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Marc Ivaldi

A Structural Analysis of Expectation Formation

Based on Business Surveys of French Manufacturing Industry

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To Anne-Marie

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INTRODUCTION

> "The method of modern economic investigation is the same as the method of all science. Economics studies facts, and seeks to arrange the facts in such ways as make it possible to draw conclusions from them . . .
>
> "Where does the economist get his facts from?"
>
> Sir John R. Hicks [1942]

1. Economic Issues and Business Surveys

Economists have long recognized that describing the economic state today and forecasting its evolution tomorrow are achieved by modelling the formation of expectations. Doing so, they take into account a natural and permanent activity of the human being: At each instant, each decision requires a prediction.

Let me recall briefly the usual arguments that justify a study devoted to the formation of expectations. In the Arrow-Debreu world, assuming that neither moral hazard nor adverse selection can exist, all individual plans are made compatible in all markets at once (i.e., at each date in all contingencies), and moreover, the resulting equilibrium allocation is a Pareto optimum. This abstract construction sheds light on the complexity that economists face when they cope with time and uncertainty, and also on the salient features that a scheme of expectation should satisfy in order to put such a world in concrete form.

In reality, the economic structure is incomplete and puzzling: Nothing guarantees that agents will share the same perceptions on the continuum of states; agents may also find it difficult to reduce the uncertainty due to the future expectations of other agents. Economists have addressed these questions in various ways from either a theoretical or an empirical point of view. In order to deal with the departures from the abstract model, one response for modeling individual behavior in face of uncertainty is to postulate rational expectations.

In an economy with uncertainty but with complete markets, this assumption means that people expect what actually happens so that the solution is identical to that of an Arrow-Debreu world. In such an economy where there is no reason for the agents to make systematic errors, such an expectation formation model allows us to say that assuming rational expectations is perhaps the answer to the search, as defined by J. Hicks [1977], for a model where expectations do not appear as "autonomous influences that come in from outside, (but) as elements that are molded in the course of the process that is being analyzed."

The usual justification of this hypothesis is that the behavior of expectation should be consistent with the foundations of economic theory. Specifically, since it is costly to acquire information about the future, agents may have incentives to behave rationally when making predictions as the expected reward could be large. (From this point of view, it should be remarked that expectations are rational with respect to an information set which must be precisely described. As time goes in the direction of increasing entropy, some information is lost, some becomes obsolete, and new one is added, but the memory capacity may be limited and the size of the information set may stay finite.)

Closely related to this first justification, it is often argued that economic agents make rational expectations because they would be permanently using the correct or relevant theory: In other words, individuals would be intelligent and they would have reached this level of knowledge after a long evolution by learning. Finally, the hypothesis of rational expectations is also justified on a basis of arguments stemming from game theory since such expectations can be interpreted as the best strategy of an agent facing the expectations of other agents. Whatever its theoretical justification, this hypothesis must be tested since it is now a dominant paradigm of the new microeconomic foundations of macroeconomics. It also appears inseparable from models of intertemporal individual behavior. Indeed, choices of private agents derived from a dynamic stochastic optimization problem are often interpreted as ones compatible with the hypothesis of rational expectations.

Our study will use this interpretation to investigate the production behavior of French manufacturing firms in the short run. Our objective is to explain the temporal pattern of industrial production from an intertemporal model of the firm. For policy analysis, forecasting industrial production is important since it is a large component of supply and consequently an essential element for the study of business cycles.

In line of this approach, the model of production smoothing has recently received a considerable interest for at least two reasons. (See Blinder [1986] among many others.) First, it is a particular example illustrating that the economic theory by means of models based on intertemporal optimization may help us to derive a dynamic specification. Second, it seems to be flexible enough to explain various situations encountered in developped countries in consideration of the determinants of cycles. For instance, the fact that the variance of production is often greater than the variance of sales in the United States while the reverse is more often observed for European countries has received an answer by means of this model. (See Blinder [1986] and Rahiala, Terasvirta and Kanniainen [1987].) Hence confirming or denying the predictions of this model is crucial for the conduct of economic policy.

Propositions are scientific if they can be refuted by empirical tests whose conditions must be stated with care: In particular, the type of data used for the analysis plays a crucial role. To directly assess models of expectations and to understand the way in which agents actually behave can only be performed through data collected at the individual level. In order to estimate microeconomic structures, aggregate data are relevant only if particular conditions for aggregating individual behavior are fulfilled. The purpose of econometric methods based on micro data is to consistently identify behavioral models of interest from the data generating process. With respect to the above issues, business surveys are unique sources of information, as M. Nerlove stresses in his presidential address before the Econometric Society ("Expectations, Plans and Realizations in Theory and Practice," [1983]).

This dissertation offers some answers to the following questions:

i) Are stochastic dynamic models of the rational firm suited to the interpretation of survey data on production plans and realizations?

ii) Are expectations of entrepreneurs rational? Can we test the Rational Expectation Hypothesis using business survey data without the help of a behavioral model?

To provide answers to these questions, I will apply the method of structural latent variable modelling to the analysis of expectations from the French business survey data, which is summarized in the appendix of this Introduction.

2. Survey of Contents

> "An improvement upon the simple method of interviewing is the questionnaire. If a large number of people are asked the same set of questions, some will not reply, some will make guesses or answer at random, some will reply seriously. By looking over all the replies together, it may be possible to sort out the replies which are significant from those which are not. The method of questionnaires is successful only where those questioned can be persuaded to take an interest in giving full and accurate answers. Occasionally this interest is secured by paying for the information. Sometimes the appeal is to a sense of fun of the person questioned, and to his desire for social prestige. But the difficulty of getting full and accurate replies, coupled with the high cost of assembling and tabulating the answers, limits the amount of information which can be collected specifically to help the economist analyze society."
>
> Sir John R. Hicks [1942]

Still a great many people share the same opinion as J. Hicks although well-organized statistical institutes, helped by the increasing availability of powerful computers, have developed more and more accurate business surveys or consumer surveys. Perhaps the first use of business survey data for econometric research was H. Theil's [1958] seminal analysis on rational policy making and on the accuracy of entrepreneurial predictions; and since, business survey research has become increasingly more popular, as is evident in the published proceedings of the CIRET conferences that are now entering their twentieth year. To contribute to this research, this dissertation focuses on some methodological aspects about the estimation of linear models when data are drawn from surveys. It also evaluates the informational content of survey data through the answers that will be given to the two questions formulated previously. The analysis is organized in two main parts.

Our purpose in Part One is to estimate a simple theoretical model of a firm's production behavior along the lines of the production-smoothing model whose underlying assumptions are analyzed in Chapter 1. This model is based on the idea that firms try to smooth production in the face of demand and cost uncertainty. The hypotheses underlying this construction are discussed at length, and then, using a dynamic stochastic control problem, I may describe the behavior of a rational firm. The closed loop solution is a linear relation expressing how the entrepreneur sets its production plan given past information on production, demand and cost. The parameters of this feedback rule are related by closed-form relations to the structural parameters characterizing the objective function of the firm. This approach is advantageous because it offers a precise specification of the model that will be estimated, and hence a device to discuss the validity of the results. For instance, since the objective function must be convex, if estimates of structural parameters do not satisfy this assumption, it signifies that the estimation of the reduced-form model should be rejected and should be renewed.

For different assumptions on the processes governing demand and cost shocks, the production-smoothing model can explain a wide range of production behavior: The optimal solution can be either to smooth or to bunch production, and the variability of production can be greater or lower than the variability of sales depending on the size of cost shocks and on the values of the structural parameters. It is then necessary to perform an estimation to conclude which is the prevalent situation for France. Now, because the parameters must takes values on specific ranges for each case, we are able to qualify the results. Hence, in this chapter, I construct a tool to ease the interpretation of the estimations.

How could we use the business survey data to estimate the parameters of the theoretical model? Chapter 2 is devoted to the econometric specification. I propose to consider an errors-in-variable model where the variables of interest are measured with errors through survey data. In various problems, assuming measurement errors should be a standard approach, but it must be recognized that the interpretation of such a model is not straightforward. One may understand these models as a means to identify or to recover a permanent structure conditionally on some noisy signals. This point is discussed at length at the end of Chapter 2.

Two reasons explain the choice for such a model. First, the qualitative nature of the data prevent us for estimating directly the theoretical model: Consequently, it is assumed that there exists latent continuous variables that determine the categorical responses when they cross some thresholds, according to certain correspondences. (The latter may be not defined precisely in the sense that the thresholds can be random.) Second, entrepreneurs' responses to the survey questions combine different elements of information on the stochastic environment of the firm. They must be extracted from these appraisals and one possible way is through a measurement model, which can be viewed as a model of factor analysis. The appendix to Chapter 2 develops this last point, providing evidence that appraisals on inventory and order-backlog result from the evolution of demand and costs. By this way, information on these two processes which enter the feedback rule defined in Chapter 1 is indirectly obtained.

Chapter 3 is devoted to the presentation of the estimation method for a general latent variable model for discrete data, which encompasses our econometric model. Indeed, the latter is a linear structural system of variables for which all the available information is a set of indicators.

Our econometric model contains three types of variables: The first ones are the discrete variables directly observed through surveys; they are initiated, according to some correspondences (not necessarily differentiable), by the second type of variables which are called "latent measuring variables"; the latter are continuous and are used to measure through measurement equations the "true" variables, that is to say, the ones which appear in the structural equations defining the economic model, and which, for this reason, are called "latent measurable variables".

The estimation procedure includes two steps. First, the correlations between the latent measuring variables are estimated from the survey data on the discrete variables by maximum likelihood estimation. This method, called the theory of polychoric correlation coefficients, uses a Gaussian assumption to motivate the likelihood function associated with the latent variables. It is a particular implementation of pseudo-maximum likelihood estimation theory, which ensures us that the estimated correlations are consistent and which allows us to correctly compute an asymptotic covariance matrix of these correlation coefficients. (See Gourieroux, Monfort and Trognon [1984].)

Second, the parameters of the structural and measurement equations can be estimated using these coefficients and their covariance matrix by applying a version of the method of moments. The estimation is carried out by weighted least squares. This minimum distance estimator is consistent and asymptotically efficient. It is equivalent to the maximum likelihood estimator when the latent measuring variables have a normal distribution, but is actually distribution-free.

In order to justify the choice of the above two-step procedure, I return in the appendix to this chapter, to the questions raised by the estimation of linear equations on survey data. I point out that standard probit-type methods are not always adequate for the models I am considering.

Chapter 4 presents the results of estimation. The production-smoothing model appears to explain the data as the fit is rather good. By recovering information on the structural parameters, we may show that cost-of-adjusting production plays a crucial role in the production smoothing behavior. The variability of production appears to be lower than the variability of sales in France during the periods for which estimation has been performed.

As a byproduct of the empirical analysis, a forecasting procedure based on the qualitative information is proposed. First, the final form of the economic model is derived and it is shown that the behavior of industrial production can be represented by a univariate autoregressive moving average process. Second, using this structure, it is possible to compute predicted values for the latent variable of production given the survey data. This is a way to check the validity of the model by comparing with other sources of macroeconomic information and to produce a general index of production whose evolution is governed by the underlying microeconomic model. Overall, this chapter shows why a general latent variable model is a coherent methodology to estimate a model of production decisions by a rational firm.

Testing directly the Rational Expectation Hypothesis is our concern in Part Two. Compared to the first part where the rationality of production expectations is studied in the context of a behavioral model, we take up the question by specifying *ad hoc* tests; that is to say, testing procedures are derived to check whether a condition for rationality is satisfied or not, without an explicit formulation of the underlying behavioral model. As stressed by Pesaran [1987], it is particularly relevant to do so. Indeed, "in the absence of direct observations on expectations, empirical analysis of the expectation formation process can be carried out only indirectly, and conditional on the behavioural model which embodies the expectational variables. This means that conclusions concerning the expectation formation process will not be invariant to the choice of the underlying behavioural process." Using business survey data, one may avoid this problem. Several procedures for performing such direct tests are proposed in the economic literature. They are discussed in Chapter 5, where the focus is on the relation between the type of data and the relevant test.

Usually, the Rational Expectation Hypothesis is stated as follows: There exists an information set such that the observed prediction (i.e., the prediction collected by a survey) is identical to the optimal prediction, which is defined as the minimum mean square error predictor and which is obviously not observable. In this case, it can be shown that a necessary and sufficient condition for the prediction to be rational is that the forecast error is orthogonal to the prediction, if the information set is the smallest σ-field containing the prediction.

When the data are quantitative, a simple way to check this condition is to test if the slope of the regression of the realized variable on its prediction is equal to one. Two necessary conditions can also be tested. First, if expectations are rational in the previous sense, then the error forecast should be white noise. Second, the processes which determine the realization and the prediction should be identical. When data are qualitative, the above condition takes the following form: Given that the prediction takes a particular category on a set of discrete values, the event that the realization falls on the same category has the highest conditional probability. These different testing procedures are implemented in Chapter 6 and 7.

A first attempt to test the Rational Expectation Hypothesis is developed in Chapter 6. In business survey analysis, categorical surprise variables are often contructed to represent unexpected changes in demand, production, prices, etc. Specifically, it is said that there is no surprise when expected and realized changes of a variable have the same direction, and that the surprise is positive or negative in the other cases. Surprise variables are often interpreted as expectational errors, i.e., as the difference between realizations and exepctations. This interpretation is in fact a translation in the discrete world of what we would easily write in the continuous world. Under this interpretation, the Rational Expectation Hypothesis holds should the time series of surprise variables exhibit no sytematic pattern. The statistical theory of discrete Markov Chains can be applied to test this consequence of the Rational Expectation Hypothesis. It is clearly rejected. However, I provide evidence that categorical surprise variables are not reducible to expectational errors, which may explain the conclusions of the preceding test. I interpret this result as an illustration (among many others in the literature) that we should never transfer analysis made for continuous variables to interpret the discrete world.

Based on the condition proposed in Chapter 5, a direct test is then presented in Chapter 7, using the structure of a latent variable model, and is applied to demand, production and price expectations from the French business survey. It is shown that the Rational Expectation Hypothesis for the latent variable associated with the demand and production is not always rejected. Estimation of the latent variable model for various periods shows that the slope of the relation between the latent realized variable and the latent expected variable is not statistically different from one. (This is not the case for prices, although the result could be conditional on the treatment of this variable, as I will explain.) This study on the accuracy of expectations is completed by a test of efficiency which consists of testing if the lag structure determining the evolution of changes of demand also governs the formation of expectations. Within the context of a latent variable model, this hypothesis is not rejected for demand. So evidence is given that the Rational Expectation Hypothesis can just be "identified" on survey data in the sense that the results are obtained by means of errors-in-variable models which must be interpreted with care as I already pointed it out. The idea that will be sustained here is that, even if individual predictions may not be rational, a behavior compatible with the Rational Expectation Hypothesis may be extracted from the data and that this behavior explains a large part of the data.

In a general conclusion, a summary of the main results is given and new steps for the econometric analysis by means of survey data are sketched.

Appendix to the Introduction: The INSEE Business-Test Questionnaire

Since 1951, the Service de la Conjoncture of the Institut National de la Statistique et des Etudes Economiques conducts a survey on activity and expectations in the industrial sector. However, the present questionnaire was established in 1962 and only small modifications have been introduced since then. Firms were surveyed three times a year, in March, June and November, until June 1978; since, they are surveyed four times a year in January, March, June, and October. This survey is one among the ten different tendency surveys that are administered by INSEE.

The data set made available to us by INSEE contains 5371 different firms which have entered in the survey at a certain period between June, 1974 and October, 1985. A very few of them stay in the sample for a long period. At each period, around 4000 firms are surveyed. On average, the attrition rate is 25%. The rate of response by question is much smaller than the overall rate. Figure A.1 gives an illustration of the attrition in the survey. If T is the duration in the state: "the firm answers the question on production change," and E means: "the firm does not answer this question any longer," the figure displays for all the firms in the sample the probability:

$$\Pr[T > t \mid E]$$

where $t = 0, \ldots, 10$ and the unit of time is the time period btween two successive surveys. This is the cumulative survival rate given the right censoring due to the exit from the sample. The median of this distribution corresponds roughly to one quarter, i.e., 50 percent of the firms will exit after answering the question on production changes only once. If they answer more than one time, they tend to keep replying. The associated hazard rate function given in Figure A.2 shows that the modeling of the attrition rate by some known functions may be not simple (the hazard rate is scaled by a factor 0.088 on the figure).

The questionnaire has four parts which are briefly presented. The variables used in the empirical studies receive more attention (their notations are mentioned).

i) Part 1:

Title - General information about the firms (gross sales, labor force, etc.).

ii) Part 2:

Information about the conditions influencing the activity of the firms (bottlenecks, capacity utilization, financial constraints, expected changes of labor force and for work time, average change of the wage rate, etc.).

iii) Part 3:

Questions pertaining to raw materials and work-in-process inventories (trend for the last three months, expected trend for the next three months, appraisals of raw materials). Expectations of the general activity in the industrial sector (production level, exports, general

Figure A.1: Cumulative Survival Rate for the Responses of Production Changes

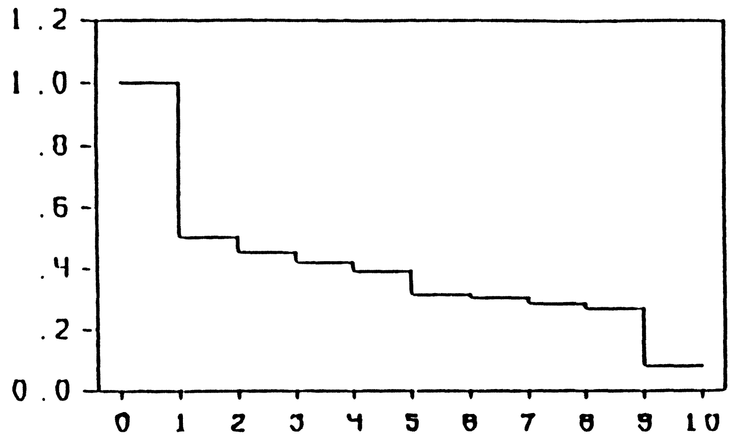
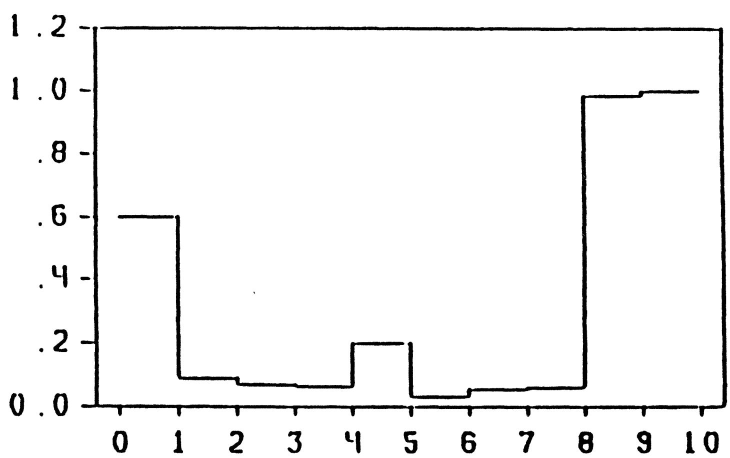


Figure A.2: Hazard Rate for the Responses of Production Changes



price level, hourly wage rate).

iv) Part 4: Questions pertaining to the products of the plant. The following questions can be given for four different products (for saving place the illustration reports only the column on the answer sheet corresponding to one product).

1. Changes of production

a. Trend for the last three or four months (notation: Q or q)

b. Expected trend for the next three or four months (notation: QS or q^e)

2. Changes of demand

a. Trend for the last three or four months (notation: D or d)

b. Expected trend for the next three or four months (notation: DE, DS or d^e)

c. Number of weeks of production in the order book

d. Appraisal of backlog of orders (if the firm has an order book) (notation: SA). The translation of the question is: Given the season, how do you appraise your backlog of orders ? Above normal-normal - below normal

Appraisal of new orders (if the firm does not have an order book)

3. Foreign demand changes

4. Lag of deliveries changes

5. Changes of finished goods inventories

a. Trend for the last three or four months

b. Appraisal on inventories (notation: LA). The translation of the question is: Given the season, how do you appraise your finished good inventories ? Above normal - normal - below normal

c. Number of weeks of production in inventory

6. Selling price changes

a. percent change of the prices

b. expected percent change of the price

c. percent change of the export price

PART ONE

FORECASTING PRODUCTION BEHAVIOR IN THE SHORT-RUN

As business survey data are a unique source of economic information which can be used to study the intertemporal behavior of individual firms, my objective in Part One is to use these data to estimate a stochastic dynamic model describing how firms determine their production decisions in the short-run. Some of the ideas underlying the analysis are now briefly introduced.

The rational firm sets its optimal plan of production by minimizing the expected discounted cost under uncertain demand and random average cost. In such an environment, the existence of adjustment costs together with the possibility of accumulating inventories and of queuing orders are incentives to anticipate the future and to alter production levels. This behavior is summarized by a feedback rule (which is a reduced-form representation of the theoretical model) determining the expected (planned) production level in terms of the past instruments and control variables. Hence, the relationships between the structural parameters (which characterize the objective function of the firm) and the reduced-form coefficients (which can be estimated) are known. The empirical work amounts to solving econometrically an inverse problem, i.e., recovering the structural parameters from the estimates of the reduced-form model. (The reason for choosing such an approach is well understood since the influential work of Lucas [1976].)

In order to estimate the optimal control rule, data on expectations are required. If such an information is not available, a model of expectation formation must be introduced, i.e., the expected variables must be replaced by some proxies such as, for instance, linear combinations of past realizations of these variables; then, we cannot test the structural behavioral relationships independently of the assumptions used to construct the model of expectation formation. So the latter could be rejected simply because the former can be badly specified (or vice versa). By observing expectations through surveys we may avoid this situation. In particular, we may separate the behavioral equations and the constraints imposed by the assumption of rational expectations.

Now, using survey data to estimate economic models raises some technical problems because they are qualitative. Indeed survey questions bear on the direction of the (expected or realized) trend in a variable, i.e., whether it is up, down, or no change. The solution proposed here is to adopt a general setting, the latent variable model for discrete data. In addition to providing a satisfactory approach for the treatment of models based on ordinal variables, the use of errors-in-latent-variable models ensures the coherence between the theoretical model and the econometric model: In particular, the rationality assumption underlying the former can be clearly imposed in the statistical model. This point will be discussed later.

The study is now developed in four chapters. The first is devoted to the presentation of the economic model and of its relations to the literature on the theory of the firm. The second chapter discusses at length the specification of the econometric model. The estimation method is explained in a third chapter. The fourth chapter presents the empirical results. Then, the final objective of Part One can be achieved since a method to forecast in the short-run the direction of economic activity from the estimates of the structural model and from survey data can be performed. In order to have a complete method for predicting the business conditions along the lines of this approach, there are still some unsolved questions which will be stated in the course of this part.

Chapter 1. The Production Smoothing Model

In the recent literature, the study of the firm's behavior takes place within the context of the production smoothing model. Initially stated by Holt et al. [1961], this paradigm is based on the idea that inventory holding is stabilizing. (Often admitted, this can be proved. See Scheinkman and Schechtman [1983], who exhibit particular assumptions under which this is true.) In this view, macroeconomic fluctuations are not due to inventories as in early models of Keynesian inspiration, but must be related to the smoothing of supply shocks. (See Blinder [1986].) To my knowledge, the only conflicting approach proposed in the recent years is a re-consideration of the Keynesian model by Laroque [1987], who interprets inventory holding as for a speculative motive, and who shows that inventories can generate cycles. Nonetheless, it must be stressed that all the studies are, in effect, looking for a new supply function compatible with the spirit of the "new classical equilibrium economies" (i.e., with the Rational Expectations Hypothesis) and with the Keynesian model. The forthcoming study will be only concerned by models where inventory plays the role of a buffer.

The next section is devoted to an overview of the literature on the production-smoothing model in order to clarify the main characteristics of the model, then presented in a second section.

1.1 Variations around a Paradigm.

Here, the basic idea is that firms try to smooth production in the face of fluctuating demand, and that they can use inventories to do so. The two main consequences of the production-smoothing model are: (i) the variability of production should be less than that of sales and (ii) firms would respond to a temporary increase (decrease) of the demand for their own products by accumulating (reducing) inventories as firms partially adjust the production level. These predictions have been proved to be contradictory to reality in various studies (see Blanchard [1983], Blinder [1986], West [1986], using in general data from the US manufacturing industry.

One first response to these puzzling findings is to introduce a cost of being away from some positive target level of inventory in the traditional linear quadratic production-smoothing model. The idea arose with the critiques by Auerbach and Feldstein [1976] of the old stock adjustment model introduced by Lovell [1961]; it has been applied by Blanchard [1983], Eichenbaum [1984], and West [1986]. If the target level of inventory is a proportion of the expected next-period sales level, then production can be more "volatile" than sales. But the inequality between the variances of sales and production implied by this revised version of the model (and derived West [1986]) is also rejected empirically. More recently, Kahn [1987] proposed a new justification of the model with an inventory target by modelling the stock-out avoidance motive; he proved that there is no _a priori_ reason to expect the variance of sales to exceed the variance of production. So the discussion along this line is still open: For instance, West [1987] points out that, when net inventories (physical inventories minus backlogs) are considered to describe their role as a buffer, the production smoothing model remains "qualitatively consistent." (See also Abel [1985].)

Another type of response to adapting the production-smoothing model with the stylized facts is to include a second source of uncertainty, which could act in the opposite direction of the demand shocks. An obvious candidate for this is the technological (or cost) uncertainty. This way is retained by Eichenbaum [1984], Maccini and Rossana [1984], Blinder [1986], Miron and Zeldes [1987]; recently Eichenbaum [1987] compared the production-smoothing model with and without cost shocks. The production-cost-smoothing model seems empirically plausible, although Miron and Zeldes [1987] found little evidence that cost shocks play any role when non-seasonally adjusted data are used.

One of the characteristics of this debate comes from the permanent interaction between the theoretical studies and the empirical tests. With respect to this debate, two points should be stressed. First, the nature of the production-smoothing model suggests the use of micro-data to infer the structural behavior as in Koenig and Nerlove [1986]. While most of the empirical studies use macro-data, the latter are adequate for studying the production-smoothing model only under particular assumptions concerning aggregation. The use of macro-data are often justified on the basis of a representative agent, i.e., on a set of very strong assumptions. For long, the use of micro-data has been advocated as a means to avoid such assumptions because they permit us to take into account a large variety of behavior.

Second, if there is a general agreement among researchers for assuming that, in the production smoothing model, production decisions must be derived by solving a dynamic stochastic optimization problem, the distinguished features of the latter are however questionable. Indeed, the most common (production smoothing) model admits a linear quadratic objective function in the perspective of applying the "first-period-certainty-equivalence" principle, which allows one to derive empirically tractable models. The certainty-equivalent optimal policies of the firms are not sensitive to market randomness due to risk aversion. Although the desirability of models integrating the risk is justified by realism, it is difficult to have a prior knowledge of the utility functions of the entrepreneurs. However, risk-sensitive behavior may be compatible with quadratic models, as shown by Clarke [1985].

Let us assume that a firm determines its optimal control rule in the context of the linear-quadratic case. In order to compute its plan according to the optimal rule, the firm must select (estimate) a vector of state variables. This choice re-introduces risk, since the firm's estimate is dependent on the uncertainty pertaining to the economic environment. Clarke builds on this conjecture and shows that Bayes estimation of the information set causes the behavior implied by the feedback rule to appear as it would be if the risk was explicitly taken into account. This result means that a knowledgeable firm should react more strongly to market stimuli than less knowledgeable firms.

Since Bayes decision making resemble risk aversion exhibited by managerial utility functions, the econometrician must use Bayesian estimation methods in order to derive expectations, although prior distributions of these variables should be hard to find.

In our case, survey data are direct observation of the entrepreneurs' expectations and appraisals. As they certainly reflect some degree of managerial uncertainty, then, on the basis of the Clarke's analysis, we may conclude that using these data is a way to take directly into account the sensitivity of firms to market randomness, without having to perform a Bayesian analysis. This deserves further research.

This discussion motivates the objective that I pursue here, which is to estimate a structural model of production behavior, along the lines of the production-cost-smoothing model, using survey data from the French industrial sector. To my knowledge, such a project has not yet been undertaken, although Koenig and Nerlove [1986] consider the joint determination of price and production decisions, using a system of conditional log-linear probabilities, which is not easy to use for structural interpretation.

It is useful, before going into the details of the analysis, to know what we can learn from some aggregate data for France about the variability of sales and production. For this purpose, I propose to compare equivalent statistics for the US and French manufacturing industries. The US situation is taken here as standard, since most of the empirical studies focusing on the production-smoothing model use data for this country and have shown that, for the US, the volatility of production is greater than for sales. Table 1.1 displays the unconditional variances of balances associated with the changes of demand and production which are collected by surveys for the two countries. Let us recall that balances are computed as the difference between the percent of respondents reporting an increase of the demand (production) and the percent of those reporting a decrease. Since the INSEE survey for France and the Dun and Bradstreet survey for the US are similar, this aggregate information, so derived, is comparable. But it must be stressed that the statistics are computed for a different number of periods in each case since we consider, for the D&B survey, eight consecutive quarters from the third one of 1986, while fourty-two periods from June 1974 are available for the INSEE survey.

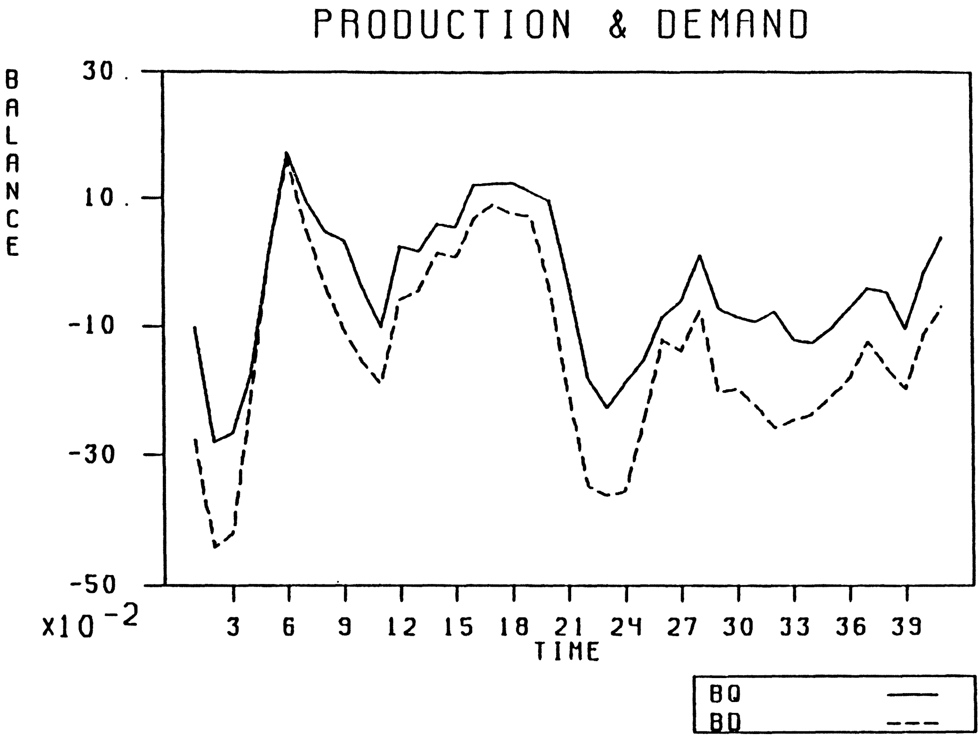
Figures of Table 1.1 confirm that, for the US, the variance of production is greater than the variance of the demand. The opposite seems to be true for France, which indicates that the production-smoothing model could well fit for the French industrial firms. Let us remark that the two series of balances for France behave very closely as it can be seen from Figure 1.1. According to the arguments advanced in the discussion of the production-smoothing model, this observation could mean that, for France, cost shocks should not be the major effect affecting the production behavior.

Table 1.1: Variances of the Balances (production and demand changes)

	PRODUCTION	DEMAND
FRANCE	1.34	2.05
UNITED STATES	1.20	0.75

(figures represent percentages)

Figure 1.1: Balances (France 1974 - 1985)



1.2. The Production Plan of a Rational Firm

Before presenting the model in detail, let us briefly present its main characteristics and how it should be interpreted. Each firm solves a stochastic control problem and the objective is to minimize expected discounted cost. There is one control variable: The production level. The firm faces two exogenous sources of uncertainty, demand (or sales) and cost shocks, which follow known stochastic processes. Inventories and backlogs (both are simultaneously present because products are heterogenous) are used to smooth out the production activity of the firm over time. Production takes place in the "intermediate" run, i.e., a change of the net inventory levels (i.e. physical inventories minus backlogs) is only due to a change in production level and cannot be alleviated by other types of adjustment decisions such as changing the delivery lags, investment, or strategic behavior. Prices cannot be manipulated on this time horizon: In some sense, prices are fixed during the periods while the production level is adjusted. (Attempts to estimate a model where prices and production are simultaneously determined have not been successful because such a model is very demanding in terms of data availability, in the context of the estimation procedure adopted here.)

1.2.1. The Firm's Optimization Program

The amount α_t of the firm's product sold to (or ordered by) consumers at period t is described by the following process:

(1.1) $\theta_1(L)\ \alpha_t = u_t$

where $\theta_1(L)$ is a polynomial in the lag operator and u_t is white-noise or is a moving-average. The exact specification for (1.1) is left as an empirical issue. The firm can always use data on new orders to determine by some time series analysis a process such as (1.1).

For producing, the firm must bear different types of cost:

(i) Cost of producing the amount q_t at time t, which is given by:

(1.2) $C_{1t} = c_1(q_t + 2\gamma_t)q_t \qquad c_1 \geq 0$

The time-dependent component γ_t of the average cost is assumed to be random; one can always represent such an effect (which is the result of different unknown or unmeasurable variables) by a stochastic process whose order is unknown at this point:

(1.3) $\theta_2(L)\ \gamma_t = v_t$

where v_t is white noise or is a moving-average. The parameter c_1 is non-negative in order to have decreasing returns, which leads the desirability of production smoothing, a low value of c_1 being associated with a strong desire to smooth production. The processes α_t and γ_t are assumed uncorrelated.

