after having taken into account the dependencies on the aforementioned explanatory variables.

2.5. Production adjustment

Model 5: $\Pr(dQ_{t+1} | \overset{+}{dQ^*_t}, \overset{+}{dD_{t+1}}, \overset{-}{dD^*_t}, \overset{+}{O^a_{t+1}}, \overset{-}{I^a_{t+1}})$

From the identity (6) and Equation (7), we get:

$$Q_{t+1} - Q^*_t = (D_{t+1} - D^*_t) - (O_{t+1} - O^*_t) + (I_{t+1} - I^*_t). \tag{15}$$

Equation (15) clearly shows that the excess or shortage in demand (relative to the expected demand), that subsists after backlog and inventory adjustments must be absorbed by a change in production relative to production plans. Thus, from the expectation equations (11) - (12) it follows that:

$$dQ_{t+1} = dQ^*_t + dD_{t+1} - (1 - f_2 - g_2)dD^*_t - O^a_{t+1} + (1 - f_1)O^a_t + I^a_{t+1} - (1 - g_1)I^a_t . \tag{16}$$

The estimation of Equation (16), is, however, difficult. Indeed, the strong association between O^a_{t+1} and O^a_t, or between I^a_{t+1} and I^a_t raises the problem of identifying the separate effects of these variables.[4] We have thus used Equations (11) - (12) which give for the backlog and inventory adjustments, when $D_{t+1} \neq D^*_t$:

$$O_{t+1} - O^*_t = \frac{f_3}{1 - f_4}(D_{t+1} - D^*_t) - \frac{f_4}{1 - f_4}(O_{t+1} - \bar{O}), \tag{17}$$

$$I_{t+1} - I^*_t = -\frac{g_3}{1 - g_4}(D_{t+1} - D^*_t) - \frac{g_4}{1 - g_4}(I_{t+1} - \bar{I}). \tag{18}$$

Then, from Equation (15), we get:

$$Q_{t+1} - Q^*_t = (1 - \frac{f_3}{1 - f_4} - \frac{g_4}{1 - g_4})(D_{t+1} - D^*_t)$$

$$+ \frac{f_4}{1 - f_4} O^a_{t+1} - \frac{g_4}{1 - g_4} I^a_{t+1} ,$$

or equivalently,

$$dQ_{t+1} = dQ^*_t + \left(1 - \frac{f_3}{1 - f_4} - \frac{g_3}{1 - g_4}\right) dD_{t+1}$$

$$-\left(1 - \frac{f_3}{1-f_4} - \frac{g_3}{1 - g_4}\right) dD^*_t$$

$$+ \frac{f_4}{1 - f_4} O^a_{t+1} - \frac{g_4}{1 - g_4} I^a_{t+1} . \tag{19}$$

In general, we have:

$$\frac{f_3}{1 - f_4} + \frac{g_3}{1 - g_4} < 1 .$$

(See equations (17) - (18).) Hence the expected signs of the explanatory variables on dQ_{t+1} are those indicated under Model 5. These signs can be understood as follows: given the same unanticipated demand surplus $D_{t+1} - D^*_t$, in order not to deviate further from the optimal levels $\overline{O}$ and $\overline{I}$, firms that find themselves at time t + 1 with backlogs of orders above normal and inventories below normal are more likely to increase their productions relative to their planned productions than firms that have backlog of orders below normal and inventories above normal at time t+1.

Table 3 summarizes the five equations of the recursive system. An "x" denotes the dependent variable(s). The expected signs of the effects of the explanatory variables on the dependent variable(s) are also indicated in the table.

3. Estimation, results, and discussion

3.1. Estimation and results

The fixed-price model is recursive. Thus the log-likelihood function for the whole system is simply the sum of the (conditional) log-likelihood functions associated with the six models composing the recursive system. It follows that the maximum-likelihood estimates of the parameters can be obtained by estimating each of the six CLLP models separately by the maximum-likelihood method.