(ii) Cost of changing the production level defined by:

(1.4) $C_{2t} = c_2(q_t - q_{t-1})^2 \qquad c_2 \geq 0$

which means that it is costly to adjust instantaneously the production level. Again this cost (which represents in particular hiring and firing costs) leads to production smoothing, a low value of c_2 favoring decisions to smooth production.

(iii) Cost of carrying over inventories or order-backlogs, given by:

(1.5) $C_{3t} = c_3(x_t - x_{t-1})^2; \qquad c_3 \geq 0$

where x_t is the stock of items at time t (x_t is interpreted as net inventories). As it takes times to adjust the production level to the new conditions of environment, the firm may carry over inventories or backlog orders and this possibility has a cost which depends upon the magnitude of the change of the stock. In other words, this cost is due to the fact that the bigger the backlog or the smaller the inventory, the lengthier the delivery period and the greater the flexibility in adapting production. Obviously we are only concerned with firms which are able to put goods in or taking them out the stock after some time periods. A low value of c_3 will encourage the use of inventories to smooth production.

The parameters c_1, c_2 and c_3 are assumed to be fixed which is a strong assumption. Indeed they could depend on state variables, i.e., total sales or inventory levels. For instance, an increase in demand, for any inventory level, increases the probability of stocking-out, which directly affects the cost of carrying over inventories, possibly through the parameter c_3. Even at this stage, these parameters are not truly structural.

The decision variable of the firm is chosen here to be the production level q_t. In this model, the program of the firm is to minimize at period 0, for a given discount factor ρ, the function:

$$(1.6)\ \lim_{T \to \infty} E_0 \left(\sum_{t=1}^{T} \rho^t \sum_{i=1}^{3} C_{it} \right)$$

subject to:

$$(1.7)\ x_t - x_{t-1} = q_t - \alpha_t \qquad t = 1,\ldots,T,\ldots$$

the latter being an accounting equation. If $(x_t - x_{t-1})$ is positive, inventories are piled up and/or the order-backlogs are reduced; otherwise, inventories are drawn down and/or orders are accumulated. (Here sales, shipments and orders are not distinct).

At time 0, the firm is assumed to have an information set Ω_0 including at least q_0 and the processes α_t and γ_t observed at periods $0,-1,\ldots,-\infty$. The problem is to choose a linear decision rule for setting q_t as a function of elements in Ω_t.

This model describes the behavior of a typical firm taking prices as given. If we were to assume that the firm was a monopoly, or at least, a firm having a monopoly power with respect to its product, the equation (1.1) would have been transformed into:

$$d_t = \alpha_t + \beta\, p_t$$

with: $\qquad \theta_1(L)\, \alpha_t = u_t$

where p_t is the price of the product, d_t the demand. Then α_t would have been interpreted as the autonomous demand. This remark is made to clarify the meaning of the above model where $\beta = 0$.

1.2.2. The Optimal Control Equation

If a sequence (q_t) for $t=1,\ldots,+\infty$ is a solution to (1.6), it must satisfy the stochastic Euler equations derived by differentiating (1.6) with respect to q_t for $t = 1,\ldots,T$. These first-order necessary conditions are:

$$(1.8)\quad E_{t-1}[\rho q_{t+1} + \psi q_t + q_{t-1}] = [c_1 E_{t-1}\, \gamma_t - c_3 E_{t-1}\alpha_t]\, c_2^{-1}$$

for $t = 1,\ldots,T\ldots$

$$\text{where:}\quad \psi = -\frac{1}{c_2}(c_1+c_3+(1+\rho)c_2)$$

and E_{t-1} is the conditional expectation given Ω_{t-1}. (The expectation should be E_0, but since: $E_0E_{t-1}(.) = E(E(.|\Omega_{t-1})|\Omega_0) = E(.|\Omega_0) = E_0(.)$ for $t = 1,\ldots,T\ldots$, we can restrict the calculus by considering the expectations with respect to Ω_{t-1}). Equations (1.8) can be obtained if some regularity conditions are met for the objective function defined by (1.6). Indeed, differentiation of this function under the integration operator is justified only if the derivative of the objective function is bounded by an integrable function. (See Serfling [1980], page 144.) This condition is satisfied here if the stochastic processes q_t, α_t, and γ_t are themselves bounded (in a sense specified below), which, in turn, must be imposed in order to get a terminal condition for our infinite horizon problem.

The transversality condition

To solve the second-order difference equation (1.8) one needs a transversality condition which is satisfied if and only if the stochastic processes q_t , α_t , and γ_t are of exponential order less than ρ^{-1} (see Bertsekas [1976], Hansen [1979], Hansen and Sargent [1980], Chow [1983]). The usual condition applied to this model is the following:

$$(1.9) \quad \lim_{T \to \infty} E\ \rho^T[(c_1+c_2+c_3)q_T - c_1\gamma_T - c_2q_{T-1} - c_3\ \alpha_T] = 0$$

By the triangle inequality, we have:

$$A = |\ \rho^T[(c_1+c_2+c_3)q_T - c_1\gamma_T - c_2q_{T-1} - c_3\alpha_T]|$$
$$\leq \rho^T(c_1+c_2+c_3)|q_T| + \rho^Tc_1|\gamma_T| + \rho^Tc_2|q_{T-1}| + c_3|\alpha_T| = B$$

If the processes are of exponential order less than $1/\rho$, that is to say:

For all t and for some $K > 0$, $|q_t| < Kz^t$, $|\alpha_t| < Kz^t$, $|\gamma_t| < Kz^t$, where $0 < z < 1/\rho$,

then:

$$B \leq (c_1+c_2+c_3)\ (\rho z)^T + c_1(\rho z)^T + c_3(\rho z)^T.$$

Now, since $\rho z < 1$, the limit of each term is zero, which shows that the equation (1.9) is satisfied. The conditions on the stochastic processes are then sufficient for the transversality condition (1.9) to hold. Generally they are also necessary. Then, for solving the program (1.6), it remains to find a solution for the difference equations (1.8).

Computation of the optimal solution

Let us consider the LHS of (1.8). Omitting the expectation operator, one can write:

$$\rho q_{t+1} + \psi q_t + q_{t-1} = (\rho L^{-1} + \psi + L)q_t$$

The polynomial in terms of the lag operator L can be factorized:

$$\rho L^{-1} + \psi + L = \rho(L^{-1} - \lambda_2)(1 - \lambda_1 L)$$

such that: $\rho(\lambda_1 + \lambda_2) = -\psi$ and $\rho\lambda_1\lambda_2 = 1$. Hence: $\rho\lambda_1 + \lambda_1^{-1} = -\psi$.

The convex function $F(\lambda) = \rho\lambda + \lambda^{-1}$ has a minimum at $\lambda = \rho^{-1/2}$. This implies that: $0 < \lambda_1 < \rho^{-1/2} < \lambda_2$, taking λ_1 as the smallest root without loss of generality. The two roots are given by:

$$\lambda = -(2\rho)^{-1} [\psi \pm (\psi^2 - 4\rho)^{1/2}].$$

The roots are positive and are real and distinct when $\psi^2 - 4\rho \geq 0$, which requires that: $(c_1+c_3)c_2^{-1} \geq 2\rho^{-1/2} - (1+\rho)$. The parameters c_1, c_2, c_3 being non-negative, the preceding inequality is true if $\rho \leq 1$, since, in this case, $(1+\rho)$ is always greater than or equal to $2\rho^{-1/2}$. Consequently, by restricting the analysis to values of the discount factor less than one, we reject noncyclical solutions.

It can be also shown that: $\lambda_1 < \rho^{-1} < \lambda_2$. Let us notice that:

$$-\psi = (c_1+c_3)c_2^{-1} + (1+\rho).$$

If $(c_1+c_3) = 0$ (which is obviously false and which would imply: $-\psi = 1 + \rho$), then λ_1 and λ_2 would be solutions of: $F(\lambda) = 1+\rho$, such that: $\lambda_1 = 1$ and $\lambda_2 = \rho^{-1}$. But since: $-\psi > (1+\rho)$, the solutions for the equation: $F(\lambda) = -\psi$ must be such that: $\lambda_1 < 1$ and $\rho^{-1} < \lambda_2$. This in turn implies that: $0 < \lambda_1 < 1 \leq \rho^{-1} < \lambda_2$. (we still have:

$\lambda_1 < \rho^{-1/2} < \lambda_2$.)

The equation (1.8) becomes:

$$E[\rho(1 - \lambda_1 L)(L^{-1} - \lambda_2)q_t] = c_2^{-1} [c_1 E_{t-1}\gamma_t - c_3 E_{t-1}\alpha_t]$$

or, after premultiplying both sides by: $[\rho(L^{-1} - \lambda_2)]^{-1}$:

$$(1.10) \quad E[(1-\lambda_1 L)q_t] = c_2^{-1} [\rho(L^{-1}-\lambda_2)]^{-1}[c_1 E_{t-1}\gamma_t - c_3 E_{t-1}\alpha_t]$$

Let us observe that:

$$[\rho(L^{-1}-\lambda_2)]^{-1} = -(\rho\lambda_2)^{-1} (1+\beta L^{-1} + \beta^2 L^{-2}+\dots]$$

$$= -\lambda_1 \sum_{j=0}^{\infty} \beta^j L^{-j}$$

where $\beta = \rho\lambda_1 = \lambda_2^{-1}$ which is less than ρ (since $\lambda_1 < \rho^{-1} < \lambda_2$).

Then, rearranging (1.10), it yields a new form of the optimal control equation:

$$(1.11) \; E_{t-1}q_t = \lambda_1 q_{t-1} + \lambda_1 [c_3 \sum_{j=0}^{\infty} \beta^j E_{t-1}\alpha_{t+j} - c_1 \sum_{j=0}^{\infty} \beta^j E_{t-1}\gamma_{t+j}] c_2^{-1}$$

As (α_t) and (γ_t) are of exponential order less than ρ^{-1} and as $\beta = 1/\lambda_2 < \rho$, the infinite weighted sums on the RHS of (1.11) are converging.

However, without additional assumptions on α_t and γ_t there is no way to have a simple form for the solution in (1.11).

The case of Markov processes of order one

Let us assume, for instance, that the two stochastic variables are Markov processes:

$$(1.12)\quad \begin{aligned} \alpha_t &= \theta_1 \alpha_{t-1} + u_t \\ \gamma_t &= \theta_2 \gamma_{t-1} + v_t \end{aligned}$$

and that they are of exponential order less than ρ^{-1}, i.e., we assume that firms can perform time-series analysis to determine the dynamic pattern of their new orders and their unit cost, and they obtain the above specification for the two random variables. If (1.12) holds, then:

$$\begin{aligned} E_{t-1}\, \alpha_{t+j} &= \theta_1^{j+1}\, \alpha_{t-1} \\ E_{t-1}\, \gamma_{t+j} &= \theta_2^{j+1}\, \gamma_{t-1} \end{aligned} \qquad \text{for } j = 0,1,2,\ldots$$

In this case, the optimal control equation (1.11) is written:

$$(1.13)\ E_{t-1}q_t = \lambda_1 q_{t-1} + \lambda_1 \left[c_3\theta_1 \left(\sum_{j=0}^{\infty} (\beta\theta_1)^j\right) \alpha_{t-1} - c_1\theta_2 \left(\sum_{j=0}^{\infty} (\beta\theta_2)^j\right) \gamma_{t-1}\right] c_2^{-1}$$

Since $\beta\theta_1 < 1$, $\beta\theta_2 < 1$, $\beta = 1/\lambda_2$ and $\lambda_1\lambda_2 = \rho^{-1}$, the infinite sums take simple forms since they are converging. Let us define:

$$g_1 = \lambda_1$$

$$(1.14)\ g_2 = \frac{\lambda_1}{c_2} \left[c_3\theta_1 \left(\sum_{j=0}^{\infty} (\beta\theta_1)^j\right) \right] = \frac{\lambda_1 c_3 \theta_1}{c_2(1-\beta\theta_1)} = \frac{\theta_1}{\rho(\lambda_2-\theta_1)} \frac{c_3}{c_2}$$

$$g_3 = -\frac{\lambda_1}{c_2} \left[c_1\theta_2 \left(\sum_{j=0}^{\infty} (\beta\theta_2)^j\right) \right] = \frac{-\lambda_1 c_1 \theta_2}{c_2(1-\beta\theta_2)} = \frac{-\theta_2}{\rho(\lambda_2-\theta_2)} \frac{c_1}{c_2}$$

Then, the optimal control rule, when (α_t) and (γ_t) are given by (1.12), is:

$$(1.15) \qquad E_{t-1}q_t = g_1 q_{t-1} + g_2\alpha_{t-1} + g_3\gamma_{t-1}$$

where the reduced forms parameters g_1, g_2 and g_3 are obtained from the structural parameters according to the following relations:

$$g_1 = \frac{1}{2\rho c_2} \left[(c_1+c_3+(1+\rho)c_2) - ((c_1+c_3+(1+\rho)c_2)^2 - 4\rho c_2{}^2)^{1/2}\right]$$

$$(1.16) \quad g_2 = 2\theta_1 c_3[c_1+c_3+(1+\rho-2\rho\theta_1)c_2 + ((c_1+c_3+(1+\rho)c_2)^2-4\rho c_2{}^2)^{1/2}]^{-1}$$

$$g_3 = -2\theta_2 c_1[c_1+c_3+(1+\rho-2\rho\theta_2)c_2 + ((c_1+c_3+(1+\rho)c_2)^2-4\rho c_2{}^2)^{1/2}]^{-1}$$

Given the preceding assumptions and remarks, it is straightforward to observe that:

i) $0 < g_1 < 1$, $g_2 \geq 0$, $g_3 \leq 0$. (θ_1 and θ_2 are assumed to be positive.)

ii) $g_1 = 0$ when $c_2 = 0$; The relation between the production plan and the past production level becomes weaker as costs of adjusting production becomes negligible. This shows the importance of these types of cost in this model, which are relevant when the production level cannot be adjusted "perfectly" i.e. instantaneously.

iii) g_2 (g_3) is an increasing function of θ_1 (θ_2), respectively.

The optimal control rule (1.15) can be written as an equation for the optimal level of net inventories. Indeed, using the fact that: $E_{t-1}\alpha_t = \theta_1\alpha_{t-1}$, we may replace (1.15) by:

$$(1.17) \qquad E_{t-1}(q_t-\alpha_t) = g_1 q_{t-1} + (g_2-\theta_1)\alpha_{t-1} + g_3\gamma_{t-1}.$$

Let us suppose a shock on the demand at time t-1. Then

$$(1.18) \quad \frac{\partial\ E_{t-1}(q_t-\alpha_t)}{\partial\ u_{t-1}} = g_2 - \theta_1 = \theta_1 \left[\frac{c_3}{\rho(\lambda_2-\theta_1)c_2} - 1\right]$$

It can be easily shown that g_2 is always less than θ_1 for any admissible values of the parameters since the expression between square brackets is always negative. (See appendix to this chapter.) Hence, the firm decreases its net inventory (i.e., the firm runs down inventories and/or builds up backlogs) in response to a positive shock on demand (since θ_1 is taken to be positive). In this sense, the optimal behavior is production smoothing. Let us consider now both a demand and a cost shock. Then:

$$(1.19) \quad dE_{t-1}(q_t-\alpha_t) = (g_2 - \theta_1)\ du_{t-1} + g_3\ dv_{t-1}$$

This shows that firms adjust their production fully as θ_1 increases (because g_2 is an increasing function of θ_1) and that the variability of production is increased due to the presence of the cost shock. Similar conclusions are already contained in the models studied by Blinder [1986] and by Koenig and Nerlove [1986].

The case of ARMA(1,1) processes

It is interesting to consider the case where the process α is an ARMA(1,1) (while γ is still Markov of order one):

$$\alpha_t = \theta_1 \alpha_{t-1} + u_t + \phi u_{t-1} \quad \text{with} \quad |\phi| < 1$$

Then: $E_{t-1}\, \alpha_{t+j} = \theta_1{}^j\, (\theta^1 + \phi)\, \alpha_{t-1}$ for $j = 0,1,\ldots$

A new term appears in the optimal control rule which becomes:

$$(1.20)\quad E_{t-1}q_t = g_1 q_{t-1} + g_2 \alpha_{t-1} + g_3 \gamma_{t-1} + g_4 u_{t-1}$$

where the parameters g_1, g_2, g_3 are given by equations (1.14) and where the new reduced form parameter g_4 is defined by:

$$(1.21)\quad g_4 = \frac{\lambda_1 c_3 \phi}{c_2(1-\beta\theta_1)} = \frac{\phi}{\rho(\lambda_2-\theta_1)}\frac{c_3}{c_2} = \frac{\phi}{\theta_1} g_2$$

This parameter is positive or negative depending on the sign of ϕ. The analogues of (1.17) and (1.18) are, respectively:

$$(1.22)\quad E_{t-1}(q_t-\alpha_t) = g_1 q_{t-1} + (g_2-\theta_1)\alpha_{t-1} + g_3\gamma_{t-1} + (g_4-\phi)u_{t-1}$$

$$(1.23)\quad \frac{\partial\, E_{t-1}(q_t-\alpha_t)}{\partial\, u_{t-1}} = \left[\frac{c_3}{\rho(\lambda_2-\theta_1)c_2} - 1\right](\theta_1 + \phi) = (g_2+g_4)-(\theta_1+\phi)$$

By comparing (1.18) and (1.23), it can be seen that the optimal behavior implied by an ARMA(1,1) does not differ from the AR(1) case when ϕ has the same sign as θ_1 or when it is smaller than θ_1 in absolute value. (The expression between square brackets in (1.23) is always negative, as shown in the appendix.)

Hence the optimal solution is again production smoothing, except when

ϕ and θ_1 do not have the same sign and ϕ is greater than θ_1 in absolute value, in which case the optimal behavior is to bunch production.

By symmetry, similar results hold if the cost shock follows an ARMA(1,1). (As in equation (1.20) we would have to add a stochastic component to the feedback rule.) When both processes are ARMA(1,1), production smoothing or production bunching can characterize the optimal behavior depending on the values of the parameters. As a result, the choice among the possible specifications is an empirical issue. Depending on the estimation results, it will be possible to determine what is the prevalent solution.

It can be easily checked that, given some estimates for g_1, g_2, g_3, θ_1, θ_2 and a given discount factor , one can recover values for c_1/c_2 and c_3/c_2 (we cannot separate the three parameters). If one considers the case for an ARMA(1,1) on α, equation (1.21) shows that we must add a constraint of over-identification between parameters: $g_2\phi = g_4\theta_1$ (and the like if γ is itself ARMA(1,1)).

The purpose of the following empirical part is to derive estimates for the structural parameters, i.e., to estimate the linear decision rule together with the parameters of the stochastic processes, using business survey data, which give information on expectations, or more precisely, offer some measures of $E_{t-1}\, q_t$.

Appendix to Chapter 1: Signs of the Changes of Net Inventories.

I study here the signs of equations (1.18) and (1.23). Because of the forms of these two equations, their signs depend on the sign of:

$$\text{(a1.1)} \quad \frac{c_3}{\rho(\lambda_2-\theta_1)c_2} - 1 = A$$

Since:

$$\rho(\lambda_2-\theta_1) = \frac{1}{\lambda_1} - \rho\theta_1,$$

and since:

$$\frac{1}{\lambda_1} > 1 > \rho\theta_1,$$

then, to find the sign of A, we can compare c_3/c_2 to $\rho(\lambda_2-\theta_1)$. Without loss of generality, we may set: $c_1 = 0$. Now, it can be shown that, assuming that A is positive, would be contradictory to other assumptions. Let us pose that:

(a1.2) $c_3/c_2 > \rho(\lambda_2-\theta_1)$, then some simple calculus will show that:

$$c_3/c_2 + 2\rho\theta_1 - (1+\rho) > ((c_3/c_2 + (1+\rho))^2 - 4\rho)^{1/2}$$

which is true only if:

(a1.3) $c_3/c_2 + 2\rho\theta_1 - (1+\rho) > 0.$

If (a1.3) holds, some computations allow us to obtain that:

(a1.4) $[(1+\rho) - \rho\theta_1]\ (c_3/c_2) < \rho\ (1 - \theta_1)\ (1 - \rho\theta_1)$

This inequality holds only if: $\theta_1 < 1$, since the left-hand side of (a1.4) is always positive, given the admissible values of the parameters. We have then two conditions on c_3/c_2, (al.3) and (al.4). Since:

$$\rho\ (1 - \theta_1)\ (1 - \rho\theta_1) \ < \ 1+\rho - 2\rho\theta_1,$$

given the admissible values of ρ and θ_1, the two conditions on c_3/c_2 can be satisfied together only if: $(1+\rho) - \rho\theta_1 < 1$. Now, the latter is true only if: $\theta_1 > 1$. Then (al.3) and (al.4) cannot be satisfied together and hence, the hypothesis (al.2) is always rejected and A is always negative. This proved the claim given in the chapter.

Chapter 2. The Econometric Specification Using Survey Data

In this chapter, an econometric model is specified in order to estimate the preceding theoretical relationships using business survey data. The characteristics of these data prompt three remarks.

The first one concerns the meaning of the information about expectations in surveys. It is clear that, for economists, these variables are crucial in the process of economic activity. Beliefs have always been the center of the economic debate. Two points of view can be advanced about the nature of expectations from business surveys with respect to economic theory. For the first one, expectations comprise information on the adjustment process toward an equilibrium. Although economic theory can help to characterize this equilibrium, there is no well-grounded theoretical model of such an adjustment process and hence, the specification of an empirical model cannot be strictly derived from the theory. The second point of view says that the information in surveys contain some measures (with errors) of the variables that have a precise role in the theoretical model. Specifically, the idea is to separate for a particular variable what is due to the underlying economic model and what is the consequence of the adjustment to the theoretical model, like optimization and/or, measurement errors. This view is based on the fact that most of the economic models are grounded on stationary and rationality assumptions, and that, generally, data available to estimate them do not satisfy these assumptions. Errors-in-variable models offer a structure to implement this approach, if stationary assumptions are imposed on measurement errors and if economic constraints are applied to the conditional expectations of the observed variables given the measurement errors. Here we will adopt the second point of view.

The second remark bears on the methodology that can be used to estimate models with survey data. As all variables are categorical, least squares regressions give inconsistent estimates and non-linear methods are required. In the prospect of estimating a simple linear relation between endogenous and exogenous continuous variables which we observe qualitatively, we might be tempted to replace the exogenous variables by their qualitative counterparts. But this would produce biased estimates (as argued in the Appendix of Chapter 3) because the model is then mis-specified. In this chapter, the econometric specification of the theoretical model of Chapter 1 is developed for the continuous variables assuming errors-in-variables. In order to estimate the model on survey data, a technique allowing us to pass to the continuous variables from the discrete ones is presented in the next chapter.

The last remark underlines the fact that survey data provide information on change of variables rather than on their levels. The answers of firms can be deciphered as bearing on changes in absolute values or in percent. In applied econometrics on continuous data, using first differences or variation rates on variables does not give the same results. Here, there is no practical way to choose between the two interpretations.

The representation of the information in terms of percent changes is the most intuitive and agreeable; indeed it is certainly easier for the manager to say what is the percent changes associated with a stable variable than to know precisely the absolute limits of the range for stability. Nonetheless, the interpretation of variables in absolute changes is chosen here for its tractability, and it is noticeable that, from the point of view of the manager, the two interpretations (percent versus absolute values) are very close if we are ready to assume that there are measurement errors on the thresholds. (See end of this chapter.) The consequence of the interpretation of the variables in absolute changes is that the empirical model must be written in a differenced form.

Given these remarks, we now review the different elements that will appear in the complete empirical model (whose equations are gathered in Table 2.1 at the end of this Chapter), and we discuss identification and the meaning of the structure chosen.

2.1 Outline of the Basic Equations.

There will be two parts in the empirical model: A "structural" model which contains the equations derived from the theoretical model written under the Rational Expectations Hypothesis, and a measurement model which links the variables of the structural model to the variables for which we have information through survey data (i.e., indicators).

At this point, it is important to notice that different types of latent variables will appear in the analysis. A first set of latent variables is used to explain the survey responses (the discrete variables) since the latter are produced when the former cross some thresholds. I called them the latent "measuring" variables as they serve to measure two other types of latent variables. The first type is formed by the variables which have a precise role (sense) with respect to an economic model. They are usually called the "true" variables or the latent "measurable" (or "observable") variables. These are the variables defined for the theoretical model of Chapter 1. The second type of latent variables gathers all the variables that can be measured but are not observable. These are measurement errors, errors-in-equations and the like; for this reason they may be defined as latent "unobservable" variables. (See Aigner _et al._ [1984] for a similar characterization of the latent variables.)

Until discrete variables are explicitly introduced, the word "latent" should be reserved for characterizing the "true" and "unobservable" variables. For some of the discussion, the "measuring" variables could be assumed perfectly observed (and hence they should not be designed as latent), but in order to avoid confusion later, I already indicate the difference between the types of latent variables by the following convention: A "true" variable is indicated by a tilde (~) over the letter used to name the variable, while a measuring variable is shown by a star (*). Consequently, a variable, which is neither starred nor tilded, will be discrete. The Greek symbol 'ε' and the character 'u' will be reserved for defining "unobservable" variables.

The model is now introduced. We assume that it can be defined over T periods, and that it can be applied for any individual i. Without loss of generality, the index i is suppressed.

2.1.1. The Structural Equations.

These equations correspond to the ones of the theoretical model presented in the preceding chapter. For reasons explained in the introduction of this chapter, the model must be written in a differenced form.

(i) Exogenous stochastic processes

Let us recall that these processes refer to the demand schedule and the cost shock. A priori they could be any ARMA processes as far as they satisfy some stationary conditions (see Chapter 1). For simplicity of exposition, we assume that the exogenous stochastic processes that enter in the theoretical model are defined as:

$$(2.1)\quad \begin{cases} \tilde{\alpha}_t = \theta_1\tilde{\alpha}_{t-1} + u_t^{\alpha} \\ \tilde{\gamma}_t = \theta_2\tilde{\gamma}_{t-1} + u_t^{\gamma} \end{cases}$$

and we define:

$$(2.2)\quad \begin{cases} \Delta\tilde{\alpha}_t = \tilde{\alpha}_t - \tilde{\alpha}_{t-1} \\ \Delta\tilde{\gamma}_t = \tilde{\gamma}_t - \tilde{\gamma}_{t-1} \end{cases}$$

The error terms u_t^{α} and u_t^{γ} are taken as white noise processes. The reasons for restricting ourselves to this specification are discussed later. It should be recalled here that, if $\tilde{\alpha}_t$ or $\tilde{\gamma}_t$ are ARMA(1,1) for instance, there would be some new components in the optimal rule as seen in Chapter 1. This would not change the discussion below.

(ii) Determination of the production plan

If we assume that the error terms u_t^{α} and u_t^{γ} in (2.1) are white noise processes to simplify exposition, then, using the notation: $E_{t-1}\tilde{q}_t = \tilde{q}_t^e$, equation (1.12) defining the optimal control, is:

$$\tilde{q}_{t+1}^e = g_1\tilde{q}_t + g_2\tilde{\alpha}_t + g_3\tilde{\gamma}_t$$

Substracting $\tilde{q}_t$ from both sides yields:

$$\tilde{q}_{t+1}^e - \tilde{q}_t = (g_1-1)\tilde{q}_t + g_2\tilde{\alpha}_t + g_3\tilde{\gamma}_t$$

Renaming g_1-1 by g_1', and assuming that the preceding equation is also true at time t-1, one derives an equation in terms of changes:

$$\tilde{q}^e_{t+1}-\tilde{q}_t = (\tilde{q}^e_t-\tilde{q}_{t-1}) + g_1'(\tilde{q}_t-\tilde{q}_{t-1}) + g_2(\tilde{\alpha}_t-\tilde{\alpha}_{t-1}) + g_3(\tilde{\gamma}_t-\tilde{\gamma}_{t-1})$$

or, with a more compact notation:

$$(2.3) \qquad \Delta\tilde{q}^e_{t+1} = \Delta\tilde{q}^e_t + g_1'\Delta\tilde{q}_t + g_2\Delta\tilde{\alpha}_t + g_3\Delta\tilde{\gamma}_t$$

where: $\Delta\tilde{q}^e_{t+i} = \tilde{q}^e_{t+i}-\tilde{q}_{t+i-1}$ $i=0,1$ and $\Delta\tilde{q}_t = \tilde{q}_t-\tilde{q}_{t-1}$. Under this new form, the linear decision rule of the firm can be estimated using survey data. If expected changes are rational, then:

$$(2.4) \qquad \Delta\tilde{q}_{t+1} = \Delta\tilde{q}^e_{t+1} + \Delta u_{t+1}$$

where $\Delta u_{t+1} = u_{t+1} - u_t$ and the expectational error u_t is white noise. Since expectations are derived from a model where firms act rationally, one must require that realizations must be obtained from the expectations according to the Rational Expectation Hypothesis. If this was not true, then it would mean that some stochastic elements (known by the firm) have been omitted. But this would be contradictory with the assumptions underlying the theoretical model.

Equations (2.1) to (2.4) are basically the reduced form of the theoretical model.

2.1.2 The Measurement Equations.

The variables in the structural equations are measured with errors by some variables (later, themselves observed by survey data).

(i) Measuring the production variables

We assume:

$$(2.5) \quad \begin{cases} \Delta q_t^* = \Delta\tilde{q}_t + \varepsilon_t^q \\ \Delta q_t^{e*} = \Delta\tilde{q}_t^e + \varepsilon_t^{qe} \end{cases}$$

where Δq_t^*, Δq_t^{*e} are latent measuring variables (for which we have available discrete information from surveys). The measurement errors can be serially correlated, but this is an empirical issue. Equations (2.5) are standard in errors-in-variable models.

The measurements errors can have various interpretations. They can be seen as noisy components that prevent the firm from answering the survey questions according to the predictions derived from the theoretical model. These random components represents unanticipated elements such as technical failures of the production process, change of the government policy, etc. In fact they could be partly anticipated by firms but not by the econometricians, or the reverse. Indeed, it may be difficult for the firm to measure the effect of policy changes at a given point of time, while the econometrician, acting always ex-post, can explicitly take into account these shocks. On the contrary, entrepreneurs have a finer knowledge of their production processes than economists. The role and the meaning of the measurement errors are more completely justified and studied at the end of this chapter.

(ii) Measuring the exogenous stochastic processes

The French business survey has questions on different aspects of the activity of firms, like bottlenecks, capacity utilization, financial constraints which could be used in a more general model. However the information on cost factors is poor, the only available variable is the rate of change of the wage bill. Often firms do not answer this question, which makes its use very difficult, given that we need a panel of firms to estimate our model.

However, the survey contains appraisals on inventories and new orders, i.e., the answers to the questions relative to the adequacy of inventories (of finished goods) and of orders (backlogs or future sales). Specifically, respondents to the surveys are asked if they consider the quantities of products ready for sale (inventories) as greater than normal, normal, or less than normal (and the question is similar for backlogs of orders). I have proposed an interpretation of this information as measuring the deviation of the actual state for the firm from its optimal path (see Ivaldi [1987]). One result of this study is that the appraisals of inventories and order-backlogs are determined by two main stochastic factors affecting the environment of the firm, namely demand and cost. Thus the appraisals are measurements (with errors) for these two unobservable factors. Some empirical arguments justifying this interpretation are given in the Appendix to this chapter.

Based on this descriptive analysis, we introduce here a factor model for measuring the components $\tilde{\alpha}_t$ and $\tilde{\gamma}_t$. We define:

$$
(2.6) \begin{cases} L_t^* = \lambda\tilde{\alpha}_t + \tilde{\gamma}_t + \varepsilon_t^l \\ S_t^* = \tilde{\alpha}_t + \mu\tilde{\gamma}_t + \varepsilon_t^s \end{cases}
$$

where L_t^* and S_t^* are, respectively, the latent inventory and order-backlog appraisal variables (for which we have categorical data in surveys).

Obviously there are no definitive arguments that can justify the use of inventory and order-backlog appraisals as measures of demand and cost factors. Our choice is only grounded on the interpretation of these appraisal variables and some empirical evidence given in the appendix. For instance, one generally observes from the data that managers say their inventory to be "below (above) normal" when their incoming orders and their sales are increasing (decreasing); and they judge their order-backlogs "too high (low)" when they observe a strong (weak) demand. Many press releases from statistical institutes which produce business surveys support these relationships. This means that L_t^* should be negatively related with $\tilde{\alpha}_t$ $(\lambda < 0)$ and that S_t^* and $\tilde{\alpha}_t$ should vary in the same direction (what we assume by measuring $\tilde{\alpha}_t$ in terms of the unit of S_t^*).

The introduction of $\tilde{\gamma}_t$ as a component of the appraisals is based on the argument that, if the entrepreneur observes a large shock in production costs, he would expect an higher level of cost next period and he would then find his inventories (order-backlogs) to be too high (low). Indeed, his activity could no longer correspond to the optimal level and he would prefer to have a lower level of production and to sell more. This is why we have assumed that the inventory appraisal variable is positively related to $\tilde{\gamma}_t$ (which is assumed by taking the unit of this variable as the one for $\tilde{\gamma}_t$) and the order-backlog appraisal variable depends negatively $(\mu < 0)$ on $\tilde{\gamma}_t$.

Moreover, this interpretation of the appraisal variables can be related to the meaning of the theoretical model presented in the previous chapter. In such a model, the firm equates the expected marginal revenue of an additional unit of production to its expected cost, both being equal to the shadow value of the stock. Equation (1.8) can be easily rearranged to obtain this classical optimality condition, the shadow value of the net inventories being associated with the constraint (1.7) at each period. The firm chooses its optimal plan to satisfy this condition, implying that the optimal production plan will depend on the past production level and the shadow value of the net inventories. The latter is a function of the state variables, namely demand and cost changes. Hence one may consider that the inventory and order-backlog appraisals could be taken as indirect observations for the location of the schedule relating this shadow value to the state of firm, as Koenig and Nerlove [1986] have proposed. (See also Nerlove [1986].) In some sense, equations (2.6) are a linear representation for this interpretation of the theoretical model.

In addition, if the measurement model (2.6) is used, it is easy to observe that the model says that the expected production plan is a function of L^* and S^*, the appraisal variables. (From 2.6, $\tilde{\alpha}_t$ and $\tilde{\gamma}_t$ are obtained as function of L^* and S^*; then it remains to write the equation (2.4) in terms of the appraisal variables.) Under this form, the expected change of production is a linear function of variables which measure the distance between the actual levels of inventories and order-backlogs from their optimal levels. Hence, our theoretical model could correspond to a classical adjustment model.

Finally, the estimation results for the model under investigation will confirm the conjecture that the inventory and order-backlog appraisals are together measures of demand and cost variables.

2.2 An Identifiable Specification.

The basic equations of the model to be estimated are: (2.1), (2.3), (2.4), (2.5), (2.6) together with the identities (2.2). This system constitutes a latent variable model. To specify completely the model, we need to define its time structure and to discuss the question of its identifiability by studying an example.

2.2.1 Identification

It is not possible to identify the parameters of the empirical model from a single cross-section. To obtain an identified model, we must assume that the parameters entering the empirical model are stable over several periods, i.e., should not be time-dependent. Under this condition, the number of variables in the empirical model increases with the number of periods, while the number of parameters stays the same. Consequently, a panel is required to perform the estimation. (Joreskog [1978b] has already studied this type of problems. See also Aigner *et al.* [1984].)

However it is not easy to determine the smallest number of periods that should be considered in order to get identification. To understand this point, let us consider the following example which is a classical errors-in-variable model, defined for period t=0:

$$\eta_0 = \alpha\, \xi_0 + \zeta_0$$
$$y_0^* = \eta_0 + \varepsilon_0$$
$$x_0^* = \xi_0 + \delta_0$$

Let us assume that: (y_0^*, x_0^*) are jointly normally distributed with means 0, variances 1 and correlation $\rho_0(x,y)$. The parameters to be estimated are:

$$\alpha,\ \mathrm{Var}(\zeta_0)=\psi_0,\ \mathrm{Var}(\xi_0)=\phi_0,\ \mathrm{Var}(\varepsilon_0)=\sigma_0^2(\varepsilon),\ \mathrm{Var}(\delta_0)=\sigma_0^2(\delta)$$

Given an estimate of $\rho_0(x,y)$, the correlation between x^* and y^* obtained on a cross-section of individuals surveyed at time t=0, it is not possible to estimate the five structural parameters.

Let us assume that data for the model are available for several periods and that the following parameters are stable overtime, i.e.:

$$\psi_t = \psi,\ \sigma_t^2(\varepsilon) = \sigma_\varepsilon^2,\ \sigma_t^2(\delta) = \sigma_\delta^2 \qquad \text{for any } t,$$

and let us write the preceding model over T periods:

$$\eta = \alpha\, I_T\, \xi + \zeta$$
$$y^* = \eta + \varepsilon$$
$$x^* = \xi + \delta$$

with η, ξ, ζ, y^*, x^* being T by 1 vectors, and I_T the identity matrix of order T. Since the number of exogenous variables is increased, the number of elements of the covariance matrix between these variables increases; this T by T matrix is denoted:

$$E(\xi\xi') = \Phi$$

Let us consider the following structure for Φ:

$E(\xi_t \, \xi_{t+i}) = \phi_i$ for any $t = 1,2,\ldots,T$ and i such that: $t \leq t+i \leq T$.
Now, the knowledge of the correlation matrix for the vector $(y^{*\prime}, x^{*\prime})$ gives us $(2T^2\text{-}T)$ estimated correlations to identify (T+4) structural parameters (the 5 previous parameters and (T-1) covariances of the exogenous variables). For T large enough, identification is achieved.

In practice the number of time periods retained to specify the model is the result of a compromise between the identification problem and the estimation conditions. Indeed, the technique used to estimate the model requires panel data with no missing observation. As firms neither answer each survey nor all questions in a given survey, the number of firms that stay in the survey on successive periods decreases drastically. Thus, to obtain a sample large enough we must restrict the number of periods, as long as identification is not lost. (Let us recall that identification is not achieved if the initial information matrix is singular. But this way of checking for identification depends upon the initial estimates.)

The model of the preceding section cannot be identified if one considers less than two periods on which we assume stability of the parameters. This means that the equations of the model should be estimated for at least three periods. As the model contains 4 variables $(\Delta q_t^*, \Delta q_t^{e*}, L_t^*, S_t^*)$, and as the initial conditions for the stochastic processes $\tilde{\alpha}_t$ and $\tilde{\gamma}_t$ have to be specified we should consider at least 14 variables. Moreover the linear decision rule (2.3) contains as an explanatory variable the expectation made one period backward; in order to estimate this equation at time $t = 1$, it is necessary to observe this expectation at time $t = 0$. Finally, the relation (2.4) links the realization of the variable at time T+1 with its expectation made at time T. So the empirical model should at least contain 16 variables belonging to 4 successive surveys.

In the sequel, I call the period of the last survey taken into account in the estimation, the ending period. From the 5371 firms that are included in the INSEE business survey (when one considers all the surveys from June 1974 to November 1985), only 386 firms answer the 16 questions necessary to estimate the model when the ending period is January 1985. By increasing the number of periods used to estimate the model we would put at stake the robustness of the estimates.

Obviously this method does not ensure that the panel of firms will be representative of the structure of the French industry, so that there is no way to deal with the heterogeneity inherent in such a sample. Nevertheless, experience on these data have shown that large firms keep answering to successive surveys while small firms do not. Since large firms are more numerous than small firms when one builds a panel with no missing data out of the successive surveys, we partly take care of the heterogeneity. The effect of firm size and response rates in this framework is a topic of future research.

2.2 The Complete Model.

The complete empirical model is summarized in Table 2.1. There are 16 "observable" latent variables, 31 latent "unobservable" variables and 20 parameters to be estimated. Several comments should be made regarding this specification:

i) It is always possible to specify that the measurement errors follow a particular pattern. Here only the measurement error on the expectation variable for production is assumed to follow an autoregressive process of order 1. (See equation (2.7)(g). But results will be given without this assumption.) Indeed, it appeared at the estimation stage that this specification gives better results. Given the discussion on the role of the measurement errors in section 2.1.2 (i), this assumption shows that some stochastic exogenous elements are not taken into account in the structural model. Hence, even if the latter is based on the Rational Expectations Hypothesis, it does not mean that the observed behavior is coherent with this assumption.

ii) If a covariance has not been specified, it is assumed to be zero. In particular, one may think that measurement errors could be correlated among themselves. Some of these correlations can be identified but were never significant.

iii) We assume that, for period 0 (i.e., the first (initial) period covered by the model):

$V(\tilde{\Delta} q_1^e) = 1, \quad V(\tilde{\alpha}_0) = 1, \; V(\tilde{\gamma}_0) = 1,$

where $V(.)$ denotes a variance. Only one of these three conditions appeared to be necessary for identification. But under these three conditions, the maximum likelihood procedure is more stable and gives better results in terms of the goodness-of-the fit without changing very much the values of the parameters. Moreover, these constraints are initial conditions and there is no way to choose one rather than another one.

iv) The structural equations can be collected to form the following system:

$$\eta = B\,\eta + \zeta$$

where η contains all the latent endogenous and exogenous variables, and the measurement errors (ε^{qe}, ε^{q}, u^1, u^s). This implies that the elements on the lines of the matrix B corresponding to these errors can be zeros. For instance, the structural equation for u_1^1 is: $u_1^1 = \zeta_k$ if u_1^1 is the k-th variable in η; hence, we must impose: $V(u_1^1) = V(\zeta_k) = \sigma_1^2$.

v) An error-in-equation (u_t) has been added to the linear rule determining production plans as we may expect that this rule cannot be applied strictly by the firm, and that we may have not taken into account all the variables.

vi) The measurement equations can be collected to form the following system:

$$y^* = \Gamma\,\eta$$

where y^* contains all the latent variables that will be "observed" through survey data.

Alternative statistical specifications are not numerous given the basic relations of the model and given the assumptions necessary to estimate a latent variable model. This will ensure the validity of the estimation results. However let us recall that the model of Table 2.1 is based on the assumptions that the processes for demand and cost shocks are AR(1), which must be empirically verified.

The object of the next chapter is to present a method to estimate such a model. Before I do this, some additional remarks on the meaning of the measurement errors and the link between the continuous and discrete variables is warranted. Then we will explicitly define the indicators used to observe the latent measuring variables.

Table 2.1: Specification of the Empirical Model

Structural equations

$$\text{(a)}\quad \Delta\tilde{q}^{e}_{t+1} = g_1'\Delta\tilde{q}_t + g_2\Delta\tilde{\alpha}_t + g_3\Delta\tilde{\gamma}_t + \Delta\tilde{q}^{e}_t + u^{e}_t \qquad t = 1,2,3$$

$$\text{(b)}\quad \Delta\tilde{q}_{t+1} = \Delta\tilde{q}^{e}_{t+1} + \Delta u_{t+1} \qquad t = 0,1,2,3$$

$$\text{(c)}\quad \tilde{\alpha}_t = \theta_1\,\tilde{\alpha}_{t-1} + u^{\alpha}_t \qquad t = 1,2,3$$

$$\text{(2.7)}\quad \text{(d)}\quad \tilde{\gamma}_t = \theta_2\,\tilde{\gamma}_{t-1} + u^{\gamma}_t \qquad t = 1,2,3$$

$$\text{(e)}\quad \Delta\tilde{\alpha}_t = \tilde{\alpha}_t - \tilde{\alpha}_{t-1} \qquad t = 1,2,3$$

$$\text{(f)}\quad \Delta\tilde{\gamma}_t = \tilde{\gamma}_t - \tilde{\gamma}_{t-1} \qquad t = 1,2,3$$

$$\text{(g)}\quad \varepsilon^{qe}_t = \rho\,\varepsilon^{qe}_{t-1} + u^{qe}_t \qquad t = 1,2,3$$

Measurement equations

$$\text{(a)}\quad \Delta q^{e*}_t = \Delta\tilde{q}^{e}_t + \varepsilon^{qe}_t \qquad t = 1,2,3,4$$

$$\text{(b)}\quad \Delta q^{*}_t = \Delta\tilde{q}_t + \varepsilon^{q}_t \qquad t = 1,2,3,4$$

$$\text{(2.8)}\quad \text{(c)}\quad L^{*}_t = \lambda\tilde{\alpha}_t + \tilde{\gamma}_t + \varepsilon^{1}_t \qquad t = 0,1,2,3$$

$$\text{(d)}\quad S^{*}_t = \tilde{\alpha}_t + \mu\tilde{\gamma}_t + \varepsilon^{s}_t \qquad t = 0,1,2,3$$

Endogenous latent (measurable) variables (1)

$$\xi_0 = ((\Delta\tilde{q}^{e})^4_2,\ (\Delta\tilde{q})^4_1,\ (\tilde{\alpha})^3_1,\ (\tilde{\gamma})^3_1,\ (\varepsilon^{qe})^3_1,\ (\varepsilon^{q})^3_1,\ (\varepsilon^{1})^3_1,\ (\varepsilon^{s})^3_1)'$$

Endogenous latent (measuring) variables

$$x^{*}_0 = ((\Delta q^{e*})^4_2,\ (\Delta q^{*})^4_1,\ (L^{*})^3_1,\ (S^{*})^3_1)'$$

Table 2.1 (continued)

Exogenous latent (measurable) variables (2)

$$\xi_1 = (\Delta\tilde{q}_1^e,\ \tilde{\alpha}_0,\ \tilde{\gamma}_0)'$$

Exogenous latent (measuring) variables (2)

$$x_1^* = (\Delta q_1^{e*},\ L_0^*,\ S_0^*)'$$

Latent (measurable) variables

$$\eta' = (\xi_0'\ ,\ \xi_1')$$

Latent (measuring) variables

$$y^{*\prime} = (x_0^{*\prime}\ ,\ x_1^{*\prime})$$

Errors-in-equations

$\zeta' = (\ (u^e)_1^3\ ,\ (\varepsilon)_1^4\ ,\ 0')$ where 0 is the nul vector whose dimension is chosen for ζ and η to have same dimensions.

Parameters (1)

g_1'; g_2; g_3; θ_1; θ_2; λ; μ; ρ;

$$\left.\begin{array}{l} V(u_t^e) = \sigma_e^2,\quad V(u_t) = \sigma_u^2, \\ V(u_t^\alpha) = \sigma_\alpha^2,\quad V(u_t^\gamma) = \sigma_\gamma^2, \end{array}\right\}\ t = 1,2,3;$$

$V(u_0^{qe}) = \sigma_{qe_0}^2$; $V(u_t^{qe}) = \sigma_{qe}^2$;

$V(\varepsilon_t^q) = \sigma_q^2$, $t = 1,2,3$;

$V(\varepsilon_t^1) = \sigma_1^2$, $V(\varepsilon_t^s) = \sigma_s^2$, $t = 1,2,3$;

$\mathrm{Cov}(\Delta\tilde{q}_0^e\ \tilde{\gamma}_0) = \phi_{12}$; $\mathrm{Cov}(\Delta\tilde{q}_0^e\ \tilde{\alpha}_0) = \phi_{13}$;

$\mathrm{cov}(\tilde{\alpha}_0\ \tilde{\gamma}_0) = \phi_{23}$.

Table 2.1 (continued)

Glossary

$\Delta\tilde{q}^e$: "true" expected change of production

Δq^{e*}: "observable" expected change of production

$\Delta\tilde{q}$: "true" change of production

Δq^* : "observable" change of production

$\tilde{\alpha}$: latent variable for the demand schedule

$\tilde{\gamma}$: latent variable for the cost shock

L^* : appraisal on inventory (latent)

S^* : appraisal on order-backlog (latent)

---

(1) notation: $(x)_t^{t+i}$ is the vector $(x_t, x_{t+1},\ldots,x_{t+i})$ and V(X) is the variance of x.

(2) Exogenous and endogenous variables are not separated in the sequel.

2.3 Discussion of the Overall Model.

(i) To understand the meaning of the preceding model, let us consider the following errors-in-variable model:

$$\text{(A)} \qquad \begin{cases} \eta_t = \alpha\, \xi_t + u_t \\ y_t^* = \eta_t + \varepsilon_t \qquad t=1,\ldots,T \\ x_t^* = \xi_t + \delta_t \end{cases}$$

where (y_t^* , x_t^* , $t=1,\ldots,T$) are observed. Model (A) can be written:

$$\text{(B)} \qquad \begin{bmatrix} y_t^* \\ x_t^* \end{bmatrix} = \begin{bmatrix} \alpha \\ 1 \end{bmatrix} \xi_t + \begin{bmatrix} \varepsilon_t + u_t \\ \delta_t \end{bmatrix}$$

(A) and (B) is a model of factor analysis where the two observed variables share a common factor (namely, ξ_t) and also possess a specific factor (ε_t and δ_t). This remark shows that the model presented in the preceding sections can be written as a factor analysis model where the common factors of the observed variables are arranged (determined) in meaningful (structural) relations. It should be noticed that these common factors are the conditional expectations of the observed variables given the measurement errors, i.e.:

$$\text{(C)} \qquad \begin{aligned} E(y_t^* \mid \varepsilon_t) &= \eta_t \\ E(x_t^* \mid \delta_t) &= \xi_t \end{aligned}$$

when η (ξ) is independent of ε (respectively, δ). Consequently, another way to justify the chosen structure for the econometric model of this chapter is to argue that each element of a vector of stochastic processes may always be decomposed into its expectation and a residual process, and that a set of (dynamic linear) relations derived from an economic analysis relates the expectations between them, given some distributional assumptions on the residuals. From this viewpoint, the introduction of measurement errors is "natural." In addition, if we believe that, for various economic or empirical reasons, such errors must be explicitly specified, the above statistical argumentation offers the possibility to take into account these reasons in a coherent way.

The preceding standpoint implies also that the economic content of the model can be strictly concentrated in the relationships between the common factors. This is a decisive point since, without an economic model, there is no way to define (i.e., to give a name to) these factors. (In the examples (A) or (B), if the parameter of interest (i.e., a) does not have a particular meaning given from outside, then ζ_t may have no direct (economic) meaning.) Since, in this chapter, all required economic assumptions are imposed on the common factors of the econometric model, we have a way to "identify" these factors. In particular, this is why the rationality assumption which underlines the theoretical model is "identified" by the statistical model.

The situation is similar to the one which emerged with the discussion on the permanent-transitory income model of consumption in the sixties. (See Griliches [1974].) Here, the structural model based on the Rational Expectation Hypothesis is not observable, but it can be defined by the expectations of a set of observable variables conditional on the "transitory" components (i.e., the measurement errors), and it can be interpreted as the "permanent" component of the data. So, in this view, the terminology "measurement errors" or "errors-in-variable models" is perhaps not well suited, but it is usually employed in such a context.

In connection with this point, it should be noticed that all variables in a dynamic errors-in-variable model are a priori endogenous in the econometric sense, except the initial conditions. (See Florens, Mouchard and Richard [1987] on this point.) Indeed, the model is not a regression. For example, model (A) can be written:

$$\text{(D)} \qquad y_t^* = ax_t^* + w_t \quad \text{where} \quad w_t = -a\delta_t + \varepsilon_t + u_t$$

Note that, without further assumptions, x_t is not exogenous, since it is correlated with δ_t. Hence, although the words "exogenous" and "endogenous" are used in Table 2.1, they here allow us locating the variables by their position in the model, but they do not have the usual econometric meaning.

(ii) In the above discussion, the fact that the available data are ordinal is not taken into account. To complete the example of this section , let us suppose that, instead of observing y^* and x^*, two indicators are available, defined as follows:

$$\text{(E)} \quad y_t = \begin{cases} 1 & \text{if } y_t^* \geq 0 \\ 0 & \text{if } y_t^* < 0 \end{cases} \quad \text{and} \quad x_t = \begin{cases} 1 & \text{if } x_t^* \geq 0 \\ 0 & \text{if } x_t^* < 0 \end{cases}$$

Given model (A), these correspondences between discrete and continuous variables can be written:

$$\text{(F)} \quad y_t = \begin{cases} 1 & \text{if } \eta_t \geq -\varepsilon_t \\ 0 & \text{if } \eta_t < -\varepsilon_t \end{cases} \qquad \text{and} \qquad x_t = \begin{cases} 1 & \text{if } \xi_t \geq -\delta_t \\ 0 & \text{if } \xi_t < -\delta_t \end{cases}$$

Under this form, the model could take into account the case where observations are misclassified, which is one of the usual reasons advanced for introducing measurement errors in this situation. However, the interpretation given above is preferred here.

If we had considered the model formed by the correspondences (E) and the equation (D) without specifying the measurement errors (i.e., forgetting the definition of w_t), then we would have settled a regression analysis in the sense that the variable x_t^* would be a priori assumed exogenous (in the econometric sense). This remark emphasizes the discussion made above, again by pointing out that measurement errors may be indistinguishable from the disturbances usually introduced in an econometric model. Now, when measurement errors are specified, even if it is at the level of the relations defining the categorical variables, the nature of the model is different from a classical regression as already explained. Hence this is not the nature of the data which justifies the introduction of measurement errors, but it is rather the type of model required here.

Based on this discussion, it seems that, when the objective is to estimate a structural model under a set of economic assumptions (such that, for instance, the hypothesis that expectational errors are white noise), the approach in terms of errors-in-variable models is more suited since it allows us to impose the stochastic assumptions necessary to characterize (to identify) the economic model. Let us now introduce the discrete variables in relation with the latent variables defined in Table 2.1.

2.4 The set of Indicator Variables

The indicators that will be used as observations of the latent measuring variables are defined by the following correspondences:

$$(2.9) \qquad X_t = \begin{cases} 1 \text{ if } & \Delta X_t^* > \delta_t^1(X) \\ 2 \text{ if } & \delta_t^2(X) < \Delta X_t^* \leq \delta_t^1(X) \\ 3 \text{ if } & \Delta X_t^* \leq \delta_t^2(X) \end{cases} \qquad t = 1,2,3,4$$

where X is either q, q^e, LA, or SA, and X^* is either q^*, q^{e*}, L^*, or S^*. The realized and expected changes for production (q and q^e) take three categories "increase", "stay the same", "decrease", denoted respectively by 1,2,3. The inventory and order-backlog appraisal variables (LA and SA) are also trichotomous, but the categories correspond to the three cases "above normal", "normal", "below normal".

We assume that the discrete response of the firm to each survey question is triggered when the latent variable crosses some thresholds, which are assumed to be time-dependent. It must be stressed that this chosen specification for the thresholds for each variable leads to a reparametrization where they appear to be symmetric around the mean over time of the differences between the upper and lower thresholds.

To show this, we need first to explain how the thresholds can be computed.

They are usually estimated by inverting the normal cumulative density function evaluated at the empirical frequencies. This is justified by invoking the following asymptotic argument. Let P_{kt} be the true probability that x_t (x being q, q^e, LA, or SA) falls in the cell k (k=1,2,3) and let $\hat{p}_{kt}$ be the corresponding observed frequency. When n_t, the number of firms observed at time t, is large enough, it is known that $(n_t)^{1/2}(\hat{p}_{kt} - P_{kt})$ has an asymptotic normal distribution. Moreover, by Slutsky's theorem (see Monfort [1981], page 166), the variable $(n_t)^{1/2}(F^{-1}(\hat{p}_{kt}) - F^{-1}(P_{kt}))$ (where $F^{-1}(.)$ denotes here the inverse of the normal cumulative density function) is also asymptotically normal. Given this, we could write:

$$F^{-1}(1-\hat{p}_{1t}) = \hat{\delta}_t^1(x)$$
$$F^{-1}(1-\hat{p}_{1t}-\hat{p}_{2t}) = \hat{\delta}_t^2(x)$$

Now, we can always define m and r_t such that:

$$\hat{\delta}_t^1(x) = m + r_t \quad \text{and} \quad \hat{\delta}_t^2(x) = m - r_t$$

with: $m = \frac{1}{T}\sum_{t=1}^{T} (\hat{\delta}_t^1(x) + \hat{\delta}_t^2(x))$ and $r_t = \hat{\delta}_t^1(x) - \hat{\delta}_t^2(x)$ t=1,2,...,T

This specification is useful in view of explaining the temporal pattern of the thresholds, as can be seen from Figure 2.1 where upper and lower thresholds for the variable "realized change of production" (solid lines) and for the variable "expected change of production" (dashed lines) are displayed (from June 1974 to October 1985. Figure

2.2 gives a similar information for inventory and order-appraisals.

2.5 Summary

We now have an errors-in-variable model which integrates in a meaningful way the economic relations and assumptions made to build up the theoretical model. This statistical model is identifiable as explained in section 2.2, and the choice for such an approach is based on the idea that all variables are endogenous. The model for the continuous variables being completely defined, the problem is now to use the discrete information to estimate it, knowing that there exist some correspondences between the continuous and discrete variables.

Figure 2.1: Thresholds for Realized and Expected Changes of Production

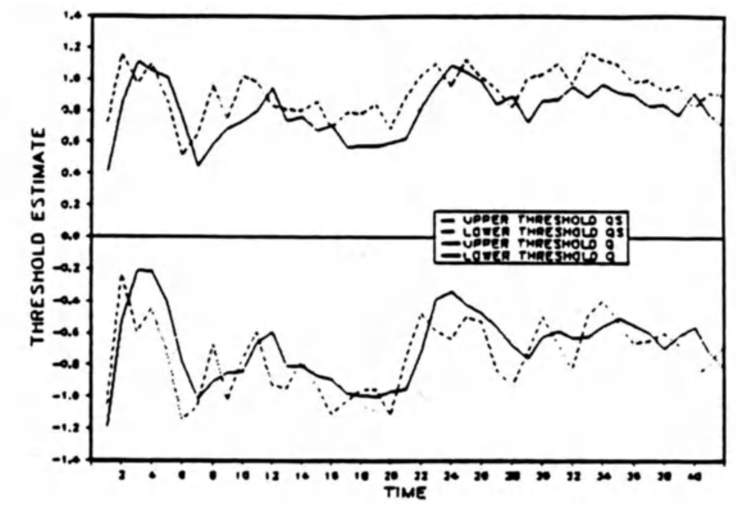
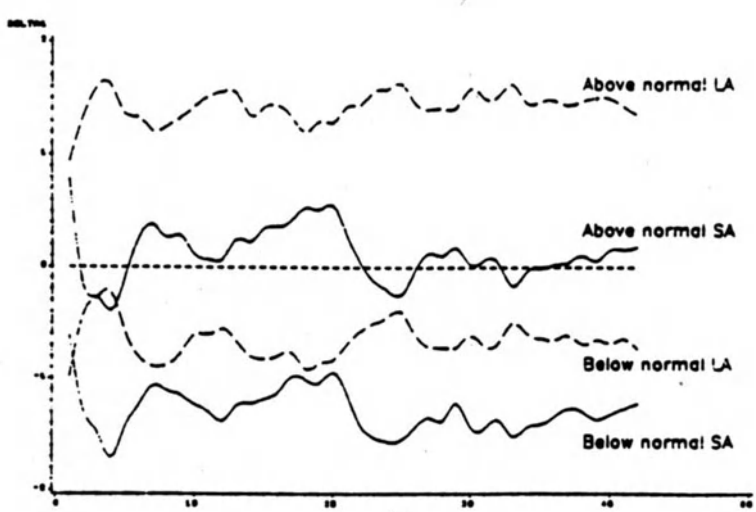


Figure 2.2: Thresholds for Appraisals on Inventory and Order-backlog



Appendix to Chapter 2: An Empirical Study of Inventory and Order-backlog Appraisals

In this appendix, some descriptive arguments are presented in order to justify the use of inventory and order-backlog appraisals to measure the demand and cost variables, as proposed in the model of Chapter 2. They are developed by means of a correpondence analysis and a covariance structure analysis.

A2.1 Correspondence Analysis

Correspondence analysis performs a projection of the individual data on the hyperplane of the factors explaining the correlations among variables, where the factors are the eigenvectors of the matrix defining this projection. The method, so-called factor analysis of correspondences, is non-parametric since no distributional assumptions are required. Let us briefly introduce this method, and then apply it to the survey data.

A2.1.1 Determining Principal Components by Correspondence Analysis

The surveys provide the analyst with a large amount of information from which one may want to extract the principal components in order to analyze the structures of the answers. Various techniques could be used in order to do so, such as classical multidimensional scaling (see Schiffman, Reynolds, Young [1981], correspondence analysis (see Benzecri [1973], Deville and Saporta [1983]), and principal components analysis. (See Heiser and Meulman [1983] for an account of the relationships between these methods.)

There are many empirical studies based on these techniques. They use graphical displays for studying the relationships between categorical variables. The idea is to interpret the eigenvectors of a matrix representing the correlations among variables as the factors explaining the similarities and dissimilarities between variables. For example, Abou and Ameller [1979] and Chazelas and Vila [1982] use it to construct an economic activity indicator, Fayolle [1980] to characterize the behavior of firms on foreign markets, etc. Correspondence analysis can also be used to study dynamic aspects (see Deville [1982]) since the surveys are usually performed regularly. It is noticeable that correspondence analysis is not based on any distributional assumptions; as an alternative, the explanatory factor analysis posits normality of the observed variables and the underlying components (see Mardia, Kent and Bibby [1979]).

The main arguments of correspondence analysis which handle only categorical variables and which are mathematically identical to canonical analysis of contingency tables can be mainly explained using the bivariate case. The central point is to compute the various canonical variables in order to plot the categories of the variables.

Let us consider a sample of n individuals who are observed through two traits T_1 and T_2, which take values on P_1 and P_2 categories, respectively. Let us define the matrices X_1 and X_2 of size (n,p_1) and $n,p_2)$ associated with the variables by:

$X_t(i,k)=1$ if individual i belongs to category k of T_t

$X_t(i,k)=0$ otherwise, t being 1 or 2.

The contingency table is obtained as: $C = X_1'X_2$. The marginal frequencies of each variable are recorded in two diagonal matrices: $D_1 = X_1'X_1$ and $D_2 = X_2'X_2$. The orthogonal projector onto the subspace spanned by the columns of $X_t(t=1,2)$ is: $P_t = X_tD_t^{-1}X_t'$, $t = 1,2$. The problem can be stated as follows:

$$\text{Max } z' \left((P_1+P_2)/2\right)z \text{ with } z'z = \text{constant},$$

i.e., we look for a numerical variable z with fixed variance such that on average the variance of z due to T_1 and T_2 is maximum.

The solution to the above problem is the eigenvector of $(P_1+P_2)/2$ associated with its greatest non-trivial eigenvalue. The categories of T_1 and T_2 can be displayed along the unique axis defined by z, and their coordinates are given by $D_1^{-1}X_1'$ and $D_2^{-1}X_2'$. The procedure can be pursued by considering the second eigenvector of $(P_1+P_2)/2$ associated with its second largest non-trivial eigenvalue; this is another extremum of the preceding program, corresponding to another variable z complementary to the first one; then the categories of T_1 and T_2 can be displayed in a plane, and so on.

The main difficulty with this method (and the related ones) is to identify the factors, i.e., to name precisely the principal components. The interpretation of the results (mainly, graphical) are subject to criticism if there is no way to determine the meaning of the axis (factors). To circumvent this problem, one should use additional variables whose definitions are unambiguous so that their relations with the axis can be easily deciphered. Nevertheless, these methods provide a very handy representation of the structure of the data through the setting of contingency tables and the computation of numerical values for the common factors of the data.

A2.1.2 Application

Correspondence analysis is convenient for survey data. Here four variables are studied: Inventory appraisals, order-backlog appraisals, realizations of demand, and the rate of change of the firm wage bills. The first two have been presented previously. The third concerns changes in demand for the product of the firm between two surveys. For the variable 'wage', the continuous information available in the INSEE business survey is categorized in five groups: Increase by less than 1 percent, between 1 and 1.5 percent, between 1.5 and 2 percent, between 2 and 2.5 percent, by more than 2.5 percent. (This is consistent with the fact that respondents round off their answers.) So the associated contingency table has 3^3 x 5 cells.

The correspondence analysis has given similar results for the eight surveys covering the years 1984-85. Only a synthesis of the results is reported. Table A2.1 gives the eigenvalues obtained for a typical quarter; it shows that three or four factors should be considered for the analysis of the four observed qualitative variables.

Table A2.1: Eigenvalues for the Factor Analysis of Inventory and Order-backlog Appraisals.

	eigenvalues	cumulative percent	percent
1	0.470	17.16	17.61
2	0.402	15.06	32.67
3	0.355	13.32	45.99
4	0.337	12.64	58.63
5	0.324	12.16	70.79
6	0.316	12.16	82.63
7	0.253	9.50	92.13
8	0.209	7.87	100.00
(sum of the eigenvalues = 2.666)			

The figures A2.1 and A2.2 summarize the locations of the variables in the vector space and their relations. The axes for the first graph correspond to the first two factors. The first figure shows that the inventory appraisal variable (LA) is negatively correlated with the order-backlog appraisal (SA) and the demand (D) variables, as expected. Clearly, both axes of this figure should be related to the conditions of the demand since one can order the variable along each axis according to the state of demand. One can also remark that axis 12 separates the firms between those adapting their production to the economic situation, and those staying in the same position when demand does not change.

The "wage" variable (W) is not reported on the first graph since it has no regular graphical pattern observed at each period, which indicates that the first two factors should certainly not be interpreted as cost variables. Now, the "wage" variable appears to be ranked according to the third axis; hence this latter should be interpreted as a cost factor. The fourth factor (axis) is possibly an indicator of the different strategies adopted by firms during the business cycle. The fact that the 'below (resp. above) normal' case for the inventory appraisal is symmetric by this axis to the 'above (resp. below) normal' case for the order-backlog appraisal may indicate that some firms choose to adjust their inventory and some to fill up the order book as a response to a change in their environment.

Summing up, the data on inventory and order appraisals seem to convey information on factors related to the economic environment of the firm and to costs. But the preceding descriptive analysis is not at all dynamic since it is based on the study of different cross-sections. The generalization of correspondence analysis to panel data is not easy to implement. Hence, in order to justify the preceding fact in a more dynamic way, I propose another type of factor analysis.

Figure A2.1 - First Display for the Factors Explaining Inventory and Order-backlog Appraisals

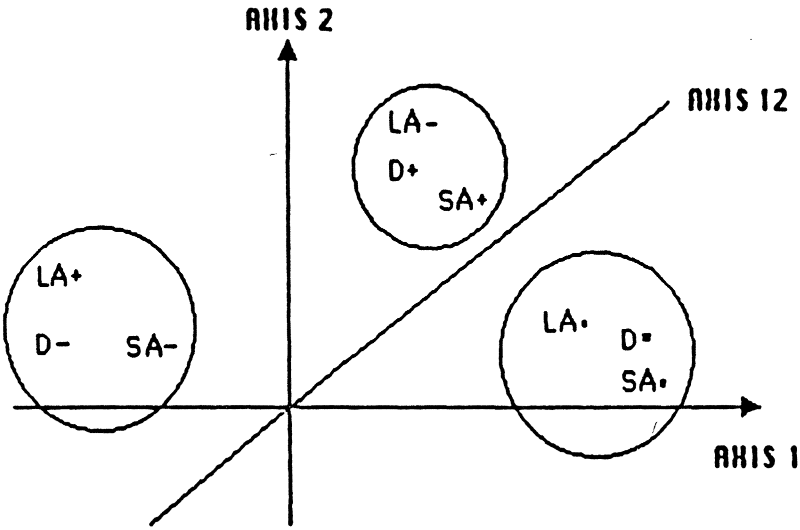
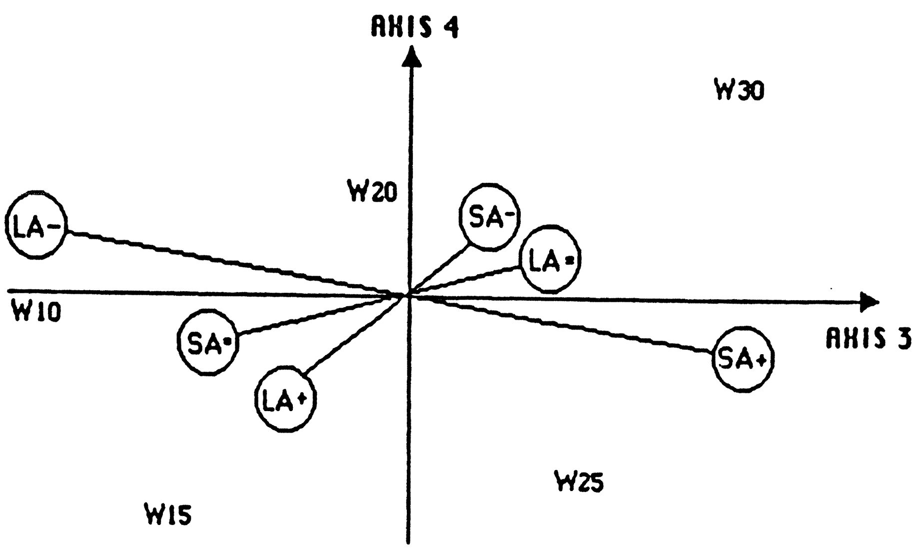


Figure A2.2 - Second Display for the Factors Explaining Inventory and Order-backlog Appraisals



A2.2 A Covariance Structure Model

Here the factors explaining the evolution of the observed variables are assumed to be random variables. The problem is to determine the nature of these stochastic processes from the knowledge of the covariance matrix of the observed variables. The model proposed here is a particular case of the latent variable linear models whose estimation is studied in the next chapter.