TABLE 3: Endogenous and Predetermined Variables of the Fixed-Price Model

		Price Adjustment	Expected Demand	Planned Production	Backlog and Inventory Adjustments		Production Adjustment
Endogenous Variables	dQ_{t+1}						×
	I^a_{t+1}					×	-
	O^a_{t+1}				×		+
	dQ^*_t			×			+
	dD^*_t		×	+	?	?	-
	dP_t	×	-				
Predetermined Variables	I^a_t			-		+	
	O^a_t	+		+	+		
	O^a_{t-1}			-			
	dD_{t+1}				+	-	+
	dD_t		+				
	dP_{t-1}	?					
	dP_{t-3}	+					
	dPG^*_t		+				
	dPG^*_{t-1}	+					
	dQG^*_t		+				

For any conditional log-linear probability model of the recursive system, we consider a model space of the ANOVA form (see, e.g. M. Nerlove and S. J. Press (1970), and for a general definition, see B. Ottenwaelter and Q. H. Vuong (1981), Q. H. Vuong (1982)). Furthermore, we exclude all trivariate and higher-order interaction effects from any of the models. Thus the included configurations in the r-th model correspond to the main effect and the bivariate effects that involve the dependent variable and one of the included explanatory variables of the r-th model. For the fourth model which has two dependent variables, we include in addition the bivariate configuration (O^a_{t+1}, I^a_{t+1}) which represents the residual association between the two endogenous variables after taking into account the dependencies on the explanatory variables.

To complete the specification of the models, it now suffices to precise which parameters are estimated in any included bivariate interaction. When the variables are trichotomous, (which is always the case here, except for the dichotomous variable dPG^*_t), the number of independent parameters that characterize a bivariate interaction is $(3-1)^2$, i.e. 4. For instance, of the nine ANOVA parameters that are associated with a bivariate interaction between trichotomous variables, only four are independent due to the usual ANOVA constraints.[5] However, because of the ordinal nature of our qualitative variables, we shall use instead the score parameterization (see L. A. Goodman (1979), S. J. Haberman (1974b), Q. H. Vuong (1982)). This latter parameterization allows us in particular to assess the direction of the effects of the explanatory variables on the endogenous variables (see Appendix).

Finally in order to reduce the number of estimated parameters the following procedure is used. We first estimated CLLP models with included configurations that are all complete, i.e. CLLP models in which none of the independent parameters of an included configuration (main effect, or bivariate effect) are a priori equal to zero. Then we restricted each included bivariate interaction effect to the so-called linear-by-linear parameter α_{11} whenever the other three score parameters of the interaction were statistically insignificant. Otherwise, the complete configuration was retained in the model. (Only the final set of estimates is presented in the following tables.)

However, conditional L.L.P. models with complete configurations were sometimes not identified or not estimable. This occurred in models containing a configuration involving two highly correlated variables. Indeed, the marginal table corresponding to these two variables often had an empty cell so that one could not identify all the parameters of the configuration, or the M.L. estimate of the model did not exist. When this happened, we started from a model in which the corresponding interaction was reduced to the linear-by-linear parameter and the quadratic-by-quadratic parameter.[6]

All the models were estimated with the program CALM written by J.P.Link (1980). This program permits the maximum-likelihood estimation of joint or conditional L.L.P. models defined by model

spaces of the ANOVA type on complete or incomplete tables.

The results are given in the following tables, one for each model. Each table presents the estimates of the linear-by-linear effect paramater for all the periods for which the model could be estimated. Under each of the explanatory variables, we indicate by a "(c)" that the configuration involving that explanatory variable and the dependent variable is complete. In addition, an asterisk for a given period indicates that there was an empty cell in the marginal table corresponding to that explanatory variable and the dependent variable. As discussed in the previous paragraph, we thus restricted the corresponding bivariate configuration to the linear-by-linear parameter and the quadratic-by-quadratic parameter.

For each interaction, we give the estimate of the linear-by-linear effect parameter α_{11}, which indicates the direction of the association, and its t-statistic in parentheses. We also give for each model and each period, the number of observations N, the number of degrees of freedom df against the saturated model, and the likelihood-ratio statistic of the model vs. the saturated model LR with its corresponding upper-tail chi-square probability.

TABLE 4: Estimates of α_{11} for the Price-Adjustment Model

dP_t given: Periods	dO^a_t +	dP_{t-1} ? (C)	dP_{t-3} + (C)	dPG^*_{t-1} +	N	df	LR (upper-tail)
6-75	.304 (2.87)	-.114 (-1.16)	.216 (2.24)	.236 (3.29)	586	88	106 (.09)
11-75	.180 (1.83)	.361 (3.57)	.252 (3.12)	.216 (3.21)	544	78	73 (.64)
3-76	.060 (.82)	.168 (2.20)	.165 (2.61)	.151 (2.89)	637	94	115 (.07)
6-76	.103 (1.31)	.138 (2.08)	.386 (4.44)	.215 (3.62)	620	92	113 (.07)
11-76	.033 (.50)	.177 (3.02)	.126 (1.80)	.115 (2.13)	648	90	115 (.04)
3-77	.277 (2.88)	.058 (.89)	.117 (1.60)	.149 (2.60)	593	92	111 (.09)
6-77	.049 (.49)	-.010 (-.09)	.167 (1.58)	.127 (1.81)	555	90	109 (.08)
11-77	.324 (3.10)	-.029 (.21)	.188 (2.09)	.114 (1.64)	576	86	98 (.18)
3-78	.023 (.27)	.226 (2.40)	.346 (4.91)	.228 (4.01)	659	92	78 (.82)
6-78	-.073 (-.86)	-.142 (1.53)	.119 (1.08)	.105 (1.61)	644	76	90 (.13)

TABLE 5: Estimates of α_{11} for the Expected-Demand Model

dD^*_t given: Periods	dD_t + (C)	dP_t -	dQG^*_t + (C)	dPG^*_t +	N	df	LR (Upper-tail)
6-74	.638 (6.76)	-.111 (-1.61)	.587 (6.21)	.580 (.54)	972	84	85 (.46)
11-74	.703 (7.56)	.059 (.86)	.611 (4.35)	.298 (4.54)	929	90	91 (.45)
3-75	.493 (6.47)	-.062 (-1.02)	.784 (6.05)	-.024 (-.46)	1158	94	112 (.10)
6-75	.534 (6.40)	.123 (1.88)	.792 (7.10)	-.0002 (.005)	1202	92	117 (.04)
11-75	.288 (4.13)	-.004 (-.07)	.893 (8.77)	.070 (1.48)	1257	96	117 (.08)
3-76	.125 (1.93)	.022 (.35)	.834 (7.39)	.096 (1.86)	1185	90	116 (.03)
6-76	.400 (5.61)	.025 (.36)	.696 (4.89)	-.026 (-.47)	1126	88	98 (.22)
11-76	.386 (4.93)	-.007 (-.12)	.879 (6.86)	.030 (.58)	1156	94	94 (.48)
3-77	.280 (3.98)	.071 (1.06)	1.002 (8.55)	.001 (.02)	1196	96	108 (.18)
6-77	.411 (5.70)	.065 (.83)	.703 (6.91)	.044 (.89)	1189	90	97 (.28)
11-77	.350 (5.14)	.097 (1.31)	.810 (8.05)	.102 (1.95)	1377	92	104 (.18)
3-78	.145 (2.03)	-.087 (1.32)	.881 (9.69)	.096 (1.86)	1269	96	146 (.00)
6-78	.255 (3.70)	.112 (1.58)	.756 (7.91)	.053 (.93)	1279	94	84 (.77)

TABLE 6: Estimates of α_{11} for the Expected-Production Model

dQ^*_t given: Periods	dD^*_t + (C)	O^a_{t+1} −	O^a_t +	I^a_t −	N	df	LR (upper-tail)
11-74	.969 (4.73)	-.149 (-.99)	1.057 (5.92)	-.208 (-1.13)	506	107	117 (.24)
3-75	1.786 (5.89)	-.059 (-.33)	1.006 (4.58)	-.384 (-1.90)	624	97	84 (.82)
6-75	1.325 (7.07)	-.125 (-.65)	1.268 (5.35)	-.363 (-2.03)	500	109	105 (.61)
11-75	1.467 (7.78)	.188 (1.02)	.517 (2.73)	-.246 (-1.54	532	103	94 (.72)
3-76	1.713 (5.98)	-.473 (2.67)	1.135 (6.29)	-.238 (-1.31)	550	107	87 (.92)
6-76	1.871 (6.20)	-.329 (1.77)	.772 (4.09)	-.392 (-1.97)	533	115	85 (.98)
11-76	1.839* (5.97)	.263 (1.56)	.746 (3.74)	.014 (.07)	536	115	102 (.79)
3-77	1.714* (5.74)	-.003 (.14)	.532 (2.64)	-.711 (-3.45)	465	109	110 (.47)
6-77	1.557 (7.09)	-.405 (2.47)	1.154 (6.27)	-.483 (-2.77)	588	117	114 (.56)
11-77	1.404 (6.33)	-.064 (.46)	.977 (5.38)	-.231 (-1.34)	576	111	134 (.07)
3-78	2.227* (6.17)	.237 (1.50)	.719 (4.04)	-.119 (-.65)	634	125	127 (.44)
6-78	1.741 (6.11)	.131 (.74)	.714 (4.02)	-.119 (-.68)	666	105	98 (.68)