The model to be estimated will cover four periods. The sample contains 458 firms responding to each of the questions concerning inventory appraisal, order appraisal, change in demand, change in the wage bill. For the latter, we have constructed three classes of variation: class 1 corresponds to a variation of the wage bill between 0 and 1.2%, class 2 to a variation between 1.2 and 2.4%, and class 3 the remainder. (This coding is chosen in order to be closer to the normality assumption, and to avoid some outliers in the sample.)

The model, given in Table A2.2, assumes that two latent processes η_1 and η_2 explain the behavior of four variables L^*, S^*, D^*, W^* and that they are autoregressive processes of order one. The stared variables are observed through the discrete variables LA, SA, D, W. I assume here that an empirical covariance matrix for the stared variables, obtained from the discrete variables, is available. The next chapter explains at length how to derive such a statistic and how to use it to estimate the parameters of latent variable models. The identification of the model in Table A2.2 is studied by different authors. (See, for instance, Maravall and Aigner [1977].)

Table A2.2: A Covariance Structure Model

$L^*_t = \lambda_{11}\ \eta 1_t + \lambda_{12}\ \eta 2_t + \varepsilon 1_t$

$S^*_t = \lambda_{s1}\eta 1_t + \lambda_{s2}\eta 2_t + \varepsilon s_t$

$D^*_t = \eta 1_t + \varepsilon d_t$

$W^*_t = \eta 2_t + \varepsilon w_t$

$\eta 1_t = \beta_1 \eta 1,_{t-1} + \zeta 1_t$ for any t = 1,2,3,4

$\eta 2_t = \beta_2 \eta 2,_{t-1} + \zeta 2_t$

$\theta_1 = \mathrm{Var}(\varepsilon 1_t)$

$\theta_s = \mathrm{Var}(\varepsilon s_t)$

$\theta_d = \mathrm{Var}(\varepsilon d_t)$

$\theta_w = \mathrm{Var}(\varepsilon w_t)$

$\psi_{11} = \mathrm{Var}(\eta_{11})$

$\psi_{21} = \mathrm{Var}(\eta_{21})$

$\psi_1 = \mathrm{Var}(\zeta 1_t)$ for any t > 1

$\psi_2 = \mathrm{Var}(\zeta 2_t)$

Table A2.3: ML Estimates for the Factor Analysis of Inventory and Order-backlog Appraisals

Parameters	Estimates	Standard Errors
λ_{11}	-0.875	0.056
λ_{12}	16.636	8.332
λ_{s1}	1.486	0.050
λ_{s2}	2.855	1.554
β_1	0.709	0.023
β_2	0.665	0.034
ψ_{11}	0.414	0.037
ψ_{21}	0.002	0.002
ψ_1	0.207	0.015
ψ_2	0.001	0.001
θ_1	0.027	0.031
θ_s	0.067	0.017
θ_d	0.586	0.021
θ_w	0.997	0.033

Strong stationarity assumptions are imposed (for instance, β_1 and β_2 are assumed constant over time), but some of them can be easily relaxed without changing the results. The estimates are gathered in Table A2.3. Almost all parameters are significant and various measures show that the fit is quite good. (For instance, the Goodness-of-Fit Index is 0.868; the coefficient of determination for the observed variables is 1.0; the squared multiple correlations are between 0.42 and 0.97. All these measures are defined later in Chapter 4.)

The fact that the two factors η_1 and η_2 are measured with the same units as D^* and W^*, respectively, is a way to identify them as related to demand and cost shocks,respectively. Given that the λ's are significantly different from zero, we have a justification for using the inventory and order-backlog appraisals as a way to measure the demand and cost variables as it is proposed in this chapter.

Let us recall that the motive of this appendix is to find a proxy for the cost shocks which play a crucial role in the model of Chapter 2. We could have used directly the "wage" variable as it is reported in the French survey. Two reasons explain why it is not possible. First, the percent increase of the wage bill is not the best measure of cost changes. Second, a very large number of firms do not answer consistently or do not answer this question at all.

The results of the present analysis confirm that the latent variable for wages is poorly determined. Indeed, the very high value of λ_{12} means that the associated factor has a very small variance. This explains why that variable is not considered in the econometric model of Chapter 2 and why a measurement model based on the inventory and order-backlog appraisal has been chosen.

Chapter 3: The General Latent Variable Model with Discrete Data

This chapter is devoted to the presentation of an estimation technique when all variables arranged in meaningful relations are ordinal. The model that we consider may be stated in a very compact way as follows. Let $\eta' = (\eta_1, \eta_2, \ldots, \eta_m)$ be a random vector of latent variables, $\zeta' = (\zeta_1, \zeta_2, \ldots, \zeta_p)$ a random vector of residuals (errors-in-equations, random disturbances terms), B a m by m non-singular matrix of regression coefficients with zeros on the main diagonal. Rather than observing η directly, we assume for the moment that we have information on $y^{*\prime} = (y_1^*, y_2^*, \ldots, y_p^*)$, a column vector of m variables which are linear functions of the m variables in η. Let Γ be a p by m coefficient matrix of the regressions for the unobserved variables in η. Then we consider:

(3.1) $$\eta = B\,\eta + \zeta$$

(3.2) $$y^* = \Gamma\,\eta$$

(3.3) $$y = g(y^*)$$

Equation (3.1) is a classical simultaneous equation system where η is a vector containing latent endogenous and exogenous variables and possibly measurement errors. These variables are measured by the vector y^* according to equation (3.2). Finally, the variables in y^* are also latent in the sense that they determine the ordinal variables in y (a column vector of dimension m) through the correspondence (3.3). (The latter usually takes the form introduced in section 2.4.) To avoid confusion between the different types of latent variables in the model, recall that η are considered "true" or "measurable" latent variables, and y^* are considered "measuring" latent variables.

Equations (3.1) and (3.2) form what is usually called the general latent variable model. It encompasses the classical simultaneous equation model, the errors-in-variable model, the factor analysis model, and has been extensively studied. (See Joreskog [1977], Joreskog and Sorbom [1977], Joreskog [1978], Muthen [1981, 1983], Bentler [1983], Long [1983], Aigner et al. [1984], Joreskog and Sorbom [1986a].) Estimation methods for such models are well known. The new element here is the introduction of equation (3.3), which complicates the estimation of the complete model. Nerlove [1987] has presented a technique for such a case. Let us briefly motivate the approach proposed here.

Setting aside equation (3.3), and assuming that all variables in y^* are observable for a while, the latent variable model can be estimated by Maximum Likelihood or by applying the Method of Moments. If all variables are centered, one requirement to implement these methods is to know the sample variance-covariance (or correlation) matrix for the observable variables. (Knowing higher moments would be useful in some situations, in particular, when variables are not normally distributed. For simplicity of exposition, we consider the simplest case.) Can we apply this approach when the data are discrete?

Directly obtained in general from a sample of quantitative data, such a sample covariance matrix must be carefully designed in our case since all the information available on y^* is qualititative. We could use the matrix of product moments for the ordinal variables in y but it is a very poor estimate of the covariances of the "measuring" latent variables. (See Joreskog and Sorbom [1986b].) The solution proposed below consists in applying the maximum-likelihood method to the estimation of the correlation matrix for the variables in y^* using the discrete data on y. This is the so-called theory of the polychoric correlation coefficient.

When this estimated correlation matrix is used in place of the unknown sample correlation matrix of vector y^*, then the log-likelihood function associated with the latent variable model becomes a pseudo log-likelihood. Now, maximizing the latter yields consistent estimators, but the asymptotic covariance matrix of the estimates is not in general consistently estimated by the inverse of minus the second partial derivatives of the pseudo log-likelihood. (See Gourieroux, Montfort, and Trognon [1984]). As an alternative, minimum distance estimators for the parameters of the latent variable model can be proposed. These estimators, which are quadratic form functions of the theoretical correlations and of the polychoric correlation coefficients, require the knowledge of a weighting matrix. An obvious candidate for the latter is an estimate of the asymptotic covariance matrix of the polychoric correlation coefficients. We may then compute correct asymptotic variances and covariances for the model parameters. Let us present this methodology in detail, first by reviewing the usual estimation method of the latent variable model, second, by presenting the theory of polychoric correlation coefficient and third, by showing how to implement these methods in practice.

3.1 Estimation for the General Latent Variable Model

Model (3.1)-(3.2) can be analyzed in different ways; here I use a very compact form of the so-called LISREL (LInear Structural RELationships) model proposed by Joreskog and Sorbom [1986a]. It may be important at that point to be precise about the word "structural."

It defines one of the two approaches proposed in the literature to study errors-in-variable models. The difference between these approaches comes from the type of treatment chosen for the vectors η in equations (3.1)-(3.2). If they are taken as incidental values of some parameters, then the latent variable model is called "functional." When the incidental values are considered as unobservable realizations of some stochastic processes (whose parameters are included in the parameters set of the model), then the errors-in-variable model is said to be "structural." (See Malinvaud [1984], Chapter 10, and Florens, Mouchart, and Richard [1987].)

To explain the difference between these two approaches, let us consider a special case of the above model.

$$y_{it}^{*} = \eta_t^1 + \eta_i^2 + \varepsilon_{it}.$$

The variability of y_{it}^{*} (for individual i at time t) is decomposed onto a time-dependent component, a individual specific effect and an error term. The functional approach for the estimation of this equation assumes that η_t^1 and η_i^2 are parameters and hence, the dimension of the parameter set increases with sample size. For the structural approach, η_t^1 and η_i^2 are variables whose distribution can be known, and hence, the dimension of the parameter set is fixed and finite. (In the example above it may contain a mean and three variances as can be easily observed).

The functional approach is usually implemented by Bayesian analysis, but seems quite untractable when we consider discrete data. We will follow the structural approach here.

Stochastic assumptions

The vector y^* is assumed to have a multivariate distribution with mean zero and covariance matrix $\Sigma = E(y^* y^{*\prime})$. The fourth-order moments of this distribution exist and are finite. From a sample of n independent observations on y^*, one may obtain S the usual unbiased estimator of Σ. If y^* has a multivariate normal distribution, then S has a Wishart distribution. Let $\sigma = \text{vecs}(\Sigma)$ and $s = \text{vecs}(S)$ where the operator vecs(.) creates a column vector of dimension $p^* = p(p+1)/2$ by stacking the non-duplicated elements of the p by p matrices Σ and S on top of each other.

Identification

Using equations (3.1) and (3.2), the so-called covariance structure equation for the general model is derived by expressing the covariance matrix of the vector (y^*) in terms of the parameter matrices of the model. In matrix notation, this equation is:

$$\Sigma = \Gamma\ (I-B)^{-1}\ \Psi\ (I-B')^{-1}\ \Gamma' = \Sigma(\theta) \tag{3.4}$$

where $\Psi = E(\zeta\zeta')$ is the covariance matrix for the errors ζ in (3.1), and where θ is the vector formed by stacking all the parameters contained in B, Γ, Ψ.

Identification of the model is achieved if equation (3.4) can be solved for a unique set of the parameters in B, Γ, Ψ in terms of the elements of Σ. The identification problem is different for each particular example and must be studied in its context. (See Long [1983a and b] for a general discussion, and in this study, see Chapter 2.)

Estimation

Given the sample covariance S, an estimate $\hat{\theta}$ of θ may be obtained by minimizing a discrepancy function, $F(\Sigma,S)$, which is a scalar valued function being twice continuously differentiable in S and Σ, and taking non-negative values ($F(\Sigma,S)=0$ if and only if $\Sigma=S$). Browne [1984] has studied the properties of the estimator obtained by minimizing quadratic form fit functions of the type:

$$(3.5)\quad F(\Sigma(\theta),S) = (s - \sigma(\theta))' \, W^{-1} \, (s - \sigma(\theta))$$

where $\sigma(\theta) = \text{vecs}(\Sigma(\theta))$ and where W is a p^* by p^* positive definite matrix. Under some regularity conditions, the estimator, called here Weighted Least Squares (WLS), is consistent and has an asymptotic normal distribution.

Now, the asymptotic distribution of $n^{1/2}(s - \sigma)$ is multivariate normal with a null mean vector and covariance matrix U whose typical element is written:

$$u_{ij,kl} = \sigma_{ijkl} - \sigma_{ij}\,\sigma_{kl}$$

where σ_{ijkl} is a fourth-order central moment. If we let $W = U$, then WLS estimators have minimum asymptotic variances within the class of estimators minimizing (3.5).

It can be shown (see Browne [1974]) that under the assumption of a multivariate normal distribution for y^*, the estimator obtained by minimizing the function defined in (3.5) is the same as the one obtained by minimizing:

$$(3.6)\quad F(\Sigma(\theta),S) = \log|\Sigma| + \mathrm{tr}\,(S\,\Sigma^{-1}) - \log|S| - p,$$

As a result, in this case, we do not need to compute the asymptotic covariance matrix of the sample variances and covariances. Since (3.6) is a linear transformation of the log-likelihood function associated to y^*, the WLS estimator is called in this case, the Maximum Likelihood (ML) estimator.

When correlation matrices are analyzed, the preceding method should be modified to take into account the fact that the diagonal elements of Σ are equal to one. If r and ρ are, respectively, the sample and population correlation vectors, and if W denotes now a consistent estimate of the covariance matrix of r, then the WLS estimator is obtained by minimizing the following discrepancy function:

$$(3.7)\quad F(\rho,r) = (r-\rho)'\begin{bmatrix} W^{-1} & 0 \\ 0 & I \end{bmatrix}(r-\rho).$$

This method is offered as a standard routine in LISREL 7, a program developped by Joreskog and Sorbom [1988]. It requires large amounts of computer memory when the number of variables is large. If $p = 16$, then W has 7260 elements (when Σ is a correlation matrix).

To apply the previous method, we need estimates for S, and possibly for W. The next question is then: In view of using the above estimation method, how can we compute the covariance or correlation matrix for variables for which only discrete data are available? The answer is given by the theory of the polychoric correlation coefficient, originally proposed by Pearson [1901]. The idea behind polychoric correlation is that the bivariate discrete distribution between two ordered categorical variables is characterized by two jointly distributed latent variables which trigger the categorical responses as they cross certain thresholds. This is the assumption we have made so far to interpret survey data. Olsson [1979] has studied the maximum-likelihood estimator of this correlation which is now presented.

3.2 ML Estimation of the Polychoric Correlation Coefficient

From the vector y^*, let us extract a pair of variables, y_1^* and y_2^*, which are observed through two categorical variables, y_1 and y_2, taking on s and r discrete values. The correspondence between each pair of variables, already introduced in (3.3) is now specified as:

$$(3.8)\quad \begin{aligned} y_1 &= i \quad \text{if} \quad a_{i-1} < y_1^* \le a_i \quad \text{for } i = 1,\dots,s \\ y_2 &= j \quad \text{if} \quad b_{j-1} < y_2^* \le b_j \quad \text{for } k = 1,\dots,r. \end{aligned}$$

The a_i's and b_j's are called thresholds and are unknown. From a sample of size n on the categorical responses, we observe n_{ij} and π_{ij} which are, respectively, the count and the probability associated with the event $y_1 = i$, $y_2 = j$, for $i = 1,\dots,s$ and $j = 1,\dots,r$. We have $\sum_i \sum_j n_{ij} = n$ and $\sum_i \sum_j \pi_{ij} = 1$.

Given that the density of the tuple (y_1^*, y_2^*) is bivariate normal, with mean $(0,0)$ and correlation ρ_{12}, and that variances set to one, the joint probabilities are defined by:

$$(3.9)\quad \begin{aligned} \pi_{ij} &= \Pr[y_1 = i,\ y_2 = j] \\ \pi_{ij} &= \Pr[a_{i-1} < y_1^* \le a_i,\ b_{j-1} < y_2^* \le b_j\ ] \\ &= \int_{a_{i-1}}^{a_i} \int_{b_{j-1}}^{b_j} f_2(u,v;\rho_{12})\ du\ dv \end{aligned}$$

where f_2 stands for the bivariate normal density and: $a_0 = b_0 = -\infty$ and $a_s = b_r = +\infty$).

As successive observations are independent, the log likelihood function of the sample is:

$$(3.10)\quad \log L = \sum_{i=1}^{s} \sum_{j=1}^{r} n_{ij} \log \pi_{ij}$$

Given (3.8), the log likelihood is a function of the thresholds:

$a'=(a_1,\ldots,a_{s-1})$ and $b'=(b_1,\ldots,b_{r-1})$, and of the correlation ρ_{12}. Olsson [1979] has derived the maximum likelihood (ML) estimation of these parameters. He proposes to use the matrix of second derivatives evaluated at the maximum to estimate the asymptotic covariance matrix of the ML estimates. The estimator of ρ_{12} is called the polychoric correlation coefficient. As defined, it is a measure of association in the contingency table.

The quality of the estimated correlation must be assessed. A Likelihood Ratio statistic can be used to test the hypothesis that it is significantly different from zero. A simple Kolmogorov-Smirnov chi-square test allows us to compare the observed bivariate frequencies to the probabilities computed from a bivariate normal distribution evaluated at the estimated thresholds and the correlation, and is the usual way to test the meaningfulness of the bivariate normality assumption. In the case of two trichotomous variables, this test has three degrees of freedom since there are eight independent empirical frequencies and five parameters (four thresholds and one correlation coefficient).

The technique presented in this section is discussed in various articles. First, Lee [1985] has generalized the preceding maximum likelihood estimation of polychoric correlations for the trivariate case. Lee and Poon [1988] have also proposed GLS approaches to estimate the correlations in the multidimensional contingency table. Second, correlations between continuous and discrete variables can also be estimated by maximum likelihood and are called polyserial correlation coefficients. (See Olsson, Drasgow, and Dorans [1982] and

Lee and Poon [1986].) In a recent article, Lee and Poon [1987] give a general presentation for the maximum-likelihood estimation of polyserial and polychoric correlation coefficients (PCC).

A two-step procedure for estimating PCC

An alternative to the maximum likelihood estimation is also proposed by Olsson. This is a two-step estimation procedure which is computationally much easier. In a first step, the thresholds are estimated from the univariate marginals of observed frequencies, i.e., consistent estimators of the thresholds are given by:

$$a_i = F_1^{-1}(p_{i\cdot}) \qquad i = 1, 2, \ldots, s-1$$
$$b_j = F_1^{-1}(p_{\cdot j}) \qquad j = 1, 2, \ldots, r-1$$

where F_1 is the univariate normal distribution, and:

$$p_{i\cdot} = n^{-1} \sum_{j=1}^{r} \sum_{k=1}^{i} n_{kj} \qquad p_{\cdot j} = n^{-1} \sum_{i=1}^{s} \sum_{k=1}^{j} n_{ik}$$

In the second step, these estimates are inserted in the remaining first-order condition which characterizes the maximum likelihood estimator. Specifically one solves for the equation:

$$\left.\frac{\partial \log L}{\partial \rho}\right|_{a,b} = 0$$

Monte-Carlo studies have shown that the two-step estimators are very close to the ML estimates.

<u>Estimating the matrix S</u>

The use of the two-step estimation is justified by its simplicity particularly when many correlation coefficients have to be computed. (See Joreskog and Sorbom [1986b].) Indeed, we usually deal with a vector of latent variables such as the vector y^* which has more than two components in general. The practical method is to proceed by pairwise computation. For each pair of variables in y^* a correlation coefficient is estimated and then a correlation matrix (to be used in the estimation of the latent variable model) is made up with all the estimated correlations. Such a procedure does not guarantee that the resulting matrix S is positive definite, a necessary condition to perform the ML or WLS estimation of the latent variable model presented previously. In order to satisfy this condition, we must select a sample of individuals with no missing data. In other words, when we have more than two variables, all marginal tables (which are used to estimate the thresholds) must come directly from the same overall contingency table. Indeed, if we have a sample for several variables with missing data, pairwise deletion in the data set may create a situation where the thresholds corresponding to each latent variable are not the same for every estimated correlation involving that variable because each correlation is computed on different samples. Since the two-step procedure is used to estimate the correlations, the resulting correlation matrix may not be positive definite. Obviously, considering only panel with no missing data does not guarantee that we will obtain a positive definite matrix. But it is easy to find examples showing that computation of the correlations, after having performed pairwise deletion in a panel with missing data, finally produces a matrix which is not positive definite, while, by listwise deletion (i.e., creation of a panel without missing data) on the same data set we end up with a matrix satisfying positive definitiveness. Here we will consider only panel with no missing data, acknowledging that this point deserves further research. Let us remark that procedures (Ridge estimation) exist to deal with non positive definite matrices. (See Joreskog and Sorbom [1988].)

Estimating the matrix W

Asymptotic variances and covariances for the polychoric correlations could be obtained by evaluating the inverse of the information matrix at the last stage of the maximization of the log-likelihood function (3.10). But, when correlations are estimated via the two-step procedure, asymptotic covariances are not available directly. A solution is proposed by Joreskog and Sorbom (1986b) in this case. Some new notation is necessary to define the asymptotic covariance matrix W of the polychoric correlations. If f_1 represents the normal density function, we denote by:

$$\nu_{hm} = \frac{N}{n_h} (f_1(a_h(m)) - f_1(a_{h-1}(m))) \qquad h = 1,2,3$$

the estimated normal score of the m^{th} discrete variable of the vector y defined by the correspondence (3.3), when it takes the category h with frequency n_h/N, i.e., when the associated latent variable falls in the interval $(a_{h-1}(m)\ ,\ a_h(m))$ whose limits have been estimated previously. For large samples, the means of the normal scores should be equal to zero. If $n(i,j,k,l)$ is the count associated with the cell ($z_g = i$, $z_h = j$, $z_r = k$, $z_s = l$), where y_m ($m=g,h,r,s$) is the m^{th} variable of the vector y and i,j,k,l takes values on the set {1,2,3}, then a typical element of the asymptotic covariance matrix W is consistently estimated by:

$$(3.11)\quad w_{gh,rs} = \sigma_{gh,rs} - \rho_{gh}\,\rho_{rs} \qquad g \neq h,\ r \neq s,\quad g,h,r,s = 1,2,3,4$$

$$\text{where: } \sigma_{gh,rs} = \frac{1}{N} \sum_{i=1}^{3} \sum_{j=1}^{3} \sum_{k=1}^{3} \sum_{l=1}^{3} n(i,j,k,l)\, \nu_{ig}\, \nu_{jh}\, \nu_{kr}\, \nu_{ls}$$

i.e., $\sigma_{gh,rs}$ are estimates of the fourth-order central moments.

Given estimates of S and W, we may estimate of the latent variable model as proposed in section 3.1.

3.3 Properties of the Method and Remarks

To summarize, the method for estimating a latent variable model when the data for all variables are discrete has two stages. In the first stage, the correlation matrix of the latent variables which trigger the responses to survey when they cross some thresholds are estimated directly from the discrete data using polychoric correlation coefficients. Instead of using a Maximum Likelihood estimation, these correlations are often estimated themselves by applying a two-step procedure. In the second stage, a method of moments is applied to estimate the parameters of the model using the WLS estimator.

The main reason for using the previous procedure to estimate the latent variable model for discrete data is that the Full-Information Maximum-Likelihood estimation of the whole model would involve the computation of multiple integrals. Progress in the speed and the accuracy of computers may allow the direct estimation by FIML in the future. The technique presented here is much easier to implement, and should give estimates equivalent in quality to FIML estimates.

However, a certain contradiction between section 3.1 and 3.2 is noticeable. The advantage of the WLS method presented before is that it is distribution-free and that it allows us to compute correct variances and covariances of the parameter estimates. But we need a distributional assumption, specifically normality, to compute the polychoric correlation coefficients. Can we reconcile these two parts of the method? What is the role of the normality assumption with respect to the overall model?

Two remarks can be made to answer these questions. First, it is not necessary to impose normality to obtain estimates of the thresholds as it is proposed above, since asymptotic results justify this way of estimating them. (See Chapter 2, section 2.4.) Second, from the point of view of the pseudo-maximum likelihood theory, the normality assumption is just used in motivating the likelihood function required to estimate the correlation coefficient, i.e., it is a way to obtain a consistent estimate of a correlation. Then, by mean of WLS estimation, we can obtain consistent estimates of the model parameters and correct asymptotic variances for the latter. Hence the normality assumption does not play a crucial role, except obviously when it is imposed.

For all these reasons, the method developed in this chapter is attractive, but it presents several difficulties in applied work. In particular, the estimation of the fourth order moments is precise enough only if very large samples are available. When this condition is not met, it is better to impose normality and then to estimate the model by minimizing the function (3.6), i.e., by computing the ML estimator. The estimated variances of the parameters would not be correct, but we must notice here that the loss of efficiency in applying the ML rather than the WLS estimator appear to be small. (See Chapter 7, section 7.3.)

In the appendix to Chapter 3, I attempt to motivate the use of the previous approach instead of standard Probit methods. The latter could be adopted to estimate structural models even if we assume measurement errors. (Contrary to Tobit models for which maximum likelihood estimators may be inconsistent in presence of errors in the dependent variable, such a situation in case of a probit model just complicates the identification of the parameters, since the measurement error can be indistinguishable from the structural disturbance. However ML estimators remain consistent if the likelihood function is correctly specified. (See Stapleton and Young [1984].)) However, in our case, where all variables are measured by means of a set of indicators, Probit-type methods do not perform well. (In a way, the procedure presented in this chapter is a Probit-type method. But this term is usually reserved for models where only endogenous variables are treated as latent variables.)

The latent variable model with discrete data includes various specifications which makes this model a very general tool to study business survey data. Nonetheless, the presentation of this approach indicates that further research is needed in order to deal with the missing data problem (inherent to survey data). The latter should be solved for improving the estimation of the polychoric correlation coefficient.

Appendix to Chapter 3: Probit-Type Models and Survey Data

Survey data sets can be viewed as panel of qualitative data with attrition: Indeed, the same individuals are surveyed several times, but they do not answer regularly. Moreover, other individuals are included as the survey is renewed. If we delete observations with missing data, then probit-type models, or more precisely, classical econometric models for qualitative or limited-dependent variables can be applied to study those data. These models allow general estimation of structural economic relations. In fact, as it will be clear later, these classical methods are not always suited to a structural analysis of survey data. This Appendix is intended to shed light on the technical difficulties imposed by this kind of data with respect to these methods, when the analyst wants to use only the individual data.

Probit-type models have been applied to survey data by many researchers: See for instance Ronning [1980, 1987], McIntosh, Schiantarelli and Low [1986a and b, 1988], Rahiala, Terasvirta and Kanniainen [1987], among others.

Let us assume that a panel data set can be extracted from a survey and let us consider the univariate multiperiod probit model:

$$\text{(A3.1)} \qquad y^*_{it} = x'_{it}\beta + \varepsilon_{it} \quad (i = 1, \ldots, N; \;\; t = 1, \ldots, T)$$

where i indexes the individuals of a cross-section, t indexes the time period in the panel, x is a vector of observed variables, ε is an unobserved disturbance, β is a vector of unknown parameters to be estimated. y^*_{it} is a continuous latent dependent variable; it is not observed. Instead, one observes a qualitative information y_{it} which takes values on two categories (without loss of generality) according to the correspondence:

$$y_{it} = \begin{cases} 1 \text{ if } y^*_{it} > 0 \\ 0 \text{ otherwise} \end{cases}$$

To complete the model, the independent variables are assumed strictly exogenous. One may assume that ε_{it} are independently and identically distributed. Finally, for any i, (ε_{it}, $t = 1, \ldots, T$) has a normal density with mean zero and covariance matrix Σ. The sample likelihood is:

$$\text{(A3.2)} \quad L(\beta,\Sigma) = \sum_{i=1}^{N} \int_{-\infty}^{\alpha_{i1}} \ldots \int_{-\infty}^{\alpha_{iT}} f(u_1, \ldots, u_T; Z_i'\Sigma Z_i)\, du_1 \ldots du_T$$

where $\alpha_{it} = (2y_{it} - 1)\, x_{it}'\beta$. Z_i is a T by T diagonal matrix with generic element $(2y_{it}-1)$, and $f(\ldots)$ is the T-variate standardized multivariate normal density. This structure allows us to present the main issues.

Case 1: If there is only one cross-section, then the estimation of the equation (A3.1) is well known (see Amemiya [1976, 1985]) and is obtained by standard routines available in different computer packages.

Case 2: Let us suppose now that we have a time-series available for one individual, and that the disturbances for the model (A3.1) are not correlated. Then again we can apply standard probit estimation as far as the exogenous variables are directly observed. But most of the variables in surveys are categorical and the vector x_{it} contains only indicators. If the preceding equation is the reduced form of an economic model, one should have generally:

$$y_{it}^{*} = (x_{it}^{*})'b + \varepsilon_{it}$$

where x_{it}^{*} is a vector of continuous latent variables for which one observes a limited form x_{it} according to some non continuous correspondence. In that instance, the problem of maximizing $L(\beta,\Sigma)$ can be complicated; indeed, one solution is to posit some distributional assumption for the vector x_{it}^{*}, but then the computational tractability of the likelihood function is not obvious.

One solution is to use the general latent variable model. Here we look at another solution which is made up by replacing the continuous latent variables by their observed indicators, so that we return to the to a model similar to the original equation (A3.1). But this solution introduces a mis-specification and, if we do not take into account this fact in the likelihood function, ML estimates of β will be inconsistent estimators of b. This claim is explained in the following example.

Let us suppose that the vector $(y,x)'$ is normally distributed with means (0,0) and correlation coefficient ρ_{xy}, and let us consider the model:

$$y = \alpha\, x + u.$$

The least-squares estimator is: $\alpha_{ls} = \rho_{xy}$. Instead of this model we estimate:

$$y = \beta \, 1_x + u$$

where 1_x is the indicator function, i.e., $1_x = 1$ if $x > 0$, and $1_x = 0$ otherwise. Then asymptotically, the estimator is β is:

$$\beta_{asy} = \frac{E(1_x y)}{V(1_x)} = 8 \, \pi^{-1/2} \, \alpha_{ls}$$

since: $V(1_x) = P\,[x > 0]\;.\;P\,[x < 0] = 1/4$,

and: $E(1_x y) = \alpha_{ls}\, E\,(x1_x) = \alpha_{ls}\,(2\pi)^{-1/2}$. (I assume that x has unit variance for simplicity.) This last result is obtained by directly applying properties of the truncated normal distribution (see Gourieroux [1984], for instance).

Thus β_{asy} is biased. In this simple example, one may correct for the bias, but this is not always possible in more general cases (several exogenous variables taking values on more than two categories). However β_{asy} has the same sign of α_{ls}. But nothing ensures us that it is always true in a more general context.

Replacing the continuous variables by their observed indicators introduces a second type of difficulty, which has been noticed by Chamberlain [1984] and which is more severe with respect to the type of models we meet in economics. It appears when the exogenous variable in the above example is a lagged endogenous variable. Let us consider the model:

(A3.3) $$y^* = \alpha\, y^*_{-1} + u \qquad \text{with:} \quad y = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

and the model:

(A3.4) $$y^* = \alpha\, y_{-1} + u\ .$$

Chamberlain remarks that the second model implies a Markov chain, since:

$$\Pr[y^*=0 \mid y^*_{-1}, y^*_{-2}, \ldots, y^*_{-T}] = \Pr[y^*=0 \mid y^*_{-1}] = \begin{cases} F(a/\sigma^2) & \text{if } y^*_{-1} > 0 \\ 0.5 & \text{if } y^*_{-1} \le 0 \end{cases}$$

if u has a normal distribution with zero mean and variance σ^2. But, for the first model, there is no way to reduce the number of variables appearing in the conditioning set of the conditional probabilities. Hence the latter involve an infinite number of variables.

Then both models have a totally different meaning. The consequence is that the exogenous variables (or lagged endogenous variables) cannot be replaced by their discrete counterparts, and probit-type analysis cannot be performed. This problem is even more severe in a general setting (i.e., in the multivariate case) and must be taken into account.

Case 3: We return to the panel data case and we assume that the exogenous variables are continuously observed. The standard difficulty is again the evaluation of T-fold integrals in equation (A3.2) when the disturbances are correlated over time, a very frequent situation.

One solution is proposed by Butler and Moffit [1982] by postulating that: $\varepsilon_{it} = \mu_i + u_{it}$ with $V(\varepsilon_{it}) = 1$ (i.e. the usual normalization in probit models) and $E(\varepsilon_{it}\ \varepsilon_{is}) = \rho$ for any $t \neq s$, i.e., the off-diagonal elements of Σ are equal so that the disturbances are "equi-correlated." Then a familiar reduction formula for the multivariate normal integral (see Gupta [1963]) can be applied to have:

$$L^*(\beta,\Sigma) = \prod_{i+1}^{N} \int_{-\infty}^{+\infty} \prod_{t=1}^{T} F([x_{it}'\beta + v\rho^{1/2}]\ [1 - \rho^2]^{-1/2}\ [2y_{it} - 1])\ f(v)\ dv$$

where F(.) and f(.) can be computed by available routines.

If no particular constraints are imposed on the covariance matrix Σ, Avery, Hansen, and Hotz [1983] have proposed a class of estimators similar to Nonlinear Instrumental Variables Estimators (see Jorgenson and Laffont [1974]). Another way to estimate the model (A3.1) is to apply the theory of the Pseudo-Maximum Likelihood (see Gourieroux, Montfort and Trognon [1984]): Roughly, this method shows that the estimator, obtained as if the disturbances in the above model were independent, is strongly consistent for the model with autocorrelated errors. But the covariance matrix of this estimator cannot be estimated by the inverse of the information matrix; this latter must be corrected to take into account the effective presence of autocorrelation. The advantage of this method is that it gives a theoretical argument to bypass the problem of evaluating the T-fold integrals in equation (A3.2) (see Gourieroux, Montfort, and Trognon [1985]).