TABLE 7: Estimates of α_{11} for the Backlog and Inventory Adjustment Model

Periods		(I^a_{t+1}, O^a_{t+1}) −	dD_{t+1} + −	dD^*_t ? ?	O^a_t +	I^a_t + (C)	N	df	LR
11-74	O^a_{t+1}	-1.080 (-6.44)	.810 (5.17)	.267 (1.73)	.902 (3.39)		467	457	327
	I^a_{t+1}		-.521 (-3.17)	.185 (1.20)		.760 (3.68)			
3-75	O^a_{t+1}	-.804 (-3.92)	.992 (4.86)	.162 (.84)	.565 (3.37)		388	406	250
	I^a_{t+1}		-.652 (-2.89)	.144 (.56)		1.109* (4.47)			
6-75	O^a_{t+1}	-.889 (-4.34)	.571 (3.03)	.062 (.32)	.924 (4.52)		431	388	247
	I^a_{t+1}		-.392 (-2.11)	-.007 (-.04)		1.217 (3.67)			
11-75	O^a_{t+1}	-.978 (-5.58)	1.130 (4.98)	-.111 (-.65)	1.120 (5.18)		444	420	261
	I^a_{t+1}		-.125 (-.84)	-.190 (-1.24)		1.167 (4.13)			
3-76	O^a_{t+1}	-.747 (-4.57)	.882 (5.04)	-.082 (-.60)	1.052 (4.73)		463	446	297
	I^a_{t+1}		-.609 (-3.88)	-.033 (-.21)		1.603 (5.92)			
6-76	O^a_{t+1}	-.564 (-3.85)	.837 (4.93)	.216 (1.47)	1.174 (6.65)		458	468	309
	I^a_{t+1}		-.424 (2.84)	-.040 (-.23)		.973 (5.43)			

TABLE 7: (Continued)

Periods		(I^a_{t+1}, O^a_{t+1}) −	dD_{t+1} + −	dD^*_t ? ?	O^a_t +	I^a_t + (C)	N	df	LR
11-76	O^a_{t+1}	-.893 (-5.30)	1.344 (4.94)	-.122 (-.75)	1.230 (6.48)		469	508	311
	I^a_{t+1}		-.289 (-1.83)	.039 (.25)		1.236 (4.31)			
3-77	O^a_{t+1}	-.918 (-4.66)	1.145 (5.31)	.181 (.95)	1.203 (5.36)		408	500	318
	I^a_{t+1}		-.241 (-1.36)	.173 (.92)		1.096 (3.89)			
6-77	O^a_{t+1}	-.594 (3.72)	1.288 (7.21)	.165 (1.02)	1.271 (7.38)		514	492	331
	I^a_{t+1}		-.551 (-3.26)	.281 (1.64)		1.515 (5.68)			
11-77	O^a_{t+1}	-.878 (-5.04)	1.058 (5.83)	.205 (1.31)	.859 (6.03)		524	492	317
	I^a_{t+1}		-.351 (-2.22)	-.007 (-.04)		.935 (4.73)			
3-78	O^a_{t+1}	-.887 (-5.62)	1.054 (5.87)	-.003 (-.02)	.736 (5.46)		589	484	320
	I^a_{t+1}		-.344 (-2.26)	-.012 (-.07)		.970 (5.42)			
6-78	O^a_{t+1}	-.347 (-2.26)	.994 (5.71)	.026 (.18)	1.558 (6.82)		580	454	263
	I^a_{t+1}		-.430 (2.82)	.083 (.52)		1.736* (4.77)			