But the remarks made for Case 2 apply here too. Indeed, let us consider a special form of equation (A3.1):

$$y_{it}^* = y_{i,t-1}^*\delta + x_{it}'\beta + v_{it}$$

Here again, replacing $y^*_{i,t-1}$ by the indicator $y_{i,t-1}$ transforms the structure of the model itself, as emphasized by Chamberlain [1984]. Estimation methods for these cases have been proposed by Heckman [1982] (see also Grether and Maddala [1982]), but they cannot be easily generalized.

All the preceding remarks show that the standard methods for studying qualitative responses models may be applied to analyze survey data. More general settings, such as simultaneous equations linear probability models can also be used (see Mallar [1977], Heckman and Macurdy [1985] for a general presentation of these models). But they are not always adequate to estimate structural models as it has been noticed, which motivates a specific approach.

Chapter 4. The Empirical Analysis and Forecasting

The model of Chapter 2 (see Table 2.1) is now estimated on four panel data sets corresponding to the four ending periods: January, March, June and October 1985. (That is to say, the first data set is made up from the four successive surveys: March-June-October 1984 and January 1985; and so on for the other data sets). The objective here is to recover the structural parameters of the theoretical model of Chapter 1 and to use the estimates for forecasting the economic activity.

4.1 Estimation of the Correlation Matrix

In order to estimate the parameters of the model using the method presented in Chapter 3, we first need to derive the correlation matrix for the sixteen latent observable variables that appear in the model (see Table 2.1 in Chapter 2). This is done by applying the two-step procedure for estimating the polychoric correlation coefficients. The matrix for the ending period October 1985 is displayed in table 4.2 (the others are not reported). It has been produced using a routine of the computer package PRELIS (see Joreskog and Sorbom [1986b]). As for the other periods, this matrix is positive definite. What can be said about the quality of these estimated correlations?

In the appendix of this chapter we give for each computed correlation, a chi-square statistic for testing the robustness of the underlying assumption of bivariate normality and a chi-square value for testing the hypothesis that the correlation is significantly different from zero. Normality is rejected in 56 cases out of 136 at the 5% level. This is partly due to the skewness of the observed distributions of the variables over the categories (see Table 4.1).

Table 4.1

Univariate Frequency Distributions

for Ordinal Variables (October 1985)

	Category		
Variable	1	2	3
DEQ1	69	233	94
DEQ2	78	252	65
DEQ3	65	240	91
DQ1	83	211	102
DQ2	60	226	110
DQ3	76	226	94
DQ4	88	218	90
L1	99	268	29
S1	36	174	186
L2	103	271	22
S2	38	186	172
L3	113	260	23
S3	41	181	174
DEQ0	75	227	94
L0	94	274	28
S0	49	158	189

DEQt is the expected change of production at time t;

DQt is the change of production;

Lt is the appraisal on inventories;

St is the appraisal on order-backlogs.

Table 4.2

Correlation Matrix to be Analyzed (October 1985)

	DEQ1	DEQ2	DEQ3	DQ1	DQ2	DQ3
DEQ1	1.0000					
DEQ2	.5382	1.0000				
DEQ3	.1564	.3271	1.0000			
DQ1	.0655	-.0107	.0957	1.0000		
DQ2	.4162	.0903	.0943	.5162	1.0000	
DQ3	.4808	.4229	.1328	.1950	.4326	1.0000
DQ4	.2307	.1612	.4855	.0966	.2211	.3743
L1	-.1285	-.1158	-.0651	-.2210	-.1747	-.1471
S1	.4933	.1891	.0424	.4371	.4821	.3376
L2	-.2440	-.2735	-.1245	-.1592	-.2240	-.1487
S2	.4535	.4552	.1492	.3780	.4355	.4508
L3	-.1486	-.1495	-.2392	-.0593	-.1958	-.1764
S3	.2625	.3121	.4497	.2333	.3228	.4996
DEQ0	.3993	.1378	.0298	.5772	.4199	.2779
L0	-.0094	-.0870	-.0584	-.1986	-.0756	.0691
S0	.2763	.1963	.0809	.4641	.4108	.2257

	DQ4	L1	S1	L2	S2	L3
DQ4	1.0000					
L1	-.0704	1.0000				
S1	.0857	-.4178	1.0000			
L2	-.0693	.7632	-.3517	1.0000		
S2	.1384	-.3160	.7530	-.3924	1.0000	
L3	-.1764	.5417	-.2441	.7277	-.2686	1.0000
S3	.3928	-.2748	.4782	-.2884	.6616	-.4319
DEQ0	-.0226	-.1757	.3294	-.1030	.2912	-.0166
L0	.1010	.7333	-.2320	.5274	-.2275	.3898
S0	.0193	-.3504	.7369	-.2431	.6872	-.1693

	S3	DEQ0	L0	S0
S3	1.0000			
DEQ0	.1926	1.0000		
L0	-.1753	-.2004	1.0000	
S0	.4607	.4578	-.4215	1.0000

Determinant = .368064D-04

As bivariate normality is rejected in several cases, let us again recall its role. This distributional assumption is used in order to estimate the correlation between the latent (observable) variables and then to estimate the structural parameters of an errors-in-variable model: This assumption merely motivates the likelihood function which in turn allows us to estimate the polychoric correlation coefficients. Without this assumption, the estimation of models on business surveys data requires alternative simplifying assumptions. In some sense, assuming normality is a second best.

Two points can be advanced for the defense of the results. First, when two variables are not jointly normal, the ML estimation of the correlation may still provide consistent estimates if the limit of the objective function attains a unique maximum at the true correlation (under some regularity conditions, see Amemiya [1985] or White [1987]). Second, when we examine many tests like this, we should compute the overall rejection rate; that is to say, if a 5% level is chosen for each hypothesis, the overall rate is much smaller.

My own experience with these data shows that the normality assumption is less often rejected (at the stage of the estimation of the correlation coefficients) as the sample size increases. For instance, a sample is obtained by pooling the two samples corresponding to the ending periods October 1984 and October 1985; the sample size is of 779 firms; normality is now rejected in 41 cases (out of 136). The results are not reported for saving space. This pooling method is based on the idea that, to a particular firm at two different dates correspond two independent individuals, which is not true in general.

Finally, the appendix to this chapter gives (for October 1985) the asymptotic variances of the polychoric correlations (the asymptotic covariances are not given to save space). Even if one must be cautious in using these statistics, they indicate that the estimated coefficients are not well determined. The standard errors for the polychoric correlation coefficients are around 0.06 which can found too large. Now these standard errors decrease when we consider larger data sets. If the four panel data (March-June-October 1984 and January 1985) are pooled, the sample size is 1557 and the standard errors of the polychoric correlation coefficients are around 0.03, which is small compared to the values of most coefficients.

4.2 Assessment of the Empirical Results

Using the correlation matrix, we apply the methodology proposed in Chapter 3 to estimate the model presented in Table 2.1. This correlation matrix is the input matrix for the computer package LISREL (see Joreskog and Sorbom [1986a]) which then performs the maximum-likelihood estimation, the initial estimates being obtained by two-stage least squares. Maximum-likelihood estimates of the parameters are given in table 4.3 (page 123) when data sets are small. The ML estimator, as it is defined in the preceding chapter, is here chosen rather than the WLS estimator since the samples are not large enough to obtain precise estimates of the covariances of the correlation coefficients. (See the discussion at the end of Chapter 3. The reasons which explain why the sample sizes are small were given in

Chapter 2, section 2.2.). The WLS estimator is applied for estimating the parameters in the case of large data sets. For this case, results are gathered in Table 4.3a.

One question to be solved is to specify the structure of the stochastic processes $\tilde{\alpha}_t$ and $\tilde{\gamma}_t$, since to each specification of these random components corresponds a specification of the optimal control equation, as it is mentionned in Chapter 1 where I have derived the feedback rule when both processes are AR(1) or ARMA(1,1). Given that the econometric model is defined over four periods, we may suspect that restricting ourselves to considering only AR(1) and ARMA(1,1) processes is acceptable. But obviously, the model of Chapter 1 can be written for any type of stationary processes.

For the first two periods, the parameter of the moving average part for $\tilde{\alpha}_t$ when it is specified as an ARMA(1,1) is not significant while it is for the two others. For these two periods, the value of this parameter was positive (and relatively small). Given the discussion at the end of Chapter 1, this indicates that the optimal behavior was production smoothing as it is the case when the process is AR(1). For the four periods, the moving average part is always slightly significant when $\tilde{\gamma}_t$ is specified as an ARMA(1,1). This means that the variability of production tends to be close to the one of sales (again given the discussion of Chapter 1), but still the optimal behavior is production smoothing.

When one of the two processes or both are ARMA(1,1), some new components appear in the optimal decision rule and some constraints of over-identification must be imposed. The software package LISREL cannot handle this type of constraint, and I use in this case a similar program written in the GAUSS language proposed by Schoenberg [1987].

For instance, when $\tilde{\alpha}_t$ is ARMA(1,1) and $\tilde{\gamma}_t$ is AR(1), then it must be true that: $g_2\ \phi = g_4\ \theta_1$, where g_4 is the parameter in the decision rule corresponding to the effect of the transitory component of demand. (See Chapter 1) When the constraints are not imposed, the complementary parameter g_4 of the optimal decision rule is never significant. Since the values of ϕ are small or are not significant, the constraint is statistically verified. This result is confirmed when the constraint is imposed.

But this situation is not always observed, in particular when the cost shock is ARMA(1,1). The only general result is that parameters (such as g_4) which correspond to the impact of the transitory components of demand and/or cost shocks are never significant. (In order to support this result, let us notice that the variance σ_u^2 reported in Table 4.3 is very small; this variance could be interpreted as the one of all components which could have been omitted in the decision rule. See also Table 2.1.)

For these various reasons, I have finally chosen to specify both processes as AR(1) since, for forecasting, I only need the total variance of the errors characterizing the processes. I discuss now the final results.

I discuss now the results given in Table 4.3. Most of the parameters are significant at the 1% level (the t-value is 2.608 for 116 degrees of freedom). The parameters which have a star in Table 4.3 are not significant at this level. For some of them, this is not disturbing; the fact that the variances of the measurement error on the production change (σ_q^2) variable is not significant means that the structural equation is close to the true model for this variable. With respect to the other parameters of interest (the first seven) of the model, one observes that only g_3 is not significant for one estimation period, and λ for two periods. All these parameters are stable over time except g_3.

We notice also that some of the variances of measurement errors on inventory appraisals (σ_1^2) are negative. This happens in LISREL since the algorithms does not impose any non-negativity constraints on the variances during the estimation process. Here these "Heywood cases" (as they are called in the literature on LISREL models) are not significant. One may set these negative variances to zero without modifying the values of the parameters of interest.

The assessment-of-fit can be judged by computing different measures. The goodness-of-fit index (GFI) gives an overall evaluation of the fit and is computed by the following formula:

$$GFI = tr(\Sigma^{-1}S - I)^2 \quad (tr(\Sigma^{-1} S)^2)^{-1}$$

where S is the matrix of polychoric correlation coefficients, Σ is the estimated covariance matrix and I is the identity matrix. For October 1985, GFI is 0.837 and, if we correct for degrees of freedom d and for the number of variables p, then the adjusted goodness-of-fit index, computed as:

$$AGFI = 1 - [(p(p+1)/2d)(1-GFI)]$$

is 0.809. (GFI values are reported on Table 4.3.)

Other measures show that each equation seems well determined and that the latent observable variables are good instruments for the latent measurable variables. For instance, the squared multiple correlations for the structural equations are all between 0.75 and 1.0. (Let us recall that the squared multiple correlation for the i^{th} structural equation is defined as 1 - (var(ζ_i) / var(η_i)), where var(ζ_i) is the variance of the errors on the i^{th} equation and var(η_i) is the variance of the latent variable determined by the i^{th} equation.).

I discuss now the results reported in Table 4.3a. As explained previously, it is possible to pool the small panel data sets. I consider the pooling data set obtained by stacking the four panel data sets used beforehand. Estimates are very similar with those of Table 4.3. There are two comments. First, the model is the same as the one of Table 2.1 except that I have set the variance of the error associated to the feedback rule equation to zero and that I have assumed here that the measurement error on expectations of production is white noise. As this new specification has a slight influence on the values of the other parameters, the assumptions made before on these errors are not crucial. Second, I report in the first column of Table 4.3a the estimates when there are no measurement errors. Compared to column two which gives results for the errors-in-variable model, there are almost no difference. However, the LR test statistic for testing the null hypothesis that the right model does not contain measurement errors against the hypothesis that the model is an errors-in-variable model allows us to reject the null. Indeed this

Table 4.3
Estimation Results
(parameters and t-values in parentheses)

Period	January 85	March 85	June 85	October 85
Size	386	381	394	396
g_1'	-0.240 (-11.4)	-0.190 (-9.3)	-0.213 (-10.4)	-0.266 (-12.1)
g_2	0.762 (10.1)	0.766 (12.0)	0.646 (13.2)	0.714 (13.4)
g_3	-0.530 (-4.2)	-0.184 (-4.5)	-0.097 (-2.9)	-0.121 (-2.4)
θ_1	0.839 (41.6)	0.861 (47.1)	0.811 (39.1)	0.797 (37.4)
θ_2	0.847 (40.2)	0.733 (27.0)	0.633 (19.2)	0.695 (23.7)
λ	-0.148 (-2.7)	-0.107 (-2.1)	-0.179 (-2.7)	-0.220 (-2.3)
μ	-0.646 (-4.4)	-0.357 (-8.4)	-0.227 (-5.0)	-0.223 (-3.3)
σ_u^2	0.267 (3.4)	0.405 (3.9)	0.584 (5.4)	0.287 (3.9)
σ_e^2	0.090 (5.2)	0.090 (5.4)	0.077 (4.8)	0.084 (4.7)
σ_α^2	0.198 (5.3)	0.220 (9.8)	0.310 (11.3)	0.318 (10.6)
σ_γ^2	0.195 (7.4)	0.440 (11.0)	0.616 (11.9)	0.527 (12.1)
$\sigma_{qe_0}^2$	0.629 (11.4)	0.541 (11.3)	0.646 (11.7)	0.431 (10.1)
ρ	0.269 (6.2)	0.290 (6.8)	0.405 (10.3)	0.427 (10.2)
$\sigma_{ue_0}^2$	0.481 (18.3)	0.543 (18.8)	0.465 (17.9)	0.480 (18.0)
σ_q^2	0.159 (1.9)	0.024 (0.2)	-0.095 (-0.8)	0.187 (2.3)
σ_1^2	0.228 (11.1)	0.051 (2.2)	-0.078 (-2.3)	-0.060 (-2.3)
σ_s^2	0.077 (6.1)	0.094 (7.3)	0.084 (5.7)	0.090 (6.0)
ϕ_{12}	-0.461 (-7.4)	-0.477 (-9.0)	-0.198 (-2.7)	-0.108 (-1.2)
ϕ_{13}	0.599 (6.6)	0.862 (48.3)	0.826 (43.3)	0.765 (32.4)
ϕ_{23}	-0.198 (-2.0)	-0.305 (-5.0)	-0.186 (-3.0)	-0.024 (-0.4)
GFI	0.812	0.830	0.821	0.837

Table 4.3a

Estimation Results
(parameters and t-values in parentheses)

Period	Pooling	Pooling
Size	1557	1557
g_1'	-0.267 (-49.0)	-0.356 (-34.3)
g_2	1.027 (31.4)	1.582 (16.2)
g_3	-0.762 (-2.1)	-0.502 (-5.8)
θ_1	0.812 (47.0)	0.924 (104.2)
θ_2	0.740 (128.5)	0.887 (96.9)
λ	-0.250 (-3.7)	-0.188 (-22.3)
μ	-0.394 (-6.8)	-0.946 (-6.8)
σ_u^2	0.309 (17.8)	0.365 (8.5)
σ_α^2	0.315 (19.5)	0.120 (7.8)
σ_γ^2	0.364 (15.8)	0.100 (7.3)
$\sigma_{qe_0}^2$		0.272 (13.7)
σ_q^2		-0.092 (-1.9)
σ_1^2		0.293 (12.5)
σ_s^2		0.173 (7.7)
ϕ_{12}	0.017 (0.3)	-0.154 (-6.6)
ϕ_{13}	0.683 (49.5)	0.399 (13.6)
ϕ_{23}	-0.212 (-10.1)	-0.625 (-33.5)
GFI	0.927	0.940

statistic is equal to 357; since the test has four degree of freedom, this value compared to the value of the chi-square indicates a clear rejection of the null hypothesis.

Overall, the estimates seem to be statistically acceptable. But they are other ways to check the consistency of the estimation. In particular, we may assess the results with respect to the predictions from the theoretical model.

4.3 Recovering the Structural Parameters.

To do this internal evaluation, we can recover the values of the structural paramaters from the estimates of the reduced-form parameters according to the relations derived in Chapter 1 to define the optimal decision rule.

i) The parameter g_1' (i.e., g_1 - 1, see chapter 2 equation (2.3)) is always negative. The discussion of the theoretical model has shown that g_1 should be less than one. Thus the values for g_1' are consistent with the theoretical model. For the four periods we have:

January 1985	$g_1 = 0.7603$
March 1985	$g_1 = 0.8097$
June 1985	$g_1 = 0.7872$
October 1985	$g_1 = 0.7345$

Let us recall that this parameter is the first order correlation of the stochastic process of the production (this is the interpretation of the parameter $\lambda_1 = g_1$ in the model). This means that that process is strongly stationary.

ii) The processes $\tilde{\alpha}_t$ and $\tilde{\lambda}_t$ can be identified as the demand variable and the cost shocks respectively.

Indeed, the theoretical model shows that if $\tilde{\alpha}_t$ is the process for the new orders coming to the firm, then its associated parameter in the optimal control equation (1.12) must be positive; the opposite should hold for $\tilde{\gamma}_t$. Given the specification of the empirical model, the results are consistent with the prediction since g_2 is positive and g_3 is negative for all periods. Consequently, the result allows to identify the variable $\tilde{\alpha}_t$ as the demand variable and $\tilde{\gamma}_t$ as the cost shocks.

iii) Using the formulas (given in chapter 1) relating the parameters of the cost functions to the parameters which have been estimated, we can compute the ratios c_1/c_2 and c_3/c_2 which are decreasing functions of the discount factor ρ. Table 4.4 gives examples of the values for these ratios. From this table the main conclusions are:

- c_1 and c_3 are less than c_2 since both ratios are less than one. This would indicate that the weight of the cost-of-adjusting production in the total cost is greater than the weights for the cost of producing and for the cost of holding inventories.

- For a given c_2, c_1 should be less than c_3, so that the relation between these weights should be: $c_1 < c_3 < c_2$. But our estimates do not give a clear idea of the ratio $c_1/3$ which varies between 1.4 and 4.4 depending on the estimation period. It is difficult to explain why there is so large a variation, but one possible reason could be that the seasonal effects are not explicitly taken into account in the empirical model.

Nonetheless, the results seems consistent with other empirical studies, such as Blanchard [1983] for a different data set.

Table 4.4

Relative Values for the Weights in the Cost Function

Ending Period	January 85		March 85		June 85		October 85	
ρ	1.0000	0.9760	1.0000	0.9760	1.0000	0.9760	1.0000	1.0000
c_1/c_2	0.2921	0.3048	0.1257	0.1301	0.0972	0.0995	0.1160	0.1189
c_3/c_2	0.4331	0.4514	0.3325	0.3509	0.3658	0.3813	0.5055	0.5227

iv) g_2 is greater than θ_1, in all periods, which is again a proof of the consistency of the estimation results. (See chapter 1 for the meaning of the relations between g_2 and θ_1.) From the estimated values, and the relations among variables in the theoretical model, some simple computations show that the empirical model implies a smaller variance for production than for demand. Let us recall that this result was expected from some prior aggregate information given in Chapter 1.

4.4 Forecasting

A byproduct of this empirical analysis is a forecasting model of the industrial activity for the French manufacturing industry. Since the econometric model includes the expected change on production, we are able to forecast the individual forecasts! The forecasting method is based on a proposition derived by Gourieroux, Monfort and Trognon [1982].

Let us recall that the structural equations that explain the behavior of the "true" change on the production level are (see Table 2.1):

$$(4.1)\quad \begin{aligned} \Delta\tilde{q}^e_t &= g_1\Delta\tilde{q}_t + g_2\Delta\tilde{\alpha}_t + g_3\Delta\tilde{\gamma}_t + \Delta\tilde{q}^e_{t-1} + u^e_t \\ \Delta\tilde{q}_{t+1} &= \Delta\tilde{q}^e_t + \Delta u_{t+1} \\ \Delta\tilde{\alpha}_t &= \theta_1\Delta\tilde{\alpha}_{t-1} + \Delta u^\alpha_t \\ \Delta\tilde{\gamma}_t &= \theta_2\Delta\tilde{\gamma}_{t-1} + \Delta u^\gamma_t \end{aligned}$$

The derivation of the last two equations is obvious. After some simple manipulations, the changes on production can be obtained as an autoregressive process given by the following model:

$$(4.2)\quad \begin{aligned} [(1-g_1L)(1-\theta_1L)(1-\theta_2L)]\Delta\tilde{q}_{t+1} &= g_2(1-\theta_2L)\Delta u^\alpha_t + g_3(1-\theta_1L)\Delta u^\gamma_t \\ &\quad + (1-\theta_1L)(1-\theta_2L)(u^e_t + \Delta u_{t+1}) \end{aligned}$$

where L is the lag operator. In other words, the "true" change in production is an autoregressive process of order 3; the right-hand side of (4.2) represents a complex moving-average process since each component in $(u_t, u^\alpha_t, u^\gamma_t, u^e_t)$ is white noise. This equation is in fact a reduced form of our model and shows how the production changes are affected by unexpected changes in sales and costs.

The equation (4.2) may also be written as:

$$(4.3) \quad \Delta\tilde{q}_t = (g_1 + \theta_1 + \theta_2)\ \Delta\tilde{q}_{t-1} - [\theta_1\theta_2 + g_1(\theta_1+\theta_2)]\ \Delta\tilde{q}_{t-2} + g_1\theta_1\theta_2\ \Delta\tilde{q}_{t-3} + w_t$$

where w_t is a process whose variance σ_w^2 can be computed from the estimates of the variances $(\sigma_u^2, \sigma_\alpha^2, \sigma_\gamma^2, \sigma_\varepsilon^2)$ and of the parameters: $g_1, g_2, g_3, \theta_1, \theta_2$. But as we do not observe $\Delta\tilde{q}_t$ we must correct (4.3) for the measurement errors. Let us recall that:

$$\Delta q_t^* = \Delta\tilde{q}_t + u_t^q$$

Then, (4.3) becomes:

$$\begin{aligned}\Delta\tilde{q}_t &= \psi_1(\Delta q_{t-1}^* - u_{t-1}^q) + \psi_2(\Delta q_{t-2}^* - u_{t-2}^q) + \psi_3(\Delta q_{t-3}^* - u_{t-3}^q) + w_t \\ &= \psi_1\Delta q_{t-1}^* + \psi_2\Delta q_{t-2}^* + \psi_3\Delta q_{t-3}^* + w_t - \psi_1 u_{t-1}^q - \psi_2 u_{t-2}^q - \psi_3 u_{t-3}^q\end{aligned}$$

Hence:

$$(4.4) \quad \Delta\tilde{q}_t = \psi_2\ \Delta q_{t-1}^* + \psi_2\ \Delta q_{t-2}^* + \psi_3\ \Delta q_{t-3}^* + v_t$$

where ψ_1, ψ_2, ψ_3 have obvious definitions and:

$$v_t = w_t - \psi_1 u_{t-1}^q - \psi_2 u_{t-2}^q - \psi_3 u_{t-3}^q$$

From the estimation results, ψ_1, ψ_2, ψ_3 and the variance (σ_v^2) of v_t can be evaluated.

We would like forecasting the change in the level of production using equation (4.4). The difficulty is that the information available on Δq^* is qualitative. What we may do is to evaluate the conditional expectations given the discrete data. For instance, let us assume that we observe a decrease of production at time t, so:

$$\Delta q_t = 1 \quad \text{i.e.} \quad \Delta q_t^* \leq \delta_t(q),$$

where $\delta_t(q)$ is a threshold and that we know: $\Delta q_{t-1}^*, \Delta q_{t-2}^*, \ldots, \Delta q_{t-k}^*$.

Then the following holds:

$$(4.5)\quad E[\Delta q_t^* \mid \Delta q_t = 1,\ (\Delta q^*)_{t-k}^{t-1}] = \sum_{i=1}^{k} \psi_i\ \Delta q_{t-1}^*$$
$$+\ \sigma_v\ E\left[\ \frac{v_t}{\sigma_v}\ \Big|\ \frac{v_t}{\sigma_v} \leq \frac{\delta_t - \Sigma\psi_i \Delta q_{t-i}^*}{\sigma_v}\ , (\Delta q^*)_{t-k}^{t-1}\ \right]$$

As v_t is normally distributed, we may compute the conditional expectations:

$$(4.6)\quad E[\Delta q_t^* \mid \Delta q_t = 1,\ (\Delta q^*)_{t-k}^{t-1}] = \sum_{i=1}^{k} \psi_i\ \Delta q_{t-1}^*$$
$$+\ \sigma_v\ \frac{f(\delta_t - \Sigma\psi_i \Delta q_{t-i}^* / \sigma_v)}{1 - F(\delta_t - \Sigma\psi_i \Delta q_{t-i}^* / \sigma_v)}$$

where f and F are the normal density and the cumulative normal distribution, respectively. The δ's are thresholds and are consistently estimated by inverting the normal cumulative density function. (This is a byproduct of the estimations of the polychoric correlation coefficients, see Chapter 3.) The relation given by (4.6) can be used for forecasting. Let us assume now that we observe the following regime for three periods, t = 1,2,3:

$\Delta q_1 = 1$ i.e. $\Delta q_1^* \leq \delta_1$

$\Delta q_2 = 1$ i.e. $\Delta q_2^* \leq \delta_2$

$\Delta q_3 = 1$ i.e. $\Delta q_3^* \leq \delta_3$

which means that production has decreased permanently over the three periods. According to (4.6) we can evaluate the following quantities using our empirical results from the preceding section:

$$\bar{\Delta q}_1^* = \sigma_v \, E\left[\frac{v_1}{\sigma_v} \,\middle|\, \frac{v_1}{\sigma_v} \leq \frac{\delta_1}{\sigma_v}\right]$$

$$(4.7) \qquad \bar{\Delta q}_2^* = \psi_1 \bar{\Delta q}_1^* + \sigma_v \, E\left[\frac{v_2}{\sigma_v} \,\middle|\, \frac{v_2}{\sigma_v} \leq \frac{\delta_2 - \psi_1 \bar{\Delta q}_1^*}{\sigma_v}\right]$$

$$\bar{\Delta q}_3^* = \psi_1 \bar{\Delta q}_2^* + \psi_2 \bar{\Delta q}_1^* + \sigma_v \, E\left[\frac{v_3}{\sigma_v} \,\middle|\, \frac{v_3}{\sigma_v} \leq \frac{\delta_3 - \psi_1 \bar{\Delta q}_2^* - \psi_2 \bar{\Delta q}_1^*}{\sigma_v}\right]$$

$$\bar{\Delta q}_4^* = \psi_1 \bar{\Delta q}_3^* + \psi_2 \bar{\Delta q}_2^* + \psi_3 \bar{\Delta q}_1^*$$

We define $\bar{\Delta q}_4^*$ as the forecast given the discrete information given by $\Delta q_1, \Delta q_2, \Delta q_3$. This <u>number</u>, which obviously is not a probability, can be positive or negative; but as we do not know the thresholds for $\bar{\Delta q}_4^*$, i.e., the thresholds in the future are not known, we cannot say if our forecast would indicate a future increase or decrease of the production level. What we can do is to compute:

$$(4.8) \qquad Q_4 = \sum_{i,j,k} \bar{\Delta q}_4^*(i,j,k) \Pr[\Delta q_1 = i, \Delta q_2 = j, \Delta q_3 = k]$$

where Δq_4^* (i,j,k) is the forecast when: $\Delta q_1 = i$, $\Delta q_2 = j$, $\Delta q_3 = k$, where i,j,k takes values on 1,2,3 corresponding to the three cases "decrease", "no change", "increase" . Q_4 is an aggregate index forecast. Table 4.5 (page 131) gives the empirical probabilities of observing one of the 27 possible regimes over the three periods: March-June-October 1985 (frequencies for other periods are similar); then values for $\Delta \bar{q}_4^*$ (corresponding to January 1986 which is outside our estimation periods), are computed with the estimated parameters from two estimation periods (ending periods: January 1985 and October 1985). (The results for the two others are similar.) This shows that there are only a very few observable regimes, and that the forecasts are similar whatever the estimation period we consider. How could we use these figures? For instance, if such a value for a particular regime is available in October 1985, say, by comparing it with the corresponding one of January 1985, we can know if the probability of a particular regime will increase or decrease. But this is not very useful. A more aggregate information will be preferred.

Table 4.6 (gives the values for Q_4 obtained when we consider the four sets of estimates for the empirical model. Q_4 is computed inside the estimation periods and outside the only one period, January 1986. The last column gives the industrial production index as it is released by

Table 4.5

Conditional Forecasts of Changes in Production

(January 1986)

Observed Regimes			Occuring Probabilities	Forecasts January 86 Ending Period: January 85	Forecasts January 86 Ending Period: October 85
1	1	1	.0128	-0.1507	-0.2133
1	1	2	.0592	5.8097	5.0286
1	1	3	.0866	7.5665	6.7755
1	2	1	.1464	-0.1507	-0.2133
1	2	2	.0000	5.8097	5.0286
1	2	3	.1642	7.5665	6.7755
1	3	1	.0000	-0.1507	-0.2133
1	3	2	.2827	5.8097	5.0286
1	3	3	.0693	7.5665	6.7755
2	1	1	.0000	-2.9477	-2.8124
2	1	2	.0000	-0.4690	-0.4297
2	1	3	.1235	2.2783	2.1940
2	2	1	.0000	-2.9477	-2.8124
2	2	2	.0000	-0.4686	-0.4297
2	2	3	.0000	2.2783	2.1940
2	3	1	.0000	-2.9477	-2.8124
2	3	2	.0000	-0.4686	-0.4297
2	3	3	.0413	2.2783	2.1940
3	1	1	.0000	-8.2312	-7.3886
3	1	2	.0000	-6.5149	-5.6820
3	1	3	.0000	0.0831	0.1250
3	2	1	.0000	-8.2312	-7.3886
3	2	2	.0000	-6.5149	-5.6820
3	2	3	.0000	0.0831	0.1250
3	3	1	.0000	-8.2312	-7.3886
3	3	2	.0000	-6.5149	-5.6820
3	3	3	.0140	0.0831	0.1250

Table 4.6

Forecasts of the Production Index

Period	Jan. 85	March 85	June 85	Oct. 85	INSEE Production Index
January 85	3.8050	3.7590	3.6294	3.3662	98
March 85	4.7047	4.6509	4.5021	4.1873	99
June 85	5.2393	7.1777	5.0011	4.6664	101
October 85	5.0102	4.9539	4.7968	4.4633	100
January 85	4.7611	4.7042	4.5453	4.2176	99

INSEE. The indices that are built according to the preceding method are consistent with the evolution of the INSEE production index as they mimic (for any set of estimates) the same pattern over time. This is a test of the consistency of our results and it is encouraging for further research. Indeed the method developed here has provided a coherent way to aggregate the individual qualitative information for forecasting the economic activity of the whole industrial sector.

Nonetheless, this method should be improved since one would prefer to forecast the probabilities that, given the past, production increases, stays the same or decreases.

4.5 Summary and Remarks

This part proposes an application of a general methodology to estimate economic structural models using business survey data. In the specific model that I have considered, the results show that the assumption of a rational behavior of production is identifiable with these data or that the latter can be interpreted as resulting from the former. The method allow us to recover the underlying cost structure where adjustment costs appear to be dominant over the other types of costs. The macroeconomic consequence of this finding is that there is a desire to keep production as constant as possible in the French industrial sector: Around seventy percent of the past production level is reproduced the next period. As costs of holding inventories or backlogging orders are not negligible, this desire for stability of the production level in the short-run is balanced by the desire to adjust the production behavior to the future economic conditions. From the estimated model, simulations could be performed to study the temporal response of the production level to unexpected shocks of sales and costs, in order to test (in particular) the variability of production compared to the variability of economic conditions.

Such simulations would be meaningful if the model contained macroeconomic or policy variables and if the price behavior was explained. This is left for further research. Nonetheless, let us remark that, in the empirical model, unexpected shocks of sales and costs are evaluated by means of the inventory and order-backlog appraisals of the managers. As soon as these data are known we could forecast the future changes of the production level. Here I have shown how to construct and to forecast an index of the production change. But this method must still be improved in order to use similar models and business survey data as a standard tool to predict the economic activity in the short-run.

Appendix to Chapter Four: Tests and Statistics

Table A4.1 Correlations and Test Statistics

(Correlation Matrix October 1985)

Polychoric Correlation Coefficient for :		Test for Normality (df = 3) Chisq.	P-value	Test of Zero Corr. Chisq.	P-value
DEQ2 VS. DEQ1	.538	22.108	.000	142.264	.000
DEQ3 VS. DEQ1	.156	36.736	.000	9.772	.002
DEQ3 VS. DEQ2	.327	8.611	.035	45.303	.000
DQ1 VS. DEQ1	.065	34.051	.000	1.690	.194
DQ1 VS. DEQ2	-.011	13.482	.004	.045	.833
DQ1 VS. DEQ3	.096	5.234	.155	3.623	.057
DQ2 VS. DEQ1	.416	17.514	.001	77.144	.000
DQ2 VS. DEQ2	.090	36.160	.000	3.223	.073
DQ2 VS. DEQ3	.094	10.368	.016	3.514	.061
DQ2 VS. DQ1	.516	24.142	.000	128.210	.000
DQ3 VS. DEQ1	.481	14.352	.002	107.934	.000
DQ3 VS. DEQ2	.423	15.759	.001	80.029	.000
DQ3 VS. DEQ3	.133	25.914	.000	7.012	.008
DQ3 VS. DQ1	.195	17.406	.001	15.341	.000
DQ3 VS. DQ2	.433	30.953	.000	84.275	.000
DQ4 VS. DEQ1	.231	17.586	.001	21.681	.000
DQ4 VS. DEQ2	.161	10.105	.018	10.391	.000
DQ4 VS. DEQ3	.486	28.822	.000	110.482	.000
DQ4 VS. DQ1	.097	9.814	.020	3.690	.055
DQ4 VS. DQ2	.221	9.571	.023	19.855	.000
DQ4 VS. DQ3	.374	20.719	.000	60.811	.000
L1 VS. DEQ1	-.128	7.036	.071	6.556	.010
L1 VS. DEQ2	-.116	4.444	.217	5.314	.021
L1 VS. DEQ3	-.065	3.404	.333	1.672	.196
L1 VS. DQ1	-.221	10.990	.012	19.845	.000
L1 VS. DQ2	-.175	5.293	.152	12.244	.000
L1 VS. DQ3	-.147	6.211	.102	8.632	.003
L1 VS. DQ4	-.070	.714	.870	1.955	.162
S1 VS. DEQ1	.493	5.297	.151	114.799	.000
S1 VS. DEQ2	.189	5.461	.141	14.393	.000
S1 VS. DEQ3	.042	1.216	.749	.709	.400
S1 VS. DQ1	.437	.713	.870	86.320	.000
S1 VS. DQ2	.482	.887	.829	108.643	.000
S1 VS. DQ3	.338	8.188	.042	48.525	.000
S1 VS. DQ4	.086	7.088	.069	2.900	.089
S1 VS. L1	-.418	5.396	.145	77.844	.000
L2 VS. DEQ1	-.244	.517	.915	24.367	.000
L2 VS. DEQ2	-.274	5.080	.166	30.957	.000
L2 VS. DEQ3	-.124	1.136	.768	6.151	.013
L2 VS. DQ1	-.159	6.131	.105	10.136	.000
L2 VS. DQ2	-.224	21.495	.000	20.411	.000
L2 VS. DQ3	-.149	10.467	.015	8.815	.003
L2 VS. DQ4	-.069	8.526	.036	1.894	.169
L2 VS. L1	.763	24.180	.000	396.061	.000
L2 VS. S1	-.352	12.154	.007	53.038	.000

Table A4.1 Correlations and Test Statistics (Continued)

Polychoric Correlation Coefficient for :		Test for Normality (df = 3) Chisq.	P-value	Test of Zero Corr. Chisq.	P-value
S2 VS. DEQ1	.454	.902	.825	94.030	.000
S2 VS. DEQ2	.455	9.801	.020	94.825	.000
S2 VS. DEQ3	.149	4.707	.195	8.880	.003
S2 VS. DQ1	.378	2.271	.518	62.174	.000
S2 VS. DQ2	.435	11.180	.011	85.577	.000
S2 VS. DQ3	.451	10.774	.013	92.689	.000
S2 VS. DQ4	.138	8.532	.036	7.626	.006
S2 VS. L1	-.316	1.609	.657	42.086	.000
S2 VS. S1	.753	15.829	.001	377.271	.000
S2 VS. L2	-.392	9.269	.026	67.555	.000
L3 VS. DEQ1	-.149	.523	.914	8.811	.003
L3 VS. DEQ2	-.150	3.333	.343	8.917	.003
L3 VS. DEQ3	-.239	2.124	.547	23.381	.000
L3 VS. DQ1	-.059	4.014	.260	1.383	.240
L3 VS. DQ2	-.196	6.103	.107	15.467	.000
L3 VS. DQ3	-.176	21.323	.000	12.494	.000
L3 VS. DQ4	-.176	7.032	.071	12.495	.000
L3 VS. L1	.542	21.939	.000	144.586	.000
L3 VS. S1	-.244	11.598	.009	24.397	.000
L3 VS. L2	.728	14.870	.002	335.396	.000
L3 VS. S2	-.269	14.089	.003	29.807	.000
S3 VS. DEQ1	.263	7.668	.053	28.398	.000
S3 VS. DEQ2	.312	6.803	.078	40.969	.000
S3 VS. DEQ3	.450	8.419	.038	92.208	.000
S3 VS. DQ1	.233	3.337	.343	22.199	.000
S3 VS. DQ2	.323	5.353	.148	44.036	.000
S3 VS. DQ3	.500	15.549	.001	118.347	.000
S3 VS. DQ4	.393	3.484	.323	67.712	.000
S3 VS. L1	-.275	1.821	.610	31.259	.000
S3 VS. S1	.478	8.994	.029	106.555	.000
S3 VS. L2	-.288	6.435	.092	34.635	.000
S3 VS. S2	.662	14.032	.003	248.839	.000
S3 VS. L3	-.432	30.479	.000	83.945	.000
DEQ0 VS. DEQ1	.399	45.266	.000	70.259	.000
DEQ0 VS. DEQ2	.138	12.931	.005	7.561	.006
DEQ0 VS. DEQ3	.030	12.312	.006	.349	.555
DEQ0 VS. DQ1	.577	17.542	.001	170.287	.000
DEQ0 VS. DQ2	.420	15.136	.002	78.722	.000
DEQ0 VS. DQ3	.278	13.185	.004	32.015	.000
DEQ0 VS. DQ4	-.023	10.908	.012	.201	.654
DEQ0 VS. L1	-.176	1.515	.679	12.391	.000
DEQ0 VS. S1	.329	1.013	.798	45.999	.000
DEQ0 VS. L2	-.103	1.841	.606	4.196	.041
DEQ0 VS. S2	.291	3.044	.385	35.345	.000
DEQ0 VS. L3	-.017	.254	.968	.108	.742

Table A4.1 Correlations and Test Statistics (Continued)

Polychoric Correlation Coefficient for :		Test for Normality (df = 3)		Test of Zero Corr.	
		Chisq.	P-value	Chisq.	P-value
DEQ0 VS. S3	.193	1.959	.581	14.945	.000
L0 VS. DEQ1	-.009	2.940	.401	.035	.852
L0 VS. DEQ2	-.087	1.387	.709	2.991	.084
L0 VS. DEQ3	-.058	3.464	.325	1.345	.246
L0 VS. DQ1	-.199	8.477	.037	15.914	.000
L0 VS. DQ2	-.076	2.430	.488	2.253	.133
L0 VS. DQ3	.069	3.245	.355	1.882	.170
L0 VS. DQ4	.101	4.303	.231	4.038	.044
L0 VS. L1	.733	28.423	.000	344.184	.000
L0 VS. S1	-.232	4.161	.245	21.943	.000
L0 VS. L2	.527	26.040	.000	135.215	.000
L0 VS. S2	-.228	4.109	.250	21.079	.000
L0 VS. L3	.390	26.557	.000	66.560	.000
L0 VS. S3	-.175	1.236	.744	12.327	.000
L0 VS. DEQ0	-.200	9.223	.026	16.216	.000
S0 VS. DEQ1	.276	9.182	.027	31.618	.000
S0 VS. DEQ2	.196	1.877	.598	15.551	.000
S0 VS. DEQ3	.081	10.250	.017	2.584	.108
S0 VS. DQ1	.464	.616	.893	99.266	.000
S0 VS. DQ2	.411	.341	.952	74.903	.000
S0 VS. DQ3	.226	9.471	.024	20.731	.000
S0 VS. DQ4	.019	4.247	.236	.147	.702
S0 VS. L1	-.350	7.004	.072	52.614	.000
S0 VS. S1	.737	5.491	.139	350.020	.000
S0 VS. L2	-.243	2.202	.532	24.180	.000
S0 VS. S2	.687	9.918	.019	279.078	.000
S0 VS. L3	-.169	8.220	.042	11.488	.000
S0 VS. S3	.461	18.238	.000	97.566	.000
S0 VS. DEQ0	.458	4.293	.232	96.110	.000
S0 VS. L0	-.421	7.853	.049	79.403	.000

Remarks : - df = number of degrees of freedoms
- Chisq. = value of the Chi-square statistic
- P-value = empirical level of significance

Table A4.2 Asymptotic Variances of Estimated Correlations

(Correlation Matrix October 1985)

R(2,1)	R(3,1)	R(3,2)	R(4,1)	R(4,2)	R(4,3)
.00236	.00394	.00347	.00397	.00411	.00397
R(5,1)	R(5,2)	R(5,3)	R(5,4)	R(6,1)	R(6,2)
.00291	.00414	.00406	.00231	.00255	.00295
R(6,3)	R(6,4)	R(6,5)	R(7,1)	R(7,2)	R(7,3)
.00396	.00369	.00280	.00363	.00394	.00253
R(7,4)	R(7,5)	R(7,6)	R(8,1)	R(8,2)	R(8,3)
.00387	.00366	.00303	.00436	.00451	.00450
R(8,4)	R(8,5)	R(8,6)	R(8,7)	R(9,1)	R(9,2)
.00403	.00426	.00429	.00438	.00307	.00409
R(9,3)	R(9,4)	R(9,5)	R(9,6)	R(9,7)	R(9,8)
.00427	.00285	.00267	.00339	.00412	.00340
R(10,1)	R(10,2)	R(10,3)	R(10,4)	R(10,5)	R(10,6)
.00416	.00416	.00453	.00432	.00422	.00440
R(10,7)	R(10,8)	R(10,9)	R(11,1)	R(11,2)	R(11,3)
.00450	.00157	.00386	.00280	.00290	.00407
R(11,4)	R(11,5)	R(11,6)	R(11,7)	R(11,8)	R(11,9)
.00311	.00289	.00279	.00399	.00386	.00111
R(11,10)	R(12,1)	R(12,2)	R(12,3)	R(12,4)	R(12,5)
.00361	.00434	.00446	.00411	.00439	.00421
R(12,6)	R(12,7)	R(12,8)	R(12,9)	R(12,10)	R(12,11)
.00423	.00420	.00296	.00422	.00188	.00408
R(13,1)	R(13,2)	R(13,3)	R(13,4)	R(13,5)	R(13,6)
.00368	.00359	.00284	.00370	.00343	.00250
R(13,7)	R(13,8)	R(13,9)	R(13,10)	R(13,11)	R(13,12)
.00305	.00402	.00272	.00409	.00161	.00328
R(14,1)	R(14,2)	R(14,3)	R(14,4)	R(14,5)	R(14,6)
.00297	.00402	.00409	.00196	.00287	.00347
R(14,7)	R(14,8)	R(14,9)	R(14,10)	R(14,11)	R(14,12)
.00398	.00422	.00343	.00449	.00355	.00447
R(14,13)	R(15,1)	R(15,2)	R(15,3)	R(15,4)	R(15,5)
.00388	.00456	.00462	.00457	.00416	.00451

Table A4.2 (Continued)

R(15,6)	R(15,7)	R(15,8)	R(15,9)	R(15,10)	R(15,11)
.00448	.00440	.00182	.00432	.00320	.00428
R(15,12)	R(15,13)	R(15,14)	R(16,1)	R(16,2)	R(16,3)
.00390	.00443	.00421	.00364	.00403	.00419
R(16,4)	R(16,5)	R(16,6)	R(16,7)	R(16,8)	R(16,9)
.00266	.00301	.00379	.00413	.00370	.00115
R(16,10)	R(16,11)	R(16,12)	R(16,13)	R(16,14)	R(16,15)
.00428	.00143	.00441	.00277	.00274	.00339

Remarks : R(i,j) is the asymptotic variance of the correlation coefficient located at the (i,j) entry of the correlation matrix given in table 2

PART TWO

SURVEY EVIDENCE ON THE RATIONALITY OF EXPECTATIONS

Data on expectations collected in business surveys offer the opportunity to test the different models of expectation formation proposed in the economic literature. For some time, economists have recognized the fact that expectations play a crucial role in economic activity, but there is considerable debate about the appropriate modeling of expectation formation, and in particular, about the rationality of expectation formation. According to Muth [1961], an expectation is said to be rational if it is the optimal point forecast based on the observation of some economic variables, and on the true model linking these variables and the predicted variables.

This definition (to be more precisely stated) implies that a scheme of expectation formation must describe precisely the information set chosen to derive the predictions, i.e., how the agents use the available information. In this part I focus on the problem of testing directly the Rational Expectation Hypothesis (REH, herein), which is a central issue in the development of macro and micro models. Numerous studies deal with this question; the literature may be classified into two types of approach.

The indirect approach for testing the REH does not require data on expectations. Let us consider a dynamic structural model involving expectations of endogenous or exogenous variables. Without information on expectations, only the reduced-form, obtained from the structural model by inserting the REH, can be estimated. Then the constraints imposed by the model of expectation formation are indistinguishable from those characterizing the structural model. In this context, any test based on the reduced-form model is a joint test of the structural model specification and of the expectation formation model. So, there is no way to confirm or not the REH, since its rejection could be the consequence of a mis-specification of the structural model (see for this type of test, Wallis [1980], Pesaran [1981], among others).

Alternatively, survey data allow one to perform non-parametric (or direct) tests of the REH, since surveys report both the expectations and the subsequent realizations for different variables. Such tests have been proposed by Theil [1958], Turnovsky and Wachter [1972], Pesando [1975], Carlson [1977], Mullineaux [1978], Friedman [1980], de Leeuw and McKelvey [1981], Brown and Maital [1981], Pesaran [1985], Taylor [1988], etc. Usually the tests bear on quantitative data such as the inflation rate, the wage rate, the stock market index. When the data are qualitative, the information is usually transformed into quantitative data before performing the test (see Gourieroux and Peaucelle [1985], Seitz [1987], for instance). A very few studies use directly the qualitative information to infer the expectation behavior, see Nerlove [1983], Gourieroux and Peaucelle [1985].

In the next chapter, I will return to the definition of rational expectations, on the precise statement of the REH, and on the different tests of the REH proposed in the literature. In the following chapter, I present evidence that the surprise variables which can be derived from survey data cannot be interpreted as expectational errors; so tests of the REH using these variables are not meaningful. In the last chapter, I will propose a direct test for the business survey data based on a latent variable model.

Chapter 5: On Testing the RE Hypothesis: A Survey

5.1 Definition and Characterizations

In Muth's definition given above, the decisive feature which differentiates rational expectations from other types of expectation behavior is the requirement of optimality. Then the question is: What is an optimal prediction? Usually it is defined as the minimum mean-square error predictor. I follow here the presentation proposed by Pradel [1985]. (See also Gourieroux and Pradel [1986].)

5.1.1 Definition

Let Ω be a family of random variables with values on $\Re^K$. The question is to predict the K-dimensional vector $y = (y_1,\ldots,y_k)'$. The optimal prediction, denoted by $e(y \mid \Omega)$, is the solution of the following problem:

$$(5.1) \qquad \min_{x \in \Omega} \; E\|y-x\|^2 = \sum_{k=1}^{K} E(y_k-x_k)^2$$

where E is the expectation operator. The set Ω is the information set. It can be the set of the possible predictions of y. In practice, the set Ω is chosen such that the solution for the above problem exists and is unique. Some examples for such a set are given below, but at this point we may recall that, when Ω is a closed vector space of square integrable random variables, the optimal prediction is the orthogonal projection, that is to say, the orthogonality conditions are satisfied (see Monfort [1980]):

$$E\,[y - e(y \mid \Omega)]\;x = 0 \quad \forall x \in \Omega$$

Given the Muthian definition, the Rational Expectation Hypothesis H is stated as follows:

(5.2) $H = (\;\exists\, \Omega \in I : y^e = e(y \mid \Omega)\;)$,

where y^e is the observable prediction of y, where I is a family of information set. So, testing the REH amounts to check for conditions ensuring that there exists an information set for which the observed prediction coincides with the (unobservable) optimal prediction.

The following lemma, proved by Gourieroux and Pradel [1986], is useful in view of characterizing H.

Lemma Let us assume that there exists a smallest element $\Omega(y^e)$ of I such that: $y^e \in \Omega(y^e) \subset \Omega$. Then the following propositions are equivalent:

(i) $\exists\, \Omega \in I : y^e = e(y \mid \Omega)$

(ii) $E\|y - y^e\|^2 \leq E\|y - x\|^2 \quad \forall x \in \Omega(y^e)$

(iii) $y^e = e(y \mid \Omega(y^e))$

The proof is short. Indeed:

(i) $\Longrightarrow$ (ii): Since $\Omega(y^e) \subset \Omega$, we have:

$$E\|y - y^e\|^2 = \min_{\chi \in \Omega} E\|y - \chi\|^2 \leq E\|y - x\|^2 \text{ for all } x \in \Omega(y^e).$$

(ii) ⟹ (iii): Since: $E\|y - y^e\|^2 \leq \min_{x \in \Omega(y^e)} E\|y - x\|^2$ and $y^e \in \Omega(y^e)$,

we deduce: $y^e = e(y \mid \Omega(y^e))$.

(iii) ⟹ (i): Obvious by taking: $\Omega = \Omega(y^e)$. Q.E.D.

Consequently, the REH is defined by the condition: $y^e = e(y \mid \Omega(y^e))$, associated with the smallest information set generated by y^e. This condition is obviously true only if the loss function is quadratic. We turn now to the question of finding simple conditions to test the REH.

5.1.2 Quantitative Data

Let Ω^e be the smallest closed vector space containing y^e, for instance, the set $(\lambda y^e$ for $\lambda \in \Re)$. Then it is trivial to show that, under some regularity assumptions, the well-known orthogonality condition, i.e., $E(y-y^e)y^e = 0$ is a necessary and sufficient condition for having a unique solution, namely $y^e = e(y \mid \Omega(y^e))$, to problem (5.1). This motivates the following result:

Property 1 (Pradel [1985]):

If data are quantitative, the hypothesis H is satisfied if and only if:

(5.3) $E(y-y^e)y^e = 0$.

That is to say, expectations are rational if the forecast errors are orthogonal to the observed prediction.

Gourieroux and Pradel [1986] point out that this characterization of the REH does not require expectations to be unbiased. Indeed, for deriving the preceding property, nothing impels the information set to contain the deterministic elements of the variable such as the trend, the seasonality, although they are observable. If there is a bias, it means that these elements are unknown since the condition for unbiasedness: $E(y - y^e)=0$ is equivalent to having: $1 \in \Omega$.

5.1.3 Qualitative Data

The characterization of the REH in the case of qualitative data is less known. For ease of exposition we need some complementary notations. Let us suppose that the variable to be predicted y is polytomous and there exists a latent quantitative variable which allows us to determine how the responses are triggered. Without loss of generality, the correspondence between these two variables is defined by means of the indicator function in the following way:

$$y = (y_1,\ldots,y_K) \quad \text{and:} \quad y_k = \mathbf{1}_{A_k}(y^*) = \begin{cases} 1 & \text{if } y^* \in A_k \\ 0 & \text{otherwise,} \end{cases}$$

where: $\bigcup_{k=1}^{K} A_k = \mathfrak{R}$ and $A_k \cap A_l = \emptyset$ for $k \neq l$.

The information set for the quantitative variable is $\Omega^* \in \mathbf{I}^*$, which generates the σ-field $\sigma(\Omega^*)$. The information set $\Omega \in \mathbf{I}$ is defined by:

$$\Omega = (x = (x_1,\ldots,x_K): x_k = \mathbf{1}_{B_k} \text{ for } k=1,\ldots,K \text{ and } B_k \in \sigma(\Omega^*)$$
$$\bigcup_{k=1}^{K} B_k = \mathfrak{R} \text{ and } B_k \cap B_l = \emptyset \text{ for } k \neq l),$$

that is, we impose the prediction to be qualitative. Now, it can be shown that the optimal prediction $x = e(y \mid \Omega)$, solution of (5.1), is given by:

$$x_k = \begin{cases} 1 & \text{if} \quad \Pr[\, y^* \in A_k \mid \sigma(\Omega^*) \,] > \max\limits_{i \neq k} \Pr[\, y^* \in A_i \mid \sigma(\Omega^*) \,] \\ 0 & \text{otherwise} \end{cases}$$

Hence, the optimal prediction (which here is not a conditional expectation) is associated with the greatest conditional probability.

This result appears to be intuitive in the dichotomous case, i.e., when the variable to be predicted is defined as:

$$y = \begin{cases} 1 & \text{if} \quad y^* \in A_0 = [0, +\infty) \\ 0 & \text{if} \quad y^* \in A_1 = (-\infty, 0[. \end{cases}$$

Given an information set, defined as the σ-field $\sigma(\Omega^*)$, the problem is to find a set $B \in \sigma(\Omega^*)$ which minimizes:

$$E[(1_{A_0} - 1_{B_0})^2 + (1_{A_1} - 1_{B_1})^2].$$

Let us remark that:

$$E[(1_{A_0} - 1_{B_0})^2 + (1_{A_1} - 1_{B_1})^2] = 2\{1 - [\, E(1_{A_0} 1_{B_0}) + E(1_{A_1} 1_{B_1}) \,]\,\}$$

since: $\quad E(1_{A_0}{}^2) + E(1_{A_1}{}^2) = 1 \quad$ and $\quad E(1_{B_0}{}^2) + E(1_{B_1}{}^2) = 1.$

Hence, we must look for a set B which maximizes:

$$E(1_{A_0} 1_{B_0}) + E(1_{A_1} 1_{B_1}).$$

Now, if we denote by b a generic element of B, it can be observed that:

$$E(1_{A_0}\ 1_{B_0}) + E(1_{A_1}\ 1_{B_1}) = E(\ 1_{B_0}\ E(A_0|b)\ ) + E(\ 1_{B_1}\ E(A_1|b)\ )$$
$$= E(\ 1_{B_0}\ Pr(A|b)\ ) + E(\ 1_{B_1}\ Pr(A_1|b)\ )$$

Let $B_0 = \{\ b \mid Pr(A_0|b) \geq Pr(A_1|b)\ \}$ and let $f(.)$ be the measurable function on the σ-field defined as: $f(b) = Pr(A_0|b) - Pr(A_1|b)$. Then it is clear that: $B = f^{-1}([0,+\infty[)$ is the solution.

Two remarks can be added. First, the preceding proof can be generalized for the polytomous case. Second, the prediction is optimal for any l^p-norm criterium, because $|1_A - 1_B|$ takes on values 0 or 1, and hence $|1_A - 1_B|^p$ does not depend on p.

How to characterize the hypothesis H when the prediction must be qualitative? By the above lemma, the REH is satisfied if and only if: $y^e = e(y \mid \Omega(y^e))$, where $\Omega(y^e)$ is the smallest element of I, containing the observable qualitative prediction y^e. Hence, when we observe: $y^e_k = 1$ for one k in $(1,\dots,K)$, the optimal prediction $x = e(y \mid \Omega(y^e))$ is given by:

$$x_i = 1 \quad \text{if} \quad Pr[\ y_i = 1 \mid y^e_k = 1] > \max_{j \neq i} Pr[\ y_j = 1 \mid y^e_k = 1]$$

$$x_i = 0 \quad \text{if} \quad Pr[\ y_i = 1 \mid y^e_k = 1] < \max_{j \neq i} Pr[\ y_j = 1 \mid y^e_k = 1]$$

Let us denote by p_{ij} the joint probability $Pr[\ y_i = 1\ ,\ y^e_j = 1]$. Using these relations, y^e_k is an optimal prediction if and only if:

for all $k = 1,\dots,K$ $p_{kk} \geq \max_{j \neq k} p_{jk}$.

since: $\Pr[\, y_j = 1 \mid y_k^e = 1] = p_{jk} / \Sigma p_{jk}$. Hence, it is stated that:

Property 2 (Gourieroux and Pradel [1986]):

If data are qualitative, the hypothesis H is satisfied if and only if:

(5.4) $p_{kk} \geq \max_{j \neq k} p_{jk}$ for all $k = 1,\dots,K$.

As pointed out by Gourieroux and Pradel [1986], rational expectations are not necessarily "correct" or "right" expectations. The latter implies that the prediction error is small which is not required for expectations to be rational. Indeed, the optimality criterion with respect to an information set does not mean that the expectation will be the best approximation of the variable when the information set is not sufficiently large.

At last, it must be stressed that the characterization of the REH in this case is based on the requirement that the expectation variable is an indicator variable as the realization. An alternative (developed by Pradel) would be to accept expectations of the qualitative variables to be quantitative. For instance, expectations can be viewed as probabilities on a finite set. As the data that I use here do not correspond to this case, it is just mentionned for sake of completeness.

5.2 Testing the RE Hypothesis in Practice.

5.2.1 Quantitative Data.

Given the characterization of the REH for quantitative data by the condition $E(y-y^e)\ y^e = 0$, a direct test can be derived by estimating first the linear model:

$$y_{it} = \beta y^e_{it} + u_{it} \qquad i = 1,\dots,N \quad t = 1,\dots,T$$

where u_{it} has mean zero and fixed variance σ^2, y_{it} is the observed realization for individual i at time t, and y^e_{it} is the observed prediction made at time t-1 for period t. Second, a statistic is used to test the null hypothesis $\beta = 1$ (which is equivalent to the REH).

On a cross-section, i.e., for a given period t_0, the test is performed by means of the classical t-statistic. Gourieroux and Pradel [1986] remark that this test is valid if the disturbance term is uncorrelated with expectations. Under the null, we may assume that the disturbance associated with the equation for individual i is independent with its own expectation and with the expectations of other individuals. (But this is not always true when, for instance, measurement errors on expectations are present; then the t-statistic should not be used if these errors are not explicitly taken into account.)

For serial data (obtained by summing the variables over index i), the independence condition is rarely met, because the realizations y being not known when the prediction is made, the forecast errors are not observable and hence, are not in the information set. So the t-statistic cannot be used any longer contrary to the usual practice. (See Brown and Maital [1981] for a complete analysis of this problem and see Gourieroux and Pradel [1986] for the correct statistic to be used in this situation.)

Two variants of the preceding test are proposed in the literature. (See Pradel [1985] for a complete survey on these types of tests.) For testing the REH together with unbiasedness, a constant term, say α, is added to the preceding regression and the F-statistic for $\alpha = 0$ and $\beta = 1$ can be used. Let us recall that unbiasedness is not required for having rational expectations. If there is a bias, it means that, although variables such as trend or seasonality are observable, the relations between y and these variables are not in the information set because they are complicated.

Another test consists of estimating the following regressions:

$$y = \alpha_0 + \sum_{j=1}^{s} \alpha_s \, y_{-j} + u$$

$$y^e = \beta_0 + \sum_{j=1}^{s} \beta_s \, y_{-j} + v$$

Then the Chow test is derived for the null: H_0: $\alpha_j = \beta_j \ \forall j=1,\ldots,s$. This is called the test of efficiency. (See Friedman [1980].) Given the preceding definitions, this is not the most general case for the REH which is tested. Indeed, the null H_0 should be stated here as:

$$H_0 = (\ \exists\Omega \ : \ y^e = e(y|\Omega) \ \text{ with}$$

$$\Omega \text{ the set of linear combinations of } 1, y_{-1}, \ldots, y_{-s} \ )$$

Obviously if the past values of y and the constant term belongs to the information set, then rejection of H_0 will cause the REH to be rejected; but if H_0 is not rejected, we are not allowed to reject the REH since it may exist an other set than the linear combinations of past values of y and of a constant term for which the REH may be verified.

5.2.2 Qualitative Data

An order statistic is necessary to test the REH given its characterization (Property 2) for the case of qualitative data. Indeed the null hypothesis imposes the parameters to be inside a space, and not, as in the usual case, on the border of this space. Let us consider a sample of size n on the prediction y_t^e observed at time t-1 and on the realized variable y_t. The data are qualitative, each variable taking on K values in a finite set of alternatives $(1,\ldots,K)$. Then the sample log-likelihood is:

$$\text{Log } L = \sum_{i,j} n_{ij} \log p_{ij}$$

where n_{ij} is the number of individuals in the cell $(y_t = i,\ y_t^e = j)$ and p_{ij} is the associated probability.

In order to estimate the model under the null, the constrained maximum likelihood estimators are computed by solving:

$$\underset{p_{ij}}{\text{Max}} \text{ Log } L$$

subject to: (i) $\sum_{i,j} p_{ij} = 1$

(ii) $p_{kk} \geq \underset{j \neq k}{\text{Max}} \; p_{jk}$ for $k = 1,\ldots,K$.

The statistic which is relevant to test the REH in this context must take into account the fact that the estimators are ordered and that not all constraints can be binding at the same time. Such a statistic has been derived by Gourieroux, Holly, and Montfort [1982] for the linear model: $y = x\beta + u$ under $R\beta \geq r$. The statistic is a weighted sum of chi-square statistics, the weights being probabilities that the parameters belong to the different cones associated with the different configurations that the inequality constraints may satisfy. This order statistic can be generalized for non-linear models (see Gourieroux and Monfort [1986]). It is difficult to compute it when the dimension of the parameter space is larger than 6: Indeed the weights are multivariate integrals which are not easy to evaluate (see Farebrother [1984]). The cost of evaluating this statistic for testing the REH seems very high.

One simple way to check these conditions for rational expectations is just to look at the contingency table giving the joint probability of y_t and y_t^e. Gourieroux and Peaucelle [1985] examines these tables when the variable of interest is the size of the labor force in the firms. The three categories are expected or realized increase, stability, decrease. Considering all the firms having answered to the French business test, they observe that the conditions $p_{kk} \geq \text{Max } p_{jk}$

$k = 1,2,3$ are only satisfied for the stability category. The authors point out that this is certainly due to the lack of a "don't know" item in the questionnaire (i.e., firms choose stability when they do not know); so the test is biased towards the rejection for the other two cases. (This measurement problem in survey data is well-known, see Nerlove [1983].) This indicates that the test for qualitative data does not seem particularly powerful.

In the literature, the test of the REH in the case of qualitative data is more usually based on some transformations of the data into quantitative variables. The basic arguments of this type of tests is that the qualitative data are ordinal information on an unobservable (latent) continuous variable. Then the necessary and sufficient condition for the REH in the case of quantitative data can be tested by using the linear regression presented above on the quantitative transformations of the qualitative information.

For instance, Pesaran and Gulamini [1982] consider a scaling technique to obtain such a quantitative transformation. A sketch for this method is presented in the dichotomous case. Given a panel of I individuals ($i=1,\ldots,I$) observed over T periods ($t=1,\ldots,T$), let:

$$p_{kl,t} = \Pr[\, y_{it} = k,\ y^e_{it} = l \,] \quad \text{with} \quad k \text{ and } l = 0,1,$$

and let us assume that there exists two latent variables y^* and y^{e*} and two numbers $\alpha < 0$ and $\beta > 0$ such that:

$$\begin{cases} y^*_{it} = \alpha & \text{if} \quad y_{it} = 0, \\ y^*_{it} = \beta & \text{if} \quad y_{it} = 1, \\ y^{*e}_{it} = \alpha & \text{if} \quad y^e_{it} = 0, \\ y^{*e}_{it} = \beta & \text{if} \quad y^e_{it} = 1. \end{cases}$$

Under the assumptions that the scales are time-invariant and are the same for both predictions and realizations, it can be seen that the condition: $E(y^*_{it} - y^{*e}_{it})y^{*e}_{it} = 0$ is equivalent to: $p_{01,t}\beta - p_{10,t}\alpha = 0$. Given the signs of α and β, the REH is stated as: $p_{01,t} = p_{10,t} = 0$. Contrary to the above characterization for qualitative data, only the errors in predicting the variable matter from a statistical point of view. This method privileges the idea of minimizing the forecast error than the concept of optimality.

Another method is to use balances, that is to say, the difference between the number of individuals reporting an increase and the numbers of those reporting a decrease. Such a procedure applies only for the trichotomous case. Let B_t and B^e_t be the balances associated with the latent realization y^*_t and the expectation y^{e*}_t, respectively. It is easy to show that the conditions for rationality applied to the balances is equivalent to the ones for the latent variables, i.e:

$$E\,(B_t - B^e_t)B^e_t = 0 \iff E\,(y^*_t - y^{e*}_t)y^{e*}_t = 0$$

if linear relations exist between latent variables and balances of the form:

$$B_t = a + b\, y^*_t$$
$$B^e_t = a + b\, y^{e*}_t$$

Arguments for the existence of such relations are given by Fansten [1976], but it is not easy to find empirical evidence for them. If they are accepted, the test of the REH can be based on the linear regression proposed in 5.2.1 for the case of quantitative data. The method is questionable on the basis that information contained in the "no change" category is not at all taken into account.

An other conversion of the raw response data into quantitative expectations and realizations series is proposed by several authors (see Taylor [1988] among others). It is sometimes obtained by computing the following series:

$$\nu_t = \alpha \frac{F^{-1}(f_t) + F^{-1}(1-r_t)}{F^{-1}(f_t) - F^{-1}(1-r_t)}$$

$$\nu_t^e = \beta \frac{F^{-1}(f_t^e) + F^{-1}(1-r_t^e)}{F^{-1}(f_t^e) - F^{-1}(1-r_t^e)}$$

where f_t (respectively, r_t) and f_t^e (respectively, r_t^e) are the proportions of respondents which report a fall (rise) at time t and expect a fall (rise) at time t-1 for period t; F(.) is the standard normal cumulant and α and β are scaling factors, chosen so that the means of the realized and expected changes over the whole sample period are equal. The two series can be used to perform the test proposed for quantitative data in 5.2.1. The main drawback here is that, although the constraints between the means of the two series are imposed, nothing is said about the correlations. Specifically, it is assumed that the conversion has no effect on the correlations between the variables, that is to say, nothing ensures us that the correlation between ν_t and ν_t^e is related to the correlation between the qualitative variables.

5.3 Summary

Let us stress the following points. First, there may exist an optimal prediction, that is to say, a solution to the program (5.1), and an information set such that the observed expectations coincide with the optimal predictions; yet this does not mean that rational expectations are "right" predictions since the forecast error can be large even at the optimal solution.

Second, the statement of the REH is dependent on the type of data available for the test. In the case of qualitative data, the correct test is not easy to derive; direct inspection of the conditions $p_{kk} \geq \text{Max } p_{jk}$ on the contingency tables is not a powerful test; it is just a means for observing if the optimal prediction and the observed expectation belong to the same set.

Third, the methods based on the transformation of the qualitative information into quantitative data use a linear regression to test the REH, assuming no correlation between the expectations and the disturbance term. This is not in general the case for serial data and this should not be the case if the data are observed with errors. Moreover conversion procedures usually impose (implicitly or explicitly) specific constraints which cannot be tested.

These remarks motivate the tests which are now proposed.

Chapter 6: Surprise Variables and Expectational Errors

In the study of causal relationships explaining expectations or plans as observed in business surveys, Nerlove [1983] has introduced "surprise" variables. Such variables are constructed in the following way.