TABLE 8: Fstimates of α_{11} for the Production-Adjustment Model

dQ_{t+1} given: Periods	dQ^*_t	dD_{t+1}	dD^*_t	O^a_{t+1}	I^a_{t+1}	N	df	LR (upper-tail)
11-74	.586 (2.42)	1.134 (4.15)	-.0004 (-.003)	.414 (2.56)	-.392 (-2.39)	517	187	185 (.53)
3-75	1.101 (4.73)	.878 (3.58)	-.506 (-2.26)	.826 (3.85)	-.015 (-.08)	420	147	126 (.89)
6-75	.563 (2.88)	1.138 (6.21)	-.418 (-2.43)	.710 (3.81)	-.143 (-.89)	523	177	173 (.58)
11-75	.980 (4.71)	1.128 (6.62	-.531 (-2.98)	.596 (3.46)	-.331 (-2.05)	551	203	172 (.94)
3-76	.768 (4.04)	1.347 (6.60)	-.186 (-1.13)	.226 (1.49)	-.643 (-3.92)	567	223	205 (.81)
6-76	1.478 (5.22)	1.218 (7.47)	-.359 (-1.89)	.212 (1.44)	-.479 (-2.72)	516	203	162 (.98)
11-76	.663 (2.85)	1.556 (6.63)	-.118 (-.59)	.014 (.09)	-.496 (-2.86)	542	189	166 (.88)
3-77	1.040 (3.97)	1.575 (8.51)	-.076 (-.35)	.490 (2.62)	-.327 (-1.75)	467	198	168 (.94)
6-77	.829 (4.31)	1.026 (5.78)	-.435 (2.54)	.590 (3.78)	-.186 (-1.18)	590	217	190 (.91)
11-77	.670 (3.77)	1.409 (5.19)	-.308 (-1.72)	.415 (2.52)	-.251 (-1.58)	578	191	172 (.84)
3-78	.904 (5.21)	1.032 (6.68)	-.173 (-1.11)	.382 (2.63)	.047 (.32)	661	236	243 (.32)
6-78	.576 (3.44)	1.017 (8.06)	-.349 (-2.22)	.139 (1.10)	-.285 (-1.92)	661	217	197 (.83)

3.2. Discussion

We now discuss the empirical results reported in the preceding tables.

a. Price-adjustment model

The sign of the effect of the variable dPG^*_{t-1} (which is used as a proxy variable for the effective variation of the general price level as perceived by each firm) on the price variation charged by each firm is expected to be positive. Empirically, we find that the corresponding parameter estimates have the correct sign for all ten periods, and is significant at the .10 significance level for eight periods. Hence, this supports the idea that firms adjust their prices to the perceived general price trend.

Although the period June 1975-June 1978 is characterized by a steady inflation, about 40% of the firms report in each survey that their prices remain stable. This can, however, be explained by the existence of two types of firms. Indeed, as mentioned earlier, some firms gradually increase their prices, while others adjust their prices only annually. Given the definition of the categories of the trichotomous variable dP_t (substantial increase, moderate increase, stability), we must have, for the second type of firms, the following yearly pattern of answers: stability, stability, substantial increase. Hence, about two thirds of those firms may answer "stability". In addition, this pattern leads to an expected positive association between dP_{t-3} and dP_t. Table 4 shows that the corresponding parameter

estimate is positive for all ten periods and is significant at the .10 level for seven of them.

The sign of the effect of the previous period change dP_{t-1} on the current price change dP_{t-1} is ambiguous. Indeed, the parameter estimates show six positive signs and four negative signs. However, the effect of dP_{t-1} on dP_t seems to be more likely positive since the parameter estimates that are significant at the .10 level are all positive.

The firm's appraisal of order backlog is indicative of the type of disequilibrium that the firm is experiencing at time t. The sign of the effect of that variable on the current price change is expected to be positive. The parameter estimates are positive for all the periods but one. In addition, these estimates have the correct sign whenever they are significant at the .10 level.

To summarize, the parameter estimates of Model 1 have the correct signs, especially when they are significant. However, the upper-tail probability of the likelihood-ratio statistic shows that, as a whole, Model 1 adjusts the data for only four out of ten periods at the .10 significance level (although the model fit the data for nine periods at the .05 level). This might be due to a misspecification of the price-adjustment model, possibly due to the omission of relevant explanatory variables or the misspecification of the dependencies which are here restricted to the bivariate interaction effects. A possible improvement of the fit might, however, result from distinguishing the two types of firms mentioned above.

b. Expected-demand model

The parameter estimates associated with past demand variations dD_t and expected general production trends dQG^*_t are all significant (at the .10 level) and positive, as expected, for the thirteen periods for which the model was estimated. Hence, expectations of demand change dD^*_t are clearly positively associated with past demand variations and expected general production trends. In addition, since the parameter estimates associated with dD_t are smaller than the parameter estimates associated with dQG^*_t (except for the first two periods), we can conclude that expected demand is less sensitive to past demand changes than to expected general production trends (which are used here as proxies to expected changes in aggregate demand).

Although the effect of individual price changes dP_t on expected demand variations dD^*_t should be negative, the parameter estimates are negative only for five out of thirteen periods. In addition all the thirteen parameter estimates are insignificant at the .10 level. Thus expected (received) demand does not seem to depend on the price that prevails during the period (t, t + 1).