For a variable X_t observed in a survey at time t, the available information is usually of the form: "increase", "stability", or "decrease" (since the last survey) and these three categories can be denoted: "1", "2", "3". Data of the same type are available for X_t^e, the expectation of X made at time t-1 for period t. The surprise variable SX is set up according to the following correspondence:

$$(6.0)\quad SX_t = \begin{cases} 1 \quad (\text{"positive" surprise}) & \text{if } X_t - X_t^e < 0 \\ 2 \quad (\text{no surprise}) & \text{if } X_t - X_t^e = 0 \\ 3 \quad (\text{"negative" surprise}) & \text{if } X_t - X_t^e > 0 \end{cases}$$

If a respondent expected an increase for X and if it turns out that X decreases, then there is a "negative" surprise, and so forth for each possible case. Various configurations could be created with more categories. Surprises or failures to fulfill a plan can be derived for prices, production, demand, i.e., any variable generally measured by business surveys.

These surprise variables play a crucial role in the Koenig-Nerlove model [1986] which explains changes of prices and production during the business cycle. It is interpreted as being distinctive of an adaptative expectations model. This interpretation comes from the idea that surprise variables, as the result of the difference 'X_t-X_t^e' would be analogous to expectational errors.

Now, if the surprise variable is interpreted as an expectational error, a test of the RE hypothesis can be obtained by testing the null hypothesis that the surprise variable is white noise. Indeed, a necessary condition for expectations to be rational is that expectational errors are uncorrelated over time. This can be easily seen in the continuous case (see Brown and Maital [1981] for instance). Using notation introduced at the outset of the last chapter, the observed prediction is rational if it is the conditional expectation given that the information set is a closed vector space of square integrable random variables, i.e.:

$$y^e = E(y \mid \Omega).$$

The forecast error is defined as: $f = y - y^e$. Hence, if expectations are rational, we must have: $E(f \mid \Omega) = 0$.

With this test, if the null hypothesis is rejected, then it is possible to conclude that expectations are not rational; otherwise, we cannot conclude. We develop now this test for the discrete variables by using the theory of Markov chains.

6.1 A Test of the REH based on the Theory of Markov Chains.

Tests about Markov chains are proposed in Anderson and Goodman [1957] (see also Bouissou, Laffont and Vuong [1986]).

a) Notation

Let x be a discrete stationary stochastic process and let X_r^s be the set $(x_t : r < t < s)$. The variable x_t takes on discrete values in the set $I_t = (1,\dots,i_t,\dots,I_t)$. The probability $p(i_1^T)$ is defined:

$$p(i_1^T) = \Pr\,[x_1 = i_1\ ,\dots,\ x_t = i_t\ ,\dots,\ x_T = i_T)$$

and $n(i_1^T)$ is the number of individuals in the cell: $(i_1,\dots,i_t,\ \dots i_T)$ of the contingency table $I_1^T = \prod_{t=1}^{T} I_t$.

The log-likelihood for the joint distribution $X_1^T = (x_1,\dots,x_t,\dots,x_T)$ is, given a sample of n independent observations:

$$\text{Log } L_0 = \sum_{i_1^T \in I_1^T} n(i_1^T) \log p(i_1^T)$$

The Maximum-Likelihood estimate of $p(i_1^T)$ is the empirical frequency:

$$\hat{p}(i_1^T) = \frac{n(i_1^T)}{n}$$

b) ML estimation under Markov assumptions:

The process x is Markov of order m if and only if:

(6.1) $\Pr[x_{t+1}|X_1^t] = \Pr[x_{t+1}|X_{t-m+1}^t]$ for any $t = m+1,\dots,T-1$.

For $m \geq 1$, the maximum likelihood estimator of $p(i_1^T)$ under the restrictions (6.1) is:

$$(6.2) \qquad \hat{p}^m(i_1^T) = \frac{\prod_{t=1}^{T-m} n(i_t^{t+m})}{\prod_{t=1}^{T-m-1} n(i_{t+1}^{t+m})}$$

Proof:

The joint probability $Pr[X_1^T]$ can be written:

$$(6.3) \quad Pr[X_1^T] = Pr[X_1^{m+1}] \prod_{t=1}^{T-m-1} Pr[x_{t+m+1} \mid X_1^{t+m}]$$

It must be true that, under the restrictions (6.1):

$$Pr[x_{t+m+1} \mid X_1^{t+m}] = Pr[x_{t+m+1} \mid X_{t+1}^{t+m}], \quad \text{for any } t = 1, \ldots, T-m-1.$$

The ML estimate of the conditional probability model $Pr[x_{t+m+1} | X_{t+1}^{t+m}]$ is: $\dfrac{n(i_{t+1}^{t+m+1})}{n(i_{t+1}^{t+m})}$

By multiplying these probabilities for $t = 1, \ldots, T-m-1$, and knowing that the ML estimate of $Pr[X_1^{m+1}]$ is just the associated empirical frequency, we obtain (6.2).

c) <u>Test of the order of a Markov chain.</u>

The Likelihood Ratio (LR) statistic for testing the null hypothesis of a Markov of order m against no restrictions on the joint probability $Pr[X_1^T]$ is given by:

$$(6.4) \qquad LR^m = 2 \sum_{i_1^T \in I_1^T} n(i_1^T) \log \frac{n(i_1^T)}{n\, p^m(i_1^T)} \qquad \text{for } m \in [1, T-2]$$

Asymptotically this statistic has a chi-square distribution and the number of degres of freedom is:

$$(6.5)\ df^{m} = \prod_{t=1}^{T} I_t - [\sum_{t=1}^{T-m} (\sum_{k=t}^{t+m} I_k) - \sum_{t=1}^{T-m-1} (\prod_{k=t+1}^{t+m} I_k)]$$

Proof:

Given the decomposition (6.3) and the restrictions (6.1), there are:

$[I_{t+m+1} \prod_{k=1}^{t+m} I_k]$ independent conditional probability $Pr[x_{t+m+1}|X_1^{t+m}]$,

and there are: $[(I_{t+m+1} - 1) \prod_{k=t+1}^{t+m} I_k]$ independent conditional

probability $Pr[x_{t+m+1}|X_{t+1}^{t+m}]$. Then the number of restrictions imposed by (6.1) is:

$$df^{m} = \sum_{t=1}^{T-m-1} [(I_{t+m+1} - 1) (\prod_{k=1}^{t+m} I_k - \prod_{k=t+1}^{t+m} I_k)]$$

which simplifies into (6.5).

d) <u>The case of White Noise process.</u>

If $m = 0$, then the process is said to be white noise. Equations (6.1) to (6.5) become:

(6.1') $Pr[x_{t+1}|X_1^t] = Pr[x_{t+1}|X_{t+1}]$ for any $t = m+1,\dots,T-1$.

$$(6.2')\ p^0(i_1^T) = \prod_{t=1}^{T} \frac{n(i_t)}{n}$$

$$(6.3')\ Pr[X_1^T] = \prod_{t=1}^{T} Pr[x_t = i_t]$$

$$(6.4') \quad LR^0 = 2 \sum_{i_1^T \in I_1^T} n(i_1^T) \log \frac{n(i_1^T)}{n\, p^0(i_1^T)}$$

$$(6.5') \quad df^0 = \prod_{t=1}^{T} I_t - \left[\sum_{t=1}^{T} I_t - (T-1) \right]$$

e) <u>Test for white noise against Markov of order m</u>

The LR statistic for this test is:

$$(6.6) \qquad LR^0 = 2 \sum_{i_1^T \in I_1^T} n(i_1^T) \log \frac{p^m(i_1^T)}{p^0(i_1^T)}$$

For n large and under the null hypothesis, this statistic has a chi-square distribution and the number of degrees of freedom is:

$$df_m^0 = df^0 - df^m,$$

where df^0 and df^m are given by (6.5) and (6.5').

f) <u>A test of the RE hypothesis</u>

If the surprise variable is interpreted as an expectational error, then we can test the RE hypothesis by testing the null hypothesis that the surprise variable is white noise against the alternative that it is a Markov process, as explained above.

This test is applied for the surprises on demand, defined according to (6.0). First, we test the null hypothesis that this variable is a Markov process of order one against no restrictions on the structure of the process. Second we can test for white noise against Markov of order one. By this method we can restrict the number of alternative hypotheses.

We need only three periods to check the restrictions for a Markov process of order one, since it is sufficient to test the following restriction:

$$Pr[x_3|x_1^2] = Pr[x_3|x_2]$$

Table 6.1 gives the results for some periods covered by the INSEE business survey. We consider for each period the set of all firms, and the set of firms reporting stable prices, in order to check if the expectation behavior of firms in a stationary environment is more compatible with the REH than in the most general case. In Table 6.1, AR(1) means Markov process of order one and WN means white noise. Clearly, if the hypothesis that the discrete surprise variable is a Markov process of order one cannot be rejected, we do reject the null hypothesis that it is a white noise process. The power of the test is very high because of the large size of the samples. Taking into account this fact, we must however conclude that here the results do not support the Rational Expectation Hypothesis.

But this last claim is based on the interpretation of the surprise variables as expectational errors. Intuitively, the derivation of the surprise as in (6.0) indicates that this variable combines information pertaining to both the expectation and the realization of the variable. In some sense the surprise is a projection of the data on a particular subspace. To argue this new interpretation, we turn now to the problem of identifying the latent surprise variable.

Table 6.1: Likelihood Ratio Tests for the REH

using the Surprise Variable for Demand.

(chi-square values and levels of significance in parentheses)

	All Firms			Firms reporting stable prices	
periods	number of observations	Test for AR(1) df = 12	Test of WN against AR(1) df = 8	number of observations	Test of WN against AR(1) df = 8
75-06	1064	14.8702 (0.2486)	31.4005 (0.000)	120	9.614 (0.293)
75-11	1157	28.5206 (0.005)	35.7748 (0.000)	198	27.163 (0.000)
76-03	1204	19.0142 (0.088)	59.6101 (0.000)	234	12.505 (0.130)
76-06	1253	8.0824 (0.7787)	77.9884 (0.000)	212	11.048 (0.199)
76-11	1252	13.7725 (0.3155)	68.3574 (0.000)	173	13.732 (0.089)
77-03	1076	19.2861 (0.0819)	66.4784 (0.000)	155	11.386 (0.181)
77-06	1098	16.7505 (0.1592)	37.1029 (0.000)	143	11.158 (0.193)
77-11	1124	24.1290 (0.0195)	36.2511 (0.000)	158	14.028 (0.081)
78-03	1188	13.2994 (0.3477)	36.1352 (0.000)	147	7.380 (0.496)
78-06	1128	25.0977 (0.0144)	78.7981 (0.000)	140	6.882 (0.549)
78-10	1077	7.9836 (0.7864)	117.618 (0.000)	134	15.467 (0.051)

Table 6.1 (continued)

79–01	1069	18.1147 (0.1122)	70.3120 (0.000)	188	17.669 (0.024)
79–03	1102	10.6175 (0.5619)	88.3835 (0.000)	200	32.259 (0.000)
79–06	1098	39.9556 (0.000)	133.481 (0.000)	215	34.228 (0.000)
79–10	1294	49.6206 (0.000)	164.138 (0.000)	166	32.617 (0.000)
80–01	1272	20.3742 (0.0603)	132.708 (0.000)	164	12.331 (0.137)
80–03	1222	33.0387 (0.000)	174.254 (0.000)	131	32.416 (0.000)
80–06	1192	36.4410 (0.000)	186.461 (0.000)	163	37.507 (0.000)
80–10	1137	18.7657 (0.0943)	140.773 (0.000)	130	24.481 (0.002)
81–01	1193	15.7366 (0.2036)	108.726 (0.000)	187	25.519 (0.001)
81–03	1143	38.1581 (0.000)	85.8567 (0.000)	186	22.837 (0.003)
81–06	1099	23.8586 (0.0213)	141.164 (0.000)	203	38.466 (0.000)
81–10	1043	19.4939 (0.0773)	103.367 (0.000)	133	21.166 (0.006)
82–01	1032	12.8187 (0.3824)	78.8156 (0.000)	136	22.484 (0.004)
82–03	1079	28.7327 (0.004)	84.0496 (0.000)	123	14.789 (0.063)
82–06	1051	20.3906 (0.060)	115.596 (0.000)	168	22.206 (0.004)

6.2 Analysis of the Latent Surprise Variable

We may assume that there exists a latent variable which triggers the categories taken by the discrete surprise variable. Specifically, it exists SD^* a continuous random variable such that the surprise on demand SD is defined by the usual correspondence:

$$SD = i \quad \text{if} \quad \delta_{i-1}(SD) \geq SD^* > \delta_i(SD)$$

where $i = 1,2,3$ which correspond to the categories "1", "2", "3", and the δ's are the thresholds ($\delta_0(SD) = +\infty$ and $\delta_3(SD) = -\infty$).

There is no general way to specify the process characterizing the latent variable. Different autoregressive specifications have been tried, but it appears that a simple Markov process of order one gives a suitable representation of the data. (Other ARMA models give good results but they are not reported since the ones presented here suffice for supporting the arguments developed in this section.)

The latent variable model is specified as follows:

$$(6.7) \quad \eta_t = b\ \eta_{t-1} + \zeta_t \qquad \text{for } t = 1, \ldots, T$$

$$(6.8) \quad SD^*_t = \eta_t + \varepsilon_t$$

$$(6.9) \quad \mathrm{Var}(\zeta_t) = \psi \quad \text{and} \quad \mathrm{Var}(\varepsilon_t) = \theta .$$

It is a simple errors-in-variable model for an autoregressive process of order one. The model is identified as soon as $T > 1$. (Identification of a similar model is discussed in Chapter 2 and also in the appendix of Chapter 2.)

To estimate this model we apply the procedure proposed in Chapter 3. We report now an estimation based on twelve successive surveys covering the years 1983-84-85. The sample is made of 614 firms for which the surprise variable on demand can be derived at each of these twelve surveys. Table 6.2 gives the matrix of all polychoric correlation coefficients.

Table 6.2

Correlation Matrix for the Surprise Variable for Demand

	SD01	SD02	SD03	SD04	SD05	SD06	SD07	SD08	SD09	SD10	SD11	SD12
SD01	1.0000											
SD02	.251	1.0000										
SD03	.086	.213	1.0000									
SD04	.065	.121	.182	1.0000								
SD05	.066	.062	-.031	.157	1.0000							
SD06	.071	.114	.149	.168	.164	1.0000						
SD07	.041	.067	.222	.054	.089	.270	1.0000					
SD08	.031	.047	.065	.145	.111	.088	.091	1.0000				
SD09	.134	-.035	.062	.032	.040	.062	.058	.171	1.000			
SD10	-.015	.201	.043	.030	.032	.228	.201	.136	.206	1.000		
SD11	.053	.111	.116	.013	-.024	.072	.114	.086	.096	.352	1.000	
SD12	.006	.044	.081	.028	-.035	.010	.043	.101	.085	.053	.188	1.000

DETERMINANT = .42447730+00

The ML estimates are (standard errors given in parentheses):

$$b = 0.729\ (0.036)$$

$$\psi = 0.118\ (0.022)$$

$$\theta = 0.745\ (0.025)$$

The goodness-of-fit index is 0.951, the adjusted goodness-of-fit index being 0.948. (See Chapter 4 for a definition of these indices.) The total coefficient of determination for the observed variables is 0.941 which means that the latent variable η is well determined. Correlation among parameter estimates are very small. These different statistics prove that the model is a good representation of the data-generating process underlying the surprise variable.

This suggests that a surprise variable has an informational content. In fact it is a combination of the variables from which it is derived. When the latent surprise variable for demand at time t is regressed on the latent variable ΔD^{e*} representing the expected change on demand made at time t-1, the correlation is significantly different from zero. Indeed, the estimation of the simple relation:

$$SD_t^* = a\ \Delta D_t^{e*} + u_t$$

has given the following result (standard deviations in parentheses):

$$a = 0.2102\ (0.012)$$

$$\sigma_u^2 = 0.9319\ (0.043)$$

Should the surprise variable be interpreted as an expectational error? The problem here comes from the definition of the surprise variable. The categories taken by SX as defined in (6.0) were obtained directly from the qualitative variables X_t and X_t^e, and then the latent variable for the surprise is introduced as in this section for the demand variable in this section. But it would be consistent to define the qualitative surprise SX from a latent variable SX^*, itself related to the latent variables X^* and X^{e*} which are used to define X and X^e. Let us consider the following example by assuming that we have first defined:

$$X = i \quad \text{if} \quad \delta_{i-1}(X) \geq X^* > \delta_i(X)$$
$$X^e = i \quad \text{if} \quad \delta_{i-1}(X^e) \geq X^{e*} > \delta_i(X^e)$$

The latent surprise variable is given by: $SX^* = X^* - X^{e*}$. We define now the qualitative surprise variable as in (6.0) but we assume that there exists two thresholds that:

$$SX = i \quad \text{if} \quad \delta_{i-1}(SX) \geq SX^* > \delta_i(SX)$$

Let us suppose that we observe: $X = 2$ (i.e., no change) and $X^e = 2$. According to (6.0) we must set: $SX = 2$. Now, in terms of the latent variables, we should have together:

$$\delta_{i-1}(SX) \geq SX^* = X^* - X^{e*} > \delta_i(SX)$$

and:

$$\delta_{i-1}(X) - \delta_i(X^e) \geq SX^* = X^* - X^{e*} > \delta_i(X) - \delta_{i-1}(X^e)$$

But there is no reasons that these two sets of inequalities define the same interval for SX^* except for some specific values of the thresholds. Hence, if we want a consistent way to define the surprise we should impose the condition that:

$$\delta_{i-1}(SX) = \delta_{i-1}(X) - \delta_i(X^e) \quad \text{and} \quad \delta_i(SX) = \delta_i(X) - \delta_{i-1}(X^e).$$

But it is trivial to show that the latter condition is not sufficient if we consider all the possible cases that X and X^e may take. (See Ivaldi [1987] for a complete study.)

Consequently, we should be cautious in interpreting the surprise variable defined by (6.0) as a good measure of the latent expectational variable, and this problem could explain the results for the tests proposed in the preceding section. We turn now to an alternative procedure for testing the Rational Expectation Hypothesis.

Chapter 7: Direct Tests of the Rational Expectation Hypothesis

The basic argument underlying the present approach is again that the qualitative nature of the observations from business surveys is just the consequence of how the survey is conducted. Indeed, the categorical responses are assumed to be initiated by some latent continuous variables. Now, the correlations among these variables can be estimated by the method of the polychoric correlation coefficient exposed in Chapter 3. Then, we may ask the following question: Using correlations between predictions and realizations estimated from business survey data, could we test on the latent variables, the necessary and sufficient condition for rational expectations?

Since the latent variables which determine the qualitative information are continuous by definition, a natural method to test the REH is then to use the condition and the method derived in Chapter 5 for quantitative variables. Let us recall that, in this case, testing the REH consists in testing whether the slope of the regression of the realized variable on the observed prediction of this variable is equal to one. This approach can be implemented here since a regression between latent variables can be estimated by means of the estimated correlations among these variables as proposed in Chapter 3.

Hence we may answer positively to the preceding question. However, for various reasons which have been discussed in the first part, the testing procedure should explicitly take into account measurement errors on the variables. The presence of such errors are justified in a similar context by several authors, for instance by Pesaran [1985], Batchelor [1986], and Taylor [1988].

Overall, the setup built to answer the preceding question is a particular case of the latent variable model for discrete data, presented in Chapter 3. Consequently, the discussions made so far on the advantages of this type of models apply here as well.

The steps of the analysis are the following: The testing procedure is proposed in section 7.2 and it is applied for the demand, production and price variables of French business survey (section 7.3); this study is completed by a model of expectation formation and a test of efficiency for the demand variable (section 7.4).

But before going into this structural analysis, could we obtain evidences of the rationality of survey expectations from a direct inspection of the data? This is the object of section 7.1.

7.1 Direct Inspection of the Contingency Tables

Let us recall that the conditions characterizing the REH in the case of qualitative data are stated as:

$$p_{kk} \geq \max_{j \neq k} p_{jk} \text{ for } k = 1, 2, \ldots,$$

where p_{jk} is the probability that the realization of a variable at time t takes the value j and its prediction for period t at time t-1 takes the value k.

By direct inspection of the count tables (i.e., by comparison of the frequencies along each column of each contingency table), we can verify whether these conditions are satisfied or not. This is not statistically satisfying since, without any statistic, there is no way to compute an empirical level of significance and hence, to evaluate the extent for which the REH can be accepted or rejected. But it is a simple way to check for the existence of information sets for which the REH seems not to be rejected.

Tables 7.1 and 7.2 display the joint empirical distributions of realizations and expectations for the changes of demand and the changes of production. The usual categories for the actual changes, i.e. "increase", "stay the same" and "decrease" are coded here by "+", "=", and "-", respectively. Analogous codes are used for the expected changes.

Table 7.1: Contingency Tables for Actual vs Expected Changes of Demand
(Figures are percent)

January 1985

d \ d^e	+	-	.
+	7.49	9.13	2.39
-	5.35	30.92	9.38
.	2.27	12.47	20.60

March 1985

d \ d^e	+	-	.
+	5.35	8.50	2.14
-	5.04	33.31	8.12
.	3.97	15.87	17.70

June 1985

d \ d^e	+	-	.
+	9.09	9.91	1.57
-	7.15	32.29	7.45
.	4.57	14.55	13.42

October 1985

d \ d^e	+	-	.
+	8.15	10.97	2.32
-	7.15	35.17	9.34
.	2.63	11.41	14.04

Table 7.2: **Contingency Tables for Actual vs Expected Changes of Production** (Figures are percent)

q \ q^e	+	-	.
+	9.26	9.76	1.60
-	5.89	37.20	10.13
.	1.60	8.78	15.78

January 1985

q \ q^e	+	-	.
+	6.80	8.06	2.20
-	5.60	39.27	8.99
.	3.15	11.96	13.97

March 1985

q \ q^e	+	-	.
+	10.61	9.63	1.29
-	7.11	40.77	7.85
.	2.51	10.91	9.32

June 1985

q \ q^e	+	-	.
+	9.62	11.17	2.04
-	5.80	41.64	9.06
.	1.85	8.95	9.87

October 1985

The reasons for looking at these variables are that entrepreneurs should be cautious about the evolution of the demand as it is one of the most important sources of uncertainty for the firm, and that expectations of production changes are the result of various factors but are certainly related to expected changes of demand.

Both sets of contingency tables show that the conditions for rationality are satisfied for the four successive survey periods in 1985. (This is also true for the year 1984; the results are not reported.) The conclusion drawn from this inspection of the data is that there is no reason to a priori reject the REH for these quantity variables and that performing a statistical test is meaningful.

The reading of the tables suggests three supplementary remarks. First, it seems that there is a seasonal effect; but it is difficult to be more precise on its direction without further analysis. Second, the concentration in the no-change cell is noticeable; as previously mentionned this could be due to the lack of a "don't know" category; consequently the data could be biased, but there is no unanimity among analysts of business surveys on this point. At last, expectations are not right or correct in the sense that the following conditions:

$$p_{kk} \geq \max_{j \neq k} p_{kj} \quad \text{for } k = 1,2,\ldots,$$

(which implies comparison of the frequencies along a row of the contingency table) are never satisfied for the reported cases.

Neither statistically satisfactory nor very powerful (as explained in Chapter 5), the direct tests based on qualitative data must be completed in order to obtain a more conclusive answer on the nature of expectations contained in business survey data. I turn now to the presentation of the method which have been sketched in the introduction of this chapter.

7.2 A Test Based on a Latent Variable Model

Let us consider a sample of N firms observed in two successive periods 0 and 1. Let η_{i1} be the "true" change of a variable (for instance, demand or production of the product) of firm i at time 1 and let ξ_{i1} be the "true" expected change of this variable made at time 0 for period 1. The Rational Expectation Hypothesis is characterized, according to the discussion in Chapter 5, by the following necessary and sufficient condition which applies in the case of continuous variables:

$$(7.1) \quad E\,(\,\eta_{i1} - \xi_{i1}\,)\,\xi_{i1} = 0 \quad \text{for } i = 1,\ldots,N.$$

That is to say, expectations are rational if the forecast errors are orthogonal to the observed prediction. (Let us recall that this condition is characterized with respect to an information set, see Chapter 5.) It should be stressed that, if condition (7.1) holds for the change variables, nothing ensures that a similar condition would hold for the levels of the variables as well. A direct method to test the above condition is to estimate the linear regression:

$$\eta_{i1} = \beta\, \xi_{i1} + w_{i1} \quad \text{for } i = 1,\dots,N,$$

and to perform a test of the null hypothesis $\beta = 1$. (Under classical conditions, it is easily seen that, if β is equal to one then (7.1) holds.) The relevant statistic depends on the particular assumptions made on the disturbance term w. In any cases, the error should not be correlated with the exogenous variable. This is not satisfied when the expectation is observed with errors. Then a more general setup is required.

a) An errors-in-latent-variable model

The subscript i will be omitted since individual observations are independent. Now, the setup we propose contains the following equations:

$$(7.2)\quad \begin{cases} \text{(i)} & \eta_1 = \beta\, \xi_1 \\ \text{(ii)} & \begin{cases} y_1^* = \eta_1 + \varepsilon_1 \\ x_1^* = \xi_1 + \delta_1 \end{cases} \end{cases}$$

where y_1^* and x_1^* are the realization and expectation of the changes of the variable (demand or production), which are assumed to be perfectly known for the moment. The REH is still associated with the hypothesis $\beta = 1$. Let us notice that the absence of a disturbance term in the structural equation is usual in the literature on errors-in-variable models. (See Malinvaud (1984), Florens, Mouchart and Richard (1987).) Indeed, with respect to the consistency of the least-squares estimator, only the measurement errors on exogenous variables are disturbing. The measurement errors on endogenous variables can be combined with errors-on-equations without loss of generality. Let us notice that the system (7.2) is equivalent to the equation:

$$y_1^* = \beta\, x_1^* - \beta\, \delta_1 + \varepsilon_1$$

Under this form, it can be seen that ε_1 can contain expectational errors.

Even with quantitative data and the most standard assumptions on the error terms, the model (7.2) cannot be estimated because it is not identifiable. Indeed, there are four parameters to be estimated (β, and the variances of ξ_1, δ_1 and ε_1) but only three information, i.e., the covariance between y_1^* and x_1^* and the variances of these variables. A specific treatment of the structural model and a series of assumptions are now proposed in order to achieve identification of the model.

b) <u>The structural equation</u>

Let us consider a sample of firms having answered to three successive surveys $t = -1, 0, 1$. Assuming that the condition for rationality holds in period 0, i.e., $\eta_0 = \xi_0$, we may test the rationality of expectations in period 1 on the basis of a modified version of equation (7.2 (i)):

$$(7.3) \quad \eta_1 = \eta_0 + \beta\, \xi_1 - \xi_0$$

The null hypothesis is still $\beta = 1$. Equation (7.3) will allow us to achieve identification on a cross-section of firms for which we have information to measure the variables entering this equation. Nonetheless, its use implies particular assumptions since the exogenous variables are correlated among themselves (but independent for each individual observation).

Let us denote by:

$$\xi = (\eta_0 , \xi_1 , \xi_0)'$$

$$\eta = (\eta_1, \xi') \tag{7.4}$$

$$\Psi = E (\xi \xi')$$

No constraints are imposed on the covariance matrix Ψ. Equation (7.4) becomes:

$$\eta = B \eta + \Gamma \xi \tag{7.5}$$

where B and Γ are matrices of free and fixed parameters, defined as:

$$B = \begin{bmatrix} 0 & 1 & \beta & -1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \qquad \Gamma = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Equation (7.5) is a particular version of equation (3.1) of Chapter 3.

c) The measurement model

Let us turn now to the measurement model. Equations (7.2 (ii)) posit that there exists "measuring" variables which serve as measures of the "true" ("measurable") latent variables. This measurement model with consideration to the notations used for the structural equation (7.5) is written:

(7.6) $z^* = I\ \eta + \zeta$

where: $z^* = (y_1^*, y_0^*, x_1^*, x_0^*)'$, I is the identity matrix, and:

$$\Theta = E(\zeta\ \zeta') \quad \text{where} \quad \zeta = (\varepsilon_1^*, \varepsilon_0, \delta_1, \delta_0)'.$$

More specifically, the variances of the measurement errors are denoted by:

$$\text{(7.7)} \quad \begin{array}{l} V(\varepsilon_1) = \theta_1 \quad \text{and} \quad V(\varepsilon_1) = \theta_2 \\ V(\delta_t) = \theta_3 \quad \text{for} \quad t = 0, 1 \end{array}$$

We assume that the measurement errors associated with the expected changes ξ_1 and ξ_0 have fixed variances, and that, for the realized variables, the variances of the measurement errors may be different since no error term is introduced in the structural equation. Moreover, the errors are not correlated among themselves, hence the matrix Θ is diagonal. These assumptions mean that the measurement errors on the change in variables are stationary. (This is reasonable since by first differencing we often obtain stationary series.) These assumptions are necessary in order to achieve identification, given the absence of constraints on the covariance matrix Ψ of the exogenous variables.

The relations between the latent variables and the measurement errors must be completed. The usual conditions are imposed, that is to say:

$$(7.8)\quad \begin{aligned} &E(\eta_t\ \varepsilon_t) = 0 = E(\xi_t\ \delta_t) \quad \text{for } t = 0, 1 \\ &E(\eta_t\ \delta_{t'}) = 0 = E(\xi_t\ \varepsilon_{t'}) \quad \text{for } t \text{ and } t' = 0, 1 \end{aligned}$$

Here these conditions are acceptable, except for $E(\xi_1\ \varepsilon_0)$. Indeed one may think that the "true" prediction ξ_1 made at time 1 contains information on the measurement errors (which in turn may contain expectational errors) observed at time 0. In fact this unconditional expectation is equal to zero. Indeed:

$$\begin{aligned} E(\xi_1\ \varepsilon_0) &= E(\xi_1\ y_0) - E(\xi_1\ \eta_0) \quad \text{by equation (7.6)} \\ &= E(\xi_1\ (E(y_0 \mid I_0)) - E(\xi_1\ \eta_0) \end{aligned}$$

where I_0 is an information set which includes necessarily ε_0. Then:

$$E(y_0 \mid I_0) = \eta_0$$

again by equation (7.6). Hence: $E(\xi_1\ \varepsilon_0) = 0$.

d) Data-generating-correspondences

Let us introduce the qualitative information. We observe the ordinal variable y_t and x_t defined by the usual correspondences:

$$(7.9)\quad \begin{aligned} &y_t = k \text{ if } a_{k-1,t} > y_t^* \geq a_{kt} \\ &x_t = k \text{ if } b_{k-1,t} > x_t^* \geq b_{kt} \end{aligned} \qquad k = 1,2,3$$

where the a's and b's are thresholds (which can be infinite). These correspondences define the three categories taken by the demand or production variables (see the preceding section). They allow us to interpret the variables y_t^* and x_t^* of the model as latent variables which initiate the survey responses when they cross the thresholds. Adopting the convention introduced in the first part, we refer to latent variables of the vector z^* as latent "measuring" variables and to the ones in η as latent "measurable" variables.

d) Stochastic assumption

Finally, the vector $(y_1^*,\ y_0^*,\ x_1^*,\ x_0^*)'$ has a multivariate distribution with mean vector $(0,0,0,0)'$, and correlation matrix $\Sigma=(\rho_{ij})$. The assumption that the means are zero can always be satisfied by redefining the thresholds in equation (7.9) accordingly. The fact that the variances are set to one is required to identify the stochastic model, but does not prevent obtaining consistent estimators of the parameters.

e) Identification

The parameters to be estimated are: β, θ_1, θ_2, θ_3, and the 6 elements of the matrix Ψ. The model is identified if a unique value for each parameter can be found in terms of the elements of the correlation matrix $\Sigma = (\rho_{ij})$ of the vector $z^* = (y_1^*,y_0^*,x_1^*,x_0^*)'$. ($\rho_{ij}$ is the correlation of the i^{th} and j^{th} element of z^*.) For the model defined by equations (7.5) and (7.6), the system to be solved is given by the correlation structure equation:

$$(7.10)\quad \Sigma = (I-B)^{-1}\ \Gamma\ \Psi\ \Gamma'\ (I-B')^{-1} + \Theta$$

and it can be easily verified that a unique solution exists.

f) Estimation method

The model is estimated along the lines of the approach proposed in Chapter 3. First, the correlations between the measuring variables are estimated according to the theory of the polychoric correlation coefficient. Second, the parameters of the system formed by equations (7.5) and (7.6) are estimated by means of the weighted least squares method.

g) Summary

Using the theory of polychoric correlation coefficients, we obtain information on the realized and predicted variables. Our purpose is to test the REH, that is to say, to test whether there exists an information set such that the prediction (which is observable in the sense that we can get some information such as its correlation with the realization) is equal to the optimal predictor, as defined in Chapter 5. To implement the test when measurement errors are present, I use a special form of the regression usually considered to perform such a test. Since the test is meaningful under some circumstances, the latter are imposed by means of a latent variable model.

7.3 Application: Demand, Production, Prices.

The empirical tests are performed for the variables, demand and production, as they are defined in section 7.1. But results for the price variable are also discussed below.

7.3.1 REH Tests for the Demand Variable

a) Empirical correlation matrices

Since observed variables in the model are ordinal, their correlation matrix Σ must be estimated as a matrix of polychoric correlation coefficients (according to the method presented in Chapter 3) for future use as input of the estimation procedure. For a particular period t, the preceding model involves three consecutive dates: We only consider data set for firms having answered all the variables included in the model. The empirical results reported here concern four different periods of time:

period (1) October 1983-January-March 1984

period (2) March-June-October 1984

period (3) October 1984-January-March 1985

period (4) March-June-October 1985.

For each of these periods, the matrix of the polychoric correlation coefficients between the latent "observable" variables is reported in Table 7.3 where d denotes the change of the demand and d^e the expected change for this variable. The standard errors (given in parentheses) of these correlations coefficients show that all of

Table 7.3: Matrices of Polychoric Correlation Coefficients
(d and d^e = actual and expected changes of demand)

Period (1): June-October 1984 January 1985; number of observations=1628

d_2	d_1	d^e_1	d^e_0
1.000			
.444 (.00067)	1.000		
.531 (.00053)	.287 (.00082)	1.000	
.257 (.00086)	.432 (.00067)	.313 (.00082)	1.000

Period (2): October 1984 January-March 1985;number of observations=1588

d_2	d_1	d^e_1	d^e_0
1.000			
.553 (.00051)	1.000		
.400 (.00074)	.301 (.00084)	1.000	
.400 (.00073)	.531 (.00055)	.402 (.00084)	1.000

Period (3): January - March - June 1985; number of observations = 1609

d_2	d_1	d^e_1	d^e_0
1.000			
.469 (.00061)	1.000		
.426 (.00068)	.280 (.00085)	1.000	
.355 (.00077)	.387 (.00074)	.490 (.00062)	1.000

Period (4): March - June - October 1985; number of observations =1595

d_2	d_1	d^e_1	d^e_0
1.000			
.371 (.00073)	1.000		
.458 (.00065)	.323 (.00081)	1.000	
.263 (.00086)	.428 (.00068)	.437 (.00069)	1.000

them are significant. These standard errors are the square roots of the diagonal elements of the covariance matrix of the polychoric correlation coefficients. This matrix is itself computed as proposed in Chapter 3, where it is denoted W. (The estimated covariances of the polychoric correlations are not reported to save space.)