The expected general price trend dPG^*_t gives, however, better results than the individual price change. Indeed, the four parameter estimates that are significant at the .10 level are all positive, as expected. Only three parameter estimates are negative (but they are all insignificant).

To summarize, expected demand depends positively on expected general production, on past individual demand, and somewhat on expected general price. On the other hand, individual price does not affect firm's expected demand. This latter result is probably due to the two types of price behavior mentioned earlier. Finally, Model 2 fits the data better than Model 1 does. Indeed, at the .10 level, we cannot reject Model 2 for nine out of thirteen periods.

c. Expected-production model

Using the same data set, H. König, M. Nerlove, and G. Oudiz (1979) estimated the conditional probability distributions $Pr(dQ^*_t | O^a_t, dD^*_t, dD_t)$ and $Pr(dQ^*_t | I^a_t, dD^*_t, dD_t)$, for firms without and with inventories.[7] They found that expected changes in production depended positively on appraisals of backlog, expected changes in demand, and past changes in demand for firms without inventories. For firms with inventories, the signs of the dependencies were the same with the exception that expected changes in production depended negatively on appraisal of inventories.

Our expected production model does not include the past demand change as an explanatory variable. On the other hand, the lagged appraisal of order backlogs is introduced. In addition, we consider only firms with inventories since both appraisals of backlogs and inventories are used.

Expectations of demand changes and appraisals of current order backlogs have positive and significant effects on expected or planned changes in production for all twelve periods. The parameter estimates associated with the other two explanatory variables, which are lagged appraisals of order backlogs and appraisals of current inventory levels, are neither always significant at the .10 level nor always negative. However, on the whole, the signs of these two effects are those expected, i.e., both negative, since the parameter estimates associated with O^a_{t-1} and I^a_t are negative respectively for eight and eleven periods out of twelve estimated periods. Moreover, whenever the parameter estimates are significant at the .10 level, they are negative.

H. König, M. Nerlove, and G.Oudiz (1979) found that expectations of future demand were the most relevant in explaining production plans. Our empirical results agree with theirs since the parameter estimate associated with dD^*_t is the largest in absolute value. Moreover, since the parameter estimate associated with O^a_t is always larger, in absolute value, than the parameter estimate associated with I^a_t, we can also say that, given expectations of future demand, firm's production plans are more sensitive to levels of order backlogs than to levels of inventories. Finally, Model 3 fits the data quite well since it cannot be rejected at the .10 level for eleven out of twelve periods.

d. Order backlog and inventory adjustment model

Model 4 is estimated without distinguishing firms that experience a surprise in demand ($dD_{t+1} \neq dD^*_t$) from firms that do not

($dD_{t+1} = dD^*_t$). Given levels of order backlog and inventory at time t, an increase in demand during period (t, t + 1) relative to the previous expected demand tends to increase the level of order backlogs, and to decrease the level of inventory held at time t + 1. This is quite supported by the results of Table 7. Indeed, the signs of the effects of dD_{t+1} on O^a_{t+1} and I^a_{t+1} are respectively positive and negative for all twelve periods. In addition, the parameter estimates associated with the effect of dD_{t+1} on O^a_{t+1} are all significant at the .10 level, while the parameter estimates associated with the effect of dD_{t+1} on I^a_{t+1} are significant for ten out of twelve periods. Moreover, in all twelve periods, the estimate of α_{11} for the effect of dD_{t+1} on O^a_{t+1} is greater than the estimate of α_{11} for the effect of dD_{t+1} on I^a_{t+1}. This suggests that an unanticipated change in demand leads to an adjustment of the level of order backlogs and to a simultaneous opposite but weaker adjustment of the inventory level.

The parameter estimates associated with the effect of dD^*_t on O^a_{t+1} or I^a_{t+1} are all insignificant at the .10 level (with the exception of November 1974 for O^a_{t+1}). Moreover the estimates do not have the same sign for either one of the dependent variables. The signs of the effects of demand expectations on the levels of order backlogs and inventories held at time t + 1 are therefore ambiguous, as expected.

Appraisals of order backlogs and inventories respectively depend significantly and positively on the corresponding lagged appraisals for all twelve periods. Hence firms that have at time t backlog levels above normal and inventory levels below normal will still have at time t + 1 backlog levels above normal and inventory levels below normal. This supports the hypothesis that firms do not fully adjust, in one period, their order backlogs and inventories to the normal levels.