Let us remark that, given the values of the correlations between (d_2 and d_1^e) or (d_1 and d_0^e), we could reject the Rational Expectation Hypothesis. According to the REH, these correlations should be near one, which is clearly not the case here. This means that on the observed variables the REH is rejected. Finally let us notice a seasonal component, the correlations for the demand being higher in winter than in summer.

b) Estimation results

Estimates of the model are obtained using the covariance matrix W of the correlation coefficients as the weight matrix required to perform the weighted least squares estimation described in Chapter 3. Results are given in Table 7.4. For each period, the model is estimated without constraint (first column) and with the constraint $\beta = 1$ (second column), which corresponds to the orthogonality condition characterizing the REH.

Let us notice that the estimates of β when it is free are near one (except for one period), and that all other paramaters are very close for each pair of experiments. The seasonal effect is again perceptible: It seems that firms underpredict in winter and overpredict in summer.

The results are pretty good since all parameters are significant (standard errors are given under each parameter in parentheses) and that the measures of goodness of fit (GFI) are quite high. (The formulas for this measure and the following are given in Chapter 4.) We can also compute the coefficients of determination for the observed variables, which measure how well these latter serve jointly as measurement instruments for the latent variables. For the variable y_1^*, this is given by CD-Y (see Table 7.4) which is computed as: $1 - \theta_2$, since we are working with a correlation matrix. An analogous formula stands for CD-X, which gives a similar measure for the other variables all together. As these measures are high, the model is meaningful, i.e., the latent variables are well determined.

With respect to the quality of the chosen specification, one should stress the fact that all estimated covariance matrix $\Psi = (\psi_{ij})$ are always positive definite (although the LISREL model does not impose this matrix to be so during the course of the estimation). This result is an indication of a relevant specification.

The t-values for the null hypothesis $\beta = 1$ and the empirical level of significance are:

period	t-value	Significance level
(1)	0.9808	0.2648
(2)	-0.4425	0.3636
(3)	1.4766	0.1912
(4)	-0.4025	0.3741

Based on these results, the REH should not be rejected. Tests for other periods give a similar conclusion.

Table 7.4: Estimation Results for the REH Tests on the Demand Variable.
(Parameter estimates and standard errors in parentheses)

	Period (1)		Period (2)		Period (3)		Period (4)	
β	1.084	1.000	0.957	1.000	1.107	1.000	0.971	1.000
	(.09)		(.10)		(.07)		(.07)	
θ_1	0.238	0.279	0.465	0.447	0.415	0.459	0.448	0.435
	(.07)	(.06)	(.07)	(.06)	(.07)	(.06)	(.07)	(.06)
θ_2	0.436	0.414	0.204	0.215	0.454	0.426	0.515	0.524
	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)
θ_3	0.486	0.477	0.566	0.567	0.426	0.422	0.411	0.414
	(.05)	(.05)	(.05)	(.05)	(.04)	(.05)	(.05)	(.05)
ψ_{11}	0.564	0.586	0.797	0.785	0.546	0.574	0.485	0.476
	(.05)	(.05)	(.05)	(.04)	(.05)	(.05)	(.05)	(.05)
ψ_{12}	0.285	0.298	0.301	0.296	0.280	0.297	0.323	0.319
	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
ψ_{22}	0.514	0.539	0.434	0.425	0.574	0.604	0.589	0.580
	(.05)	(.04)	(.05)	(.04)	(.05)	(.04)	(.05)	(.04)
ψ_{13}	0.432	0.441	0.532	0.528	0.387	0.403	0.428	0.424
	(.03)	(.03)	(.02)	(.03)	(.03)	(.03)	(.03)	(.03)
ψ_{23}	0.314	0.313	0.317	0.317	0.490	0.490	0.437	0.437
	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
ψ_{33}	0.514	0.508	0.434	0.440	0.574	0.553	0.588	0.593
	(.05)	(.05)	(.04)	(.04)	(.04)	(.04)	(.04)	(.04)
GFI	1.000	0.998	1.000	1.000	1.000	0.999	1.000	1.000
CD-Y	0.762	0.721	0.535	0.553	0.585	0.541	0.552	0.565
CD-X	0.855	0.868	0.896	0.890	0.871	0.881	0.864	0.861

It should be recalled each test for a given period is conditional to the assumption that the REH is true for the preceding period. The interpretation to be given to the preceding results is that one can extract, from the qualitative (individual) information, variables which are compatible with the Rational Expectation Hypothesis, as long as measurement errors are specified. Indeed, the proposed test as a special case of general latent variable models means that the REH can only be tested (identified) conditionally to the measurement errors. (On the interpretation of latent variable models, see section 2.4 in Chapter 2.)

We must point out that the latent "measurable" variables are well identified as we consider a classical errors-in-variable model: Indeed, these variables (i.e., η_1, η_0, ξ_1, ξ_0) of equations (7.5) are measured in the same units as the latent "measuring" variables (i.e., the y^* and x^* variables). The next question is then: Is the use of an errors-in-variable model relevant? If the preceding model is estimated without measurement errors, the estimated value for β is 0.5716 (for period (4), similar results hold for the other periods). This would be a rejection of the Rational Expectation Hypothesis. But the goodness-of-fit index the model without measurement errors is 0.787 which is quite far from the value of this index when measurement errors are explicitly introduced. It seems that the errors-in-variable model is preferred.

7.3.2 REH Tests for the Production Variable

The method is now applied to test the rationality of the expected changes of production. However, we have imposed here that the variances of the measurement errors on the realized variables; that is to say, $\theta_1 = \theta_2$. (In fact results with and without this assumption are very much the same.) The estimates of the latent variable model for testing the REH are collected in Table 7.5. The results of the REH tests are here reported for the eight successive surveys from January 1984 to October 1985. (Matrices of polychoric correlation coefficients as well as their covariance matrices are not reported for saving space.)

The presentation of the results follows the one used for the tests on the demand. Again we report the results when β is free and when it sets to one. For each pair of experiments, the parameters values are close. Obviously models where β is free are slightly better; this can be seen by comparing the usual measures (GFI, CD-Y, CD-X) but also by looking at the values of the likelihood ratio (CHISQ) (although one must be cautious when using this statistic since it strongly depends upon the number of observations).

The estimates for β are slightly greater than one (except in October 1984). For the surveys corresponding to the months of October and January, the REH cannot be rejected for the latent measurable variables, while for the other two months, firms seem to underpredict and the REH cannot be rejected only at the 0.05 level. (Under the item

Table 7.5: Estimation Results for the REH Tests on the Production Variable (Parameter estimates and standard errors in parentheses)

Period:	8401		8403		8406		8410	
Sample size:	1651		1621		1665		1649	
β	1.084 (.07)	1.000	1.207 (.07)	1.000	1.225 (.05)	1.000	0.983 (.05)	1.000
θ_1	0.283 (.05)	0.298 (.05)	0.224 (.05)	0.251 (.04)	0.339 (.05)	0.381 (.04)	0.379 (.04)	0.378 (.04)
θ_3	0.440 (.05)	0.430 (.05)	0.516 (.05)	0.501 (.05)	0.356 (.04)	0.354 (.04)	0.363 (.04)	0.365 (.04)
ψ_{11}	0.422 (.04)	0.422 (.04)	0.584 (.04)	0.583 (.04)	0.497 (.04)	0.497 (.04)	0.430 (.04)	0.430 (.04)
ψ_{12}	0.539 (.03)	0.538 (.03)	0.494 (.03)	0.492 (.03)	0.547 (.03)	0.538 (.02)	0.543 (.03)	0.543 (.02)
ψ_{22}	0.208 (.05)	0.229 (.04)	0.263 (.04)	0.309 (.04)	0.272 (.04)	0.345 (.04)	0.366 (.05)	0.361 (.04)
ψ_{13}	0.274 (.02)	0.255 (.02)	0.422 (.02)	0.380 (.02)	0.493 (.02)	0.442 (.02)	0.350 (.02)	0.355 (.02)
ψ_{23}	0.506 (.03)	0.507 (.03)	0.528 (.03)	0.528 (.03)	0.482 (.02)	0.493 (.03)	0.363 (.03)	0.557 (.03)
ψ_{33}	0.291 (.05)	0.290 (.04)	0.330 (.04)	0.334 (.04)	0.526 (.04)	0.523 (.04)	0.443 (.04)	0.443 (.04)
GFI	1.000	0.999	1.000	0.998	1.000	0.996	1.000	1.000
CD-Y	0.717	0.702	0.776	0.749	0.661	0.619	0.621	0.622
CD-X	0.921	0.920	0.904	0.898	0.924	0.915	0.907	0.906
CHISQ	1.31 (.25)	2.86 (.24)	2.31 (.13)	11.40 (.00)	1.05 (.31)	20.66 (.00)	0.29 (.59)	0.39 (.82)
STUD	1.21 (.22)		2.83 (.12)		4.16 (.08)		-0.32 (.38)	

Table 7.5: continued

Period:	8501		8503		8506		8510	
Sample size:	1629		1589		1631		1621	
β	1.097 (.07)	1.000	1.247 (.07)	1.000	1.240 (.06)	1.000	1.040 (.06)	1.000
θ_1	0.275 (.05)	0.293 (.04)	0.282 (.05)	0.310 (.04)	0.343 (.05)	0.386 (.05)	0.381 (.05)	0.385 (.05)
θ_3	0.427 (.05)	0.417 (.05)	0.493 (.04)	0.479 (.05)	0.372 (.04)	0.363 (.05)	0.370 (.05)	0.366 (.05)
ψ_{11}	0.435 (.04)	0.435 (.04)	0.578 (.04)	0.577 (.04)	0.463 (.05)	0.463 (.04)	0.414 (.04)	0.413 (.04)
ψ_{12}	0.573 (.03)	0.572 (.03)	0.474 (.03)	0.469 (.03)	0.485 (.03)	0.472 (.03)	0.481 (.03)	0.479 (.03)
ψ_{22}	0.245 (.05)	0.271 (.04)	0.291 (.04)	0.346 (.04)	0.192 (.04)	0.261 (.04)	0.259 (.05)	0.270 (.04)
ψ_{13}	0.328 (.02)	0.305 (.02)	0.492 (.02)	0.443 (.02)	0.407 (.02)	0.352 (.02)	0.296 (.02)	0.284 (.02)
ψ_{23}	0.548 (.03)	0.549 (.03)	0.545 (.03)	0.547 (.03)	0.430 (.03)	0.444 (.03)	0.475 (.03)	0.477 (.03)
ψ_{33}	0.321 (.04)	0.311 (.04)	0.396 (.04)	0.408 (.04)	0.487 (.04)	0.486 (.04)	0.432 (.04)	0.432 (.04)
GFI	1.000	0.999	0.998	0.995	1.000	0.996	1.000	1.000
CD-Y	0.725	0.707	0.718	0.690	0.657	0.614	0.619	0.614
CD-X	0.921	0.920	0.876	0.871	0.924	0.918	0.917	0.917
CHISQ	0.70 (.40)	3.06 (.22)	11.69 (.00)	26.34 (.00)	0.01 (.91)	17.06 (.00)	0.00 (1.0)	0.44 (.80)
STUD	1.49 (.19)		3.55 (.09)		3.84 (.09)		0.65 (.31)	

STUD, are given the t-values for the null hypothesis $\beta = 1$ as well as the empirical level of significance.) It can be seen that imposing $\beta = 1$ perturbs more the results for March and June than for the months of January and October for which the quality of the estimation is improved. There is a seasonal effect that cannot be taken into account in the context of this test where the dynamic structure is very poor. (Let us remark that the results for the model developed in the first part for explaining production behavior exhibited also a more unstable situation in March and June.)

The comments made previously for the demand variable with respect to the relevance of an errors-in-variable model apply here too. From all experiments made so far, it seems that a priori the REH is more often an acceptable assumption to characterize demand expectations than for production plans. But this could be due to the structure of the test since the dynamic model of production behavior based on the REH proposed in the first part gives a good representation of the survey data.

7.3.3 The Price Variable.

In the INSEE business survey, data on actual and expected changes on the product prices of the firms are available. The information is continuous since the respondents must answer by a percent of increase or decrease. In fact, they round off the figures so that we have grouped data. In that case it is appropriate to derive an ordinal variable; but it is not easy to realize such a transformation because the distributions of the responses for this variable strongly depend on the inflation rate. For the years 1984-1985, the only possible way to determine a small number of categories is to consider three categories associated with: <0%, 0%, >0%.

On this basis, the joint frequency distribution for the variables p_t and p_t^e do not always satisfy the rank conditions characterizing the REH for qualitative data (the tables are not reported). Moreover, the estimates for the model used to test the REH give values for β close to or less than 0.9, for different periods.

Although the results are conditional on the coding chosen to characterize the empirical distribution of the realized and expected price changes, there is strong evidence for rejecting rationality of price expectation.

No reasons can be a priori found to explain this result compared to the previous findings for the quantity variables. The response could be found in the mechanims of price determination by firms and/or by regulatory rules.

7.3.4 A Comment on the Test and Remarks

i) Let us return to the interpretation of the model used to test the RE hypothesis. Given equations (7.3)-(7.6) a simple relation can be derived for the latent variables which are observed through the discrete information. Indeed we can write:

$$y_1^* - \gamma\, y_0^* - \gamma\, x_1^* + \gamma\, x_0^* = \varepsilon_1 - \gamma\, \varepsilon_0 - \gamma\, \delta_1 + \gamma\, \delta_0$$

As the error terms of the RHS are white noise processes, the last equation could be interpreted in terms of cointegration. (See Engle and Granger [1987].) If each variable of the LHS is assumed integrated to the order one (which could be an acceptable assumption since all variables refer to changes), then the preceding test would be a joint test of the REH and of cointegration between the realized and expected changes of demand or production. The consequence of this interpretation deserves further investigation.

ii) Two criticisms apply to the above test. First, the meaning of the measurement errors cannot be clearly established. I partly answered in Chapter 2 to this is the usual critique made to the errors-in-variable models. Second, the results for the tests of the REH are obtained in a rather static model. The next section proposes another method to test the REH in a dynamic context by specifying the underlying model of formation of expectations.

7.4 A Test of Efficiency of Demand Expectations

The object of this section is to perform a test of efficiency which has been defined in Chapter 5. Let us recall that, for a given variable y and its observed prediction y^e, such a test consists of estimating the following regressions:

$$y = \alpha_0 + \sum_{i=1}^{s} \alpha_s y_{-i} + u \quad \text{and} \quad y^e = \beta_0 + \sum_{i=1}^{s} \beta_s y_{-i} + v$$

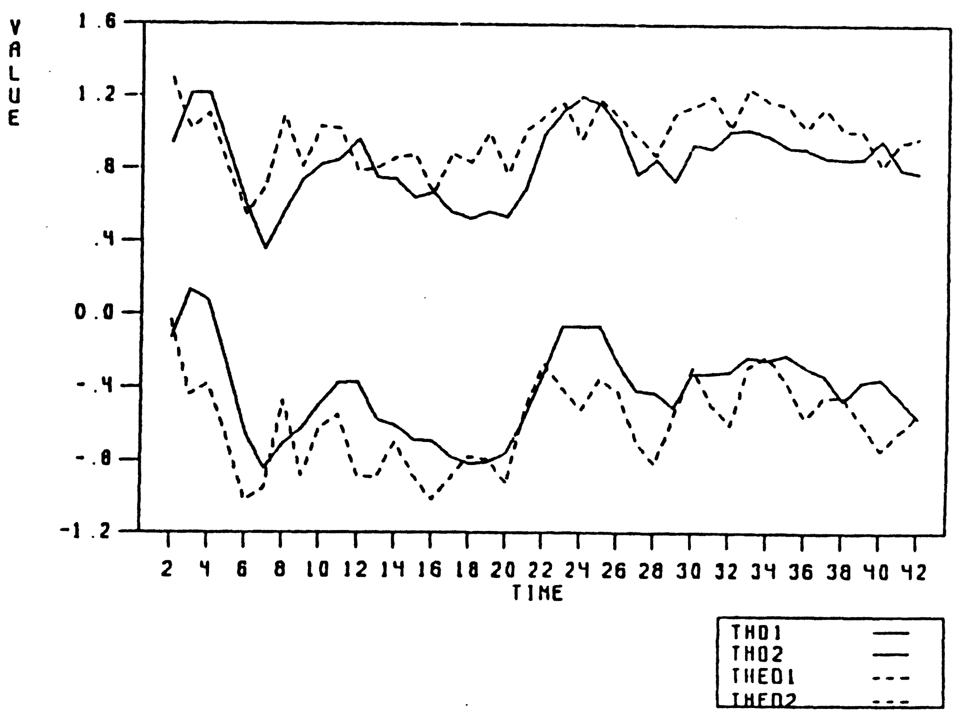
and of testing the null: H_0^e: $\alpha_i = \beta_i$ $\forall i$. If the past values of y and the constant term belongs to the information set, then rejection of H_0^e will cause the REH to be rejected. But if H_0^e is not rejected, we can only conclude that the past values of the variables are efficiently used for prediction.

There are no practical methods available to specify the process generating the expectations as observed through surveys. To achieve an acceptable specification in the context of latent variable models, the only solution is to introduce all the lagged dependent variables and then to retain the most significant on the basis of the available statistics. In view of implementing the test of efficiency, this is an acceptable method since the problem is just to describe the information set used by the firm in making predictions. However, if a stationary representation could be obtained, it would be preferred in view of using the dynamic equations defining the variables for forecasting.

The number of lags which can be introduced finally depend on the size of the samples that can be drawn from the INSEE survey: As firms do not answer all surveys or to all questions, and as we need a panel data of significant size in order to estimate a latent variable model, we must restrict the number of periods, and hence the number of variables on which the analysis is performed.

The variable that I consider here is the demand and more specifically I look for a dynamic latent variable model for the changes of demand. The information on this variable is contained in a correlation matrix obtained by means of the theory of the polychoric correlation coefficient.

Figure 7.1: Thresholds for Actual and Expected Changes in Demand



By looking at the series of thresholds for the actual and expected changes of demand, we can gain some information about the latent process. Figure 7.1 displays these thresholds computed by the inverse of the normal cumulative density function evaluated at the univariate marginals for each category taken by the ordinal variables. The solid lines represent the upper (THD1) and lower (THD2) thresholds for the realized changes of demand, the dashed lines (THED1 and THED2) corresponding to the analogous ones for the expected changes. The two series cover the period March 1975 to October 1985. Let us notice that the thresholds for each pair are quite close, but that they are moving wider apart for expectations than realizations. Nonetheless it seems that a stationary component is common to both variables.

The model is now specified. Let us notice that the lagged dependent variables that were not significant at the estimation stage have been already omitted.

7.4.1 Model Specification

The model is presented as a particular case of the general structure proposed in Chapter 3, and it is estimated by weighted least squares method. It covers eight consecutive periods, which are analyzed by means of the following system of equations:

$$(7.11) \quad \xi_{t+1} = \alpha_1 \eta_t + \alpha_2 \eta_{t-2} + \alpha_3 \eta_{t-4} + \zeta_{0t} \qquad t = 5,6,7$$

$$(7.12) \quad \eta_t = \beta \xi_t + \zeta_{1t} \qquad t = 6,7,8$$

$$(7.13) \quad y_t^* = \eta_t + \varepsilon_t \qquad t = 1,\dots,8$$

$$(7.14) \quad x_t^* = \xi_t + \delta_t \qquad t = 6,7,8$$

The meaning of the notations is also maintained: η_t represents the change in demand between t-1 and t and ξ_t is the expected change between t and t+1 for the demand; these variables are measured with errors by y_t^* and x_t^*, respectively.

Equation (7.11) says that the "true" expected changes are explained by some lags on the "true" changes of the demand, namely the present change, the change at time t-2, and the change at time t-4. Given that we consider eight periods, this autoregressive process can only be written for the periods 5, 6, 7. For the other periods which can be viewed as the initial conditions, no particular assumptions are imposed, that is to say, the covariance matrix for the first five realized changes of demand must be estimated. This matrix is denoted by:

$$\Phi \equiv (\phi_{ij}) = \mathrm{Cov}((\eta_i \ \eta_j)) \quad \text{for} \quad i,j = 1,2,\ldots,5$$

All the error terms are white noise and uncorrelated among themselves. Their variances are given by:

$$V(\zeta_{0t}) = \psi_0 \ ; \ V(\zeta_{1t}) = \psi_1 \ ; \ V(\varepsilon_t) = \theta_0 \ ; \ V(\delta_t) = \theta_1$$

Finally, the actual change and the expected change are related by equation (7.13) which allows us to perform a test of efficiency by testing only the null hypothesis: $\beta = 1$. Instead of testing: H_0^e: $\alpha_i = \beta_i \ \forall i$ as proposed at the beginning of this section, I use the familiar test, the information set being defined by the lag structure: If β equals one, the underlying process explaining the expectations of demand should be identical to the one used to construct the realizations.

7.4.2 Estimation Results

A panel of 1031 firms having answered to all the variables included in the model is drawn from the eight surveys of the years 1984 and 1985. While the matrix of polychoric correlation coefficients and the asymptotic variances of these coefficients are reported in Table 7.6, the covariances of the correlations are not given for saving space although they are used to perform the weighted least squares. All polychoric correlation coefficients are significant. (In Table 7.6 the realized change of demand is denoted by D and the expected change by DE.)

Some remarks can be made on the estimation results of the model (7.11)-(7.14), gathered in Table 7.7. First, the autoregressive process is stationary, although it is not required to perform the test of efficiency. Second, the non-stationarity of the data is taken into account by the initial conditions whose estimated covariance matrix Φ is positive-definite. Third, given the structure of the model, the variances of the expectational errors can be set to zero without changing dramatically the values of the other parameters. Let us point out that the estimated model could be used to forecast the evolution of the observed variables, given the fact that the distributions of the measurement errors are known (using the method proposed in Chapter 4).

The t-values for the hypotheis $\beta = 1$ is 1.2 (the empirical level of significance is 12%, the number of degrees of freedom being 43); we

Table 7.6: Correlation Matrix for the Test of Efficiency

	DS5	D6	DS6	D7	DS7	D8	D5	D4	D3	D2	D1
DS5	1.0000										
D6	.1971	1.0000									
DS6	.2165	.4401	1.0000								
D7	.0575	.2952	.4587	1.0000							
DS7	.0511	.3356	.3160	.5098	1.0000						
D8	.1011	.3388	.2971	.3461	.6135	1.0000					
D5	.3549	.3209	.1952	.2492	.1444	.1412	1.0000				
D4	.2368	.5750	.3444	.2936	.3624	.2875	.4659	1.0000			
D3	.2222	.2809	.0587	.1044	.1822	.2302	.2602	.2828	1.0000		
D2	.4238	.2288	.3107	.1385	.1524	.1773	.3085	.2320	.1744	1.0000	
D1	.2505	.1563	.2209	.2725	.1348	.0605	.4632	.2460	.2341	.4048	1.0000

DETERMINANT = .433586D-01

Table 7.7: Estimates of the Model for the Test of Efficiency

(estimates and standard errors in parentheses)

Parameters	Estimates
β	1.06 (0.05)
α_1	0.65 (0.06)
α_2	0.17 (0.06)
α_3	-0.13 (0.04)
ψ_0	0.17 (0.02)
ψ_1	0.03 (0.03)
θ_0	0.57 (0.04)
θ_1	0.47 (0.04)
CD-Y	0.92
CD-X	0.92
GFI	0.98

$$\Phi = \begin{bmatrix} .57\ (.04) & & & & \\ .42\ (.03) & .53\ (.06) & & & \\ .38\ (.03) & .45\ (.03) & .58\ (.06) & & \\ .39\ (.03) & .32\ (.04) & .52\ (.03) & .55\ (.06) & \\ .35\ (.03) & .31\ (.04) & .33\ (.03) & .60\ (.03) & .53\ (.06) \end{bmatrix}$$

should not reject the null hypothesis. Given the meaning of latent variable models, this result should not be interpreted as an acceptance of the Rational Expectation Hypothesis at the individual level. The correct interpretation is that a behavior compatible with this assumption can be derived from the data.

7.5 Summary

In this chapter, evidence that we can identify the Rational Expectations Hypothesis using survey data on expectations is given. Three types of tests have been performed. A first set of tests used the conditions characterizing the REH when realizations and expectations are indicator variables. The results show that we cannot reject the REH, but it is recognized that these tests are not very powerful.

By means of the second type of tests, I proposed testing the REH on the latent variables which are assumed to initiate the responses collected in surveys. For this purpose, an errors-in-variable model is developped and estimated along the lines of the method proposed in Chapter 3. The results show that the REH is not always rejected and that it is particularly acceptable for demand.

The third type of tests is based on a dynamic model in the sense that the information set used to predict the variable is defined by specifying the random process that should represent the temporal pattern of the variable of interest. Applied to the demand variable, this test, called test of efficiency in the literature, concludes that the REH should not be rejected for demand.

It must be stressed that, given that latent variable models are used for implementing the second and third types of tests, the REH could only be accepted conditionally to the measurement errors whose role in this type of models has been discussed in Chapter 2. This is why I interpret a result showing that the REH should not rejected as an indication that it is possible to extract from the survey data a behavior compatible with the REH.

Finally, two points should deserve more attention. First, the analysis in this chapter is not conclusive for price variables. Second, I noticed a similarity between the second type of test of the REH and the tests of cointegration.

CONCLUSION

This study emphasizes the advantages of interpreting the business survey data as resulting from the choices of agents who are assumed to face dynamic optimization problem. The empirical implementation of this structural analysis takes place in an errors-in-latent-variable model, which is well suited to the study of this type of data. This result is of interest to professional economists who look towards a more systematic utilization of survey data for infering the main factors at work during the business cycle. However, the methodological aspects and the economic contents of the present analysis need further improvements.

1. The translation of causal relationships among continuous economic variables in terms of their discrete counterparts observed by surveys is not direct. As a matter of fact, the conditional expectation of a continuous variable given certain historical discrete data is not identical to the one obtained if information was complete. This is why probit-type estimation of economic models is not always convenient and consistent when all variables are measured through a set of

indicators. (See appendix to Chapter 3.) A solution proposed for treating this problem assumes that the process generating the survey data is determined by the theoretical relations among economic variables interpreted as latent variables. To put this in concrete terms, I have considered structures arranged in three parts: The first one, corresponding to the economic model, is a set of linear relations among the "true" variables; the second part is a set of measurement equations of the latter variables by some "measuring" latent variables; the last part is a set of correspondences relating the measuring variables to the discrete variables as observed in surveys. (See Chapter 3.)

Full-information maximum-likelihood (FIML) estimation of such latent variable models on discrete data is conceivable should the evaluation of multiple integrals prove less burdensome in terms of computations. Multiple integrals appear necessarily since the basic idea behind the adopted solution is to recover the complete distribution of the latent variables from some partial measures coming from the surveys. Under certain circumstances depending on the admissible error tolerance, the size of the economic model and the sample size, it could be worthwhile to implement the FIML method since routines for approximating multiple integrals are available.

In Chapter 3, an alternative method is presented. If one has available of an asympotic covariance matrix for the covariances or correlations of the observed variables, a minimum distance estimator, called the weighted least squares (WLS) estimator can be computed which gives consistent and asymptotically efficient estimates. Moreover it is distribution free which is rather convenient when one has to deal with survey data. While this method can be easily implemented when data are quantitative, it requires different steps when data are qualitative.

In the first step, the correlation matrix of the latent variables entering the economic model is estimated as a matrix of polychoric correlation coefficients. This method is motivated as a special case of the pseudo-maximum likelihood theory. In practice, the correlation for each pair of variables entering in the measurement model is computed separatly. The main reason for doing so is again to avoid computation of multiple integrals that would be required if we were to estimate directly the correlation matrix for all variables at once. Pairwise computation is much faster and easier but does not guarantee that the final product of the procedure will be a positive-definite correlation matrix, a condition which is desirable for performing the WLS estimation of the structural model in the second step. To obtain this condition, I argue that it is sufficient (but not necessary) to consider panel data set with no missing values. Indeed, in this case, the marginal frequencies used to estimate each correlation coefficient are computed from marginal tables which are all coming from the same full contingency table. Compelling ourselves to use panel data with no missing values seems to be a way to avoid meaningless correlations, i.e., correlations having a sign contracdicting the most common economic sense.

But, the price to pay for using this pairwise estimation is double. First, estimates of the correlations can be biased although Monte-Carlo experiments have shown that this is not the case. Second, the dimension of models to be estimated must be reduced. Indeed, as firms answer neither all questions of a survey nor all surveys, sample sizes decrease more rapidly as the number of variables included in the econometric model increases. This is, of course, disappointing when most of the business surveys are regularly conducted and cover long period of time.

The missing data problem merits more attention. Information on the conduct of surveys may allow us to use, in certain instances, classical methods for dealing with missing data, such as imputation-based procedures. However, it is not always possible to obtain such information. It may be that the quest for a more powerful solution for estimating polychoric correlations should be directed toward the extension of model-based procedures for the special case of business survey data which are categorical but also repeated. In particular, we may think of applying the EM algorithm introduced by Demspster, Laird and Rubin [1977], which is often used in econometrics with qualitative data.

Besides the problem of estimating the correlations properly, the WLS estimator requires the knowledge of a correct asymptotic covariance matrix of the estimated correlations. Typical elements of such a matrix are the fourth-order moments of the observed variables. These moments are here computed by using normal scores since the variables are ordinal. By this way, a correct weight matrix is obtained but it could be useful to look for other methods such as non-parametric techniques.

Finally, two additional remarks should be made. First, at each step of the application of the WLS estimation, large sample sizes are highly desirable which, again, poses the problem of the treatment of missing data in surveys. Second, WLS estimation is computationally burdensome which may necessitate imposing gaussian assumptions in order to obtain a fit function which is easier to optimize. In this case, estimates of the model remain consistent because the procedure is still justifiable by the pseudo-maximum likelihood theory, but they are not efficient. The alternative is either to consider a simpler model estimated with a fully efficient method or to use an easily computable solution which, in any case, gives consistent estimates.

Apart from these estimation problems, the applicability of latent variable models requires that equations of the economic model are linear which impels us to choose particular assumptions in order to derive economic relations that fit within this structure.

2. The empirical analysis developed in Chapter 4 supports the idea that the production-smoothing model explains the behavior of firms of French manufacturing industry facing demand and cost uncertainty. This result is obtained in the context of a Keynesian model in the sense that the production level is adjusted to demand. In this model, discussed in Chapter 1 and 2, firms are assumed to be price-takers at the time production decisions are made. In the short-run, these assumptions are likely for the French manufacturing industry.

Despite its link with the Keynesian model, our findings contradict early theories of Keynesian inspiration that inventories are responsible for the macroeconomic fluctutations. In fact, production behavior appears to be stabilizing. This is so for two reasons: (i) Cost shocks are not prevailing in the determination of production plans compared to demand shocks and (ii) the relative weight of adjustment costs of production in the cost function is higher than the ones related to costs of carrying-over net inventories and to production costs.

The analysis on which these conclusions are based allows us to represent the temporal pattern of the production variable as an autoregressive process whose lag structure and parameters are determined by the parameters of the behavioral model. (See Chapter 4.) We are then able to forecast the evolution of the production level by using directly the business surveys.

To improve this forecasting model, further development is required. First, the number of periods on which the analysis is conducted is too small. This may explain in particular why the optimal behavior is production smoothing. Indeed, over a short horizon, if demand is stable enough, it may not be worthwhile to bunch production. Second, no policy variables are taken into account in the decision of the firms. It would be interesting to simulate the responses of firms to policy changes. The introduction of such variables could be done within the structure of a latent variable model. Third, the economic model is too simple to detail the production process. It is known that the relations among the components of inventories could play a crucial role in the adjustment process. However, going in this direction relies on the availability of data. Fourth, the strategic behavior of firms should be introduced. For technical reasons related to the estimation method used here, I did not succeed in estimating a model of the firm having a monopoly power on its product market. But more fundamentally, continuous-state, discrete-time models chosen for their convenience are not necessarily the relevant setup to analyze the evolution of the price variable. When many institutional elements such as contracts and transaction costs are advanced to explain prices, discrete-state models may be more suited in that case. As an example, we can think of a search model to derive the pricing behavior. The consequence would be to look at business survey data in terms of duration models.

Whatever the improvements that can be made to the economic model to be estimated, the central tenet of this study has been that responses reported in business surveys can be usefully viewed in the traditional economic framework as the outcomes of choices of optimizing agents. This helps us to specify the dynamic structure of the econometric model and to guide the analysis of the empirical results.

However, the behavioral model is based on rationality assumptions as it is often the case in the literature. It is stressed in this dissertation that it is not consistent to estimate such models if these assumptions cannot be identified with the data used for the inference. Business survey data permit us to directly test the Rational Expectation Hypothesis and empirical evidences show that this assumption is not always rejected.

It must be noticed that the testing procedure I have proposed in Chapter 7 is designed to identify the REH for the latent variables that are measured with errors by the variables observed in surveys, i.e., the tests are particular examples of the general procedure used to estimate models on survey data. In this view, the REH hypothesis can be identified for the demand and production latent variables. However, it is also possible to observe through a direct inspection of the survey data that some simple conditions characterizing the REH are satisfied for the changes of demand and production. (The relation between qualitative and quantitative data with respect to the REH tests are in part studied in Chapter 6.)

In any case, all the proposed tests are aimed to check whether the observed predictions are equal to the optimal predictions, defined as the minimum mean square error predictors. Although this is the usual way to define the Rational Expectation Hypothesis, this implies that all tests are correct only with respect to this quadratic criterium. (See Chapter 5.) If we define the rational expectation as the best strategy of an individual given the best strategies of other agents, the type of objective function chosen for deriving the solution will play an important role. It does not seem superfluous to deal with this question.

As is often the case, this micro-econometric analysis by means of business surveys has just helped to initiate further investigations. However, I hope that when new attempts to explain the relations among responses to survey questions will be carried out, this study will be of some interest.

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