Finally, the fit of Model 4 is quite good since the twelve upper-tail probabilities are all very close to one.

e. Production-adjustment model

In order to test the hypothesis that expectations of production changes dQ^*_t have more informational content in explaining dQ_{t+1} than the variables included in the model for dQ^*_t, H. König, M. Nerlove, and G. Oudiz (1979) considered a model for $Pr(dQ_{t+1}|dQ^*_t, dD_t, dD^*_t, O^a_t)$ or $Pr(dQ_{t+1}|dQ^*_t, dD_t, dD^*_t, I^a_t)$, depending on whether or not firms have inventories.[8] Our Model 5 is similar, although it has dD_{t+1}, O^a_{t+1}, and I^a_{t+1} instead of dD_t, O^a_t, and I^a_t. However, the purpose and the interpretation of Model 5 is quite different.

In our model, the planned change in production is used as a reference. Thus, given the other explanatory variables of the model, a planned increase in production leads to an actual increase in production. Hence the effect of dQ^*_t on dQ_{t+1} is positive. This is supported by the corresponding parameter estimate which is positive and significant for all twelve periods.

Moreover, according to our model, firms adjust their production relative to their planned production after having adjusted

their order backlogs and inventories. Thus, given dQ^*_t, O^a_{t+1}, and I^a_{t+1}, the actual change in production is positively related to dD_{t+1} and negatively to dD^*_t. The empirical results shown in Table 8 agree with this: all the parameter estimates associated with dD_{t+1} are positive and significant at the .10 level, while all the parameter estimates associated with dD^*_t are negative (seven out of the twelve estimates being significant). It is also interesting to note that the estimate of the coefficient of dD_{t+1} in the production-adjustment model is (i) greater in absolute value than the estimate of the coefficient of dD_{t+1} in the Inventory-adjustment model for all twelve periods, and (ii) in general greater than the estimate of the coefficient of dD_{t+1} in the Backlog-adjustment model. Thus production seems more responsive to unanticipated demand shocks than inventories and even backlogs. (Recall, however, that surveys are taken about every four months.)

Given the other explanatory variables of Model 5, the appraisal of order backlog and the appraisal of inventories have respectively a positive-effect and a negative effect on the actual production change (see Section 2.5). All the twelve parameter estimates associated with O^a_{t+1} have the correct sign, while only one parameter estimate associated with I^a_{t+1} has the wrong sign (but it is insignificant at the .10 level). It is also worth noting that in any period at least one of the two parameter estimates is significant. Moreover, when the parameter estimate associated with O^a_{t+1} is significant at the .10 level, then the parameter estimate associated with I^a_{t+1} is often not significant, and vice-versa. Specifically, the periods for which only the parameter estimate associated with O^a_{t+1} is significant at the .10 level are March 1975-June 1975, June 1977-March 1978, while the periods for which only the parameter estimate associated with I^a_{t+1} is significant at the .10 level are March 1976-November 1976 and June 1978. Furthermore, these latter periods correspond to periods in which the inventory levels are above normal, while the former periods correspond to periods in which order backlogs are above normal. Hence, this suggests that the coefficients of the two appraisal variables depend on some economy-wide conditions: when the economy is expanding production adjustments are more sensitive to backlog levels than to inventory levels, while when the economy is slowing down, they are more sensitive to inventory levels than to backlog levels.

Finally, Model 5 fits the data quite well, since the model cannot be rejected at the .10 level for any of twelve periods.

4. Conclusion

On the methodological ground, our paper has shown that the CLLP model is a convenient tool for the analysis of qualitative variables. This model is analogous to the usual linear model for continuous variables. In particular, a distinction is made between endogenous and exogenous variables, and a single parameter is used to give the direction and strength of the effect of an explanatory variable on an endogenous variable. Moreover, the CLLP model allows

us to introduce recursive structures that are similar to those formulated in standard econometrics, and hence to extend the log-linear approach from a joint analysis to a structural analysis.

On the empirical ground, our study has shown that our model is validated by the data. A majority of parameter estimates have the correct signs and are significant. The results of the present paper demonstrate, first, that a fixed-price model with partial adjustments of order backlogs and inventories is consistent with our micro data. Second, production plans are shown to be strongly positively related to expected demand, and appraisals of order backlogs, and negatively to appraisals of inventories. Finally, while prices do not instantaneously adjust, production, order backlogs, and inventories all adjust to contemporaneous unanticipated demand shocks.

APPENDIX

As a simple illustration, suppose that there are only one dependent ordinal variable B. Let i and j be the indices associated with the categories of A and B, where i=1,...,I, and j=1,...,J. For any i=1,...,I-1, and any j = 1,...,J-1, let R_{ij} be the following log odd-ratio:

$$R_{ij} = \log \left[\frac{p(i+1|j+1)}{p(i|j+1)} : \frac{p(i+1|j)}{p(i|j)}\right]$$

$$= \log \frac{p(i+1|j+1)}{p(i|j+1)} - \log \frac{p(i+1|j)}{p(i|j)}$$

where $p(i|j)$ denotes the conditional probability that A is equal to i given that B is equal to j. The second equation shows that R_{ij} is also the variation in adjacent log odds at levels i and j.

In the trichotomous case, i.e., I = J = 3, the four score parameters α_{11}, α_{12}, α_{21}, α_{22} that characterize the bivariate interaction have a particularly appealing interpretation in terms of the log odd-ratios. Indeed it can be shown that:

$$\alpha_{11} = R_{..} \quad ; \quad \alpha_{12} = \frac{1}{\sqrt{3}}(R_{.2} - R_{..})$$

$$\alpha_{21} = \frac{1}{\sqrt{3}}(R_{2.} - R_{..}) \quad ; \quad \alpha_{22} = \frac{1}{3}(R_{22} - R_{2.} - R_{.2} + R_{..})$$

where $R_{..}$ is the overall mean of the R_{ij}'s, $R_{2.}$ is the mean for fixed i = 2, etc... (The coefficients $1/\sqrt{3}$ and 1/3 in the above formulae

result from the normalization adopted in Q. H. Vuong (1982).)

Thus α_{11}, which is called the linear-by-linear parameter, measures the average increase in adjacent log odds, and its sign therefore indicates the (average) direction of the effect of B on A. Moreover, since

$$R_{ij} = R_{..} + (R_{i.} - R_{..}) + (R_{.j} - R_{..}) + (R_{ij} - R_{i.} - R_{.j} + R_{..})$$

It follows that the other socre parameters of the interaction provide information on the discrepancies between the various increases in adjacent log odds and the average increase $R_{..}$. It is important to note that this interpretation of the score parameters does not require that some scale values or scores be given to the categories of each ordinal variable. In other words, one need not assume the existence of some underlying continuous variables.

When there are more than one explanatory variable, one can repeat the previous decomposition of the effect of B on A for any given value of the explanatory variables. Alternatively, one can interpret each of the score parameters that characterize the (bivariate) effect of B on A as the mean of the corresponding parameter over all possible values of the explanatory variables. However, since we restrict ourselves to CLLP models that exclude trivariate and higher order interaction effects, the conditional log odd-ratios R_{ij}, and hence the four score parameters of the effect of B on A do not depend on the value taken on by the remaining explanatory variables.

FOOTNOTES

1. This paper relies heavily on the empirical results reported in B. Ottenwaelter and Q. Vuong (1981). Research for this paper was supported by CNRS under ERA 199. We are grateful to D. Grether, J. Link, G. Oudiz, and M. Nerlove for helpful discussions.

2. We use the general production level QG_t as a proxy for the aggregate demand received by the industry.

3. For each period, we could have divided the sample into two subsamples according to whether or not dD_{t+1} was equal to dD^*_t. We have, however, preferred to use the whole sample, and to suppose that $D_{t+1} \neq D^*_t$ for all firms even when the qualitative variables dD_{t+1} and dD^*_t had the same categorical value.

4. Moreover the number of explanatory variables in Equation (16) creates a problem of memory space for the FORTRAN program we are using. This is so because our program starts from the complete contingency table which has in this case 3^8 cells. Note also that the CLLP model that corresponds to (16) and that only includes the main and bivariate interaction effects already has 30 independent parameters: two for the main effect and four for each of the seven bivariate interaction effects.

5. These ANOVA parameters are also called "deviation-contrast" parameters (see S. Kawasaki (1979), H. König, M. Nerlove, and G. Oudiz (1979), (1982)).

6. When there is a strong positive association between two trichotomous variables, the first diagonal of the corresponding marginal table has many observations. As a consequence, the score parameters α_{11} and α_{22} are significantly positive.

7. As mentioned earlier, estimated conditional probability distributions were derived from estimated joint probability distributions. In Q. H. Vuong (1982), however, we point out that joint estimation and conditional estimation are not always equivalent. This is in fact the case for the models considered in the König-Nerlove-Oudiz paper.

8. See Footnote 7.

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