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FORECASTING INDUSTRIAL PRODUCTION FROM BUSINESS SURVEY DATA FOR THE EURO_AREA

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I. INTRODUCTION

Economic prediction based on macroeconomic models is a somewhat difficult art. This has renewed interest in the analysis of the expectations of economic agents, as shown by the large number of papers on rational expectations and related concepts. Since expectations are generally unobservable, they are usually approached in an indirect way through forward or backward-looking, processes. Some business surveys, however, provide the explicit expectations of the participants concerning production indices, prices and sometimes employment in the next three to six months.

These surveys have some drawbacks, the foremost being that they recognise only three possible (subjective) answers to the future evolution of time series: increase (+), decrease (-), or no change (=). This implies a loss of information when compared to a complete numerical specification, and raises theoretical and empirical questions regarding the exact interpretation of a "no change" answer. However, it also results in considerable gain in the speed with which data become available, which is a major advantage for short-term forecasting.

In this study, we approached the use of business survey data probabilistically by weighting expectations by their probability of being "true". These probabilities are computed from indicators coming from macroeconomic variables and also from information contained in the business surveys themselves, most notably in the "no change" answers. Besides, they are allowed to follow a non-symmetrical distribution.

Section 2 presents the methodology and defines the model used. Section 3 describes the data and the estimation technique. Section 4 is devoted to an empirical application to the harmonised business data published by the European Commission.

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2. METHODOLOGY

For industrial production, business surveys contain monthly data both on the recent effective evolution of production in given firms and on the short-term expectations of the same firms about future evolution[1]. Our main concern is to see whether these data are consistent, i.e. are the firms good forecasters of their own production, in order to ensure what we should call the internal consistency of business survey data. Then of course one should also check the external consistency of these data, i.e. are business survey data able to forecast and describe the real world, a problem that will not be tackled here.

However, we can at least say that if business expectations are not even able to forecast their own realisations, they can hardly be considered good forecasters of the real, quantitative world. Therefore, the internal consistency should be ensured before any attempt to use these qualitative expectation data in a quantitative model framework.

If expectations from business surveys were always accurate, they would provide an extremely useful set of early warning indicators for those in charge of short-term forecasts. The problem is that expectations might be and in some cases are indeed wrong, leading to worse predictions than those which could have been obtained without considering the business expectations.

Let A_t be the three-dimensional vector of business expectations on production for period t+1 to t+3 with $A_t = (A_t(+), A_t(-), A_t(=))$.

$A_t(+)$ represents the percentage of enterprises who, at time t, expect their production to increase during the period; $A_t(-)$ represents the percentage of enterprises who, at time t, expect their production to decrease and $A_t(=)$ represents the percentage of enterprises who expect their production to remain stable between period t+1 and t+3.

Similarly, let R_t be the three-dimensional vector of realisation at time t, with $R_t(+)$, $R_t(-)$, $R_t(=)$ defined in the same way as for expectations, with the period being t-1 to t-3.

If expectations in business surveys were always exact forecasts, one should observe ex-post

$$R_t(k) = A_{t-4}(k) \quad (k=+, -, =) \qquad (2.1)$$

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[1] Question Q1: How has your production developed over the past three months?
Question Q5: How do you expect your production to develop over the next three months?
Thus, at time t, realisations in terms of month coverage correspond to expectations formulated at t-4

It is well known, however, that business expectations contain systematic biases both on the mean and on the variance, with respect to realisations together with a stochastic error term, i.e.

$$R_t(k) = \alpha + \beta\, A_{t-4}\,(k) + \varepsilon_t \qquad (2.2)$$

Although model (2.2) might be able to fit the data well when estimated over a long sample, its performance in forecasting work is unsatisfactory. More specifically, the model fails when it comes to predicting the precise timing of turning points, a most critical issue in short-term forecasting. In fact, since the distribution of (+), (-) and (=) in the A_{t-4} vector may, at turning-point time, be far away from the corresponding R_t distribution, coefficients α and β should be variable rather than constant throughout all business cycle phases.

Our basic postulate is that expectations are not pure random walk processes and that it is possible to define measurable criteria according to which expectations are liable to be correct or erroneous and, therefore, to attribute "probabilities of success" to the expectation vector. These probabilities may then be introduced into a suitable transformation of equation (2.2), in order to correct the distribution of the $A_{t-4}(k)$.

At the firm level, there are only two possible outcomes of the expectation process: either the expectation proves to be correct, or it proves to be wrong. We have therefore a typical binary process. Furthermore, we assume that it is possible to build a synthetic index of the measurable criteria quoted above, called, for short, the realisation index (IR).

Given differences in perception, knowledge of the market, etc., it does not seem unrealistic to suppose that at an individual level there exists for firm i a critical value IR*i, such that if the realisation index is below (above) the critical value, the expectation will be false (correct). Correct expectations will be represented by a binary variable W = 1 and false expectations by W= 0.

The critical values IR*i are unknown, but provided that the sample of firms included in the surveys is sufficiently large and representative, we may suppose at first that these critical values are approximately normally distributed.

Defined in these terms, our problem may be directly linked to the standard Probit approach (Tobin (1966), Goldfeld and Quandt(1972)) with

$$P(W = 1|IR) = P(IR^* \leq IR)$$

$$= \frac{1}{2\pi^{1/2}} \int_{-\infty}^{IR} e^{-1/2\ u2} du \qquad (2.3)$$

The Probit model, however, has some drawbacks, the major one being that the probability distribution of the critical values is symmetric. Now, as noted by Poirier (1980), if P (W = l|IR)t has a density function f (.) symmetric around zero, then δP/δIR must be the same when evaluated at values of IR yielding values of P symmetric around 1/2.

In other words, the effect of an explanatory variable on P (W = l|IR)t is the same whether P (W = l|IR)t is equal to 0.10 or to 0.90 and there is no reason why it should necessarily be so.

Finally, a case may be made for the use of logistic or "Logit" models in the frame of information theory (Theil, 1966) as more appropriate than the normal or Probit ones. Furthermore, the Logit model, as shown by Prentice (1976), may quite easily be generalised to allow for non-symmetrical distribution.

More precisely, we have then:

$$P\,(W = l|IR)_t = P(IR^* \leq IR)_t$$

$$= [1 + \exp(- \textstyle\sum_{j=1}^{N} Z_{j,t}.\ \delta_j\ ]^{-\gamma} \qquad (2.4)$$

with $\gamma>0$ and Z_{jt} the N criteria used in the realisation index IR_t

As shown by Prentice, if $0< \gamma< 1$, the density function corresponding to equation (2.4) is negatively skewed; if $\gamma > 1$, it is positively skewed. Finally, when $\gamma = 1$, we obtain the usual symmetric Logit density.

We have therefore decided to use the following methodology:

(i) estimate the probability of success for the expectation from equation (2.4) using as approximation for the observed probabilities the success frequencies given from the comparison of expectations and later realisations (see below section 3 for a more complete description of the data);

(ii) test whether the symmetry parameter γ is significantly different from one or not;

(iii) if it is not significantly different from one, compare the Logit and Probit models and select the best-fitting one;

(iv)compare the model chosen with other approaches;

3. THE DATA, THE MODEL AND THE ESTIMATION TECHNIQUE

In most studies using business survey expectations, the (+) and (-) answers are combined into the so-called balance indicator, defined as the difference between the proportions of (+) and (-). The rationale behind this indicator is that what matters is the direction of change in production series. A surplus of (+) over (-) would therefore hint towards a net positive variation in the future aggregate output of the firms. This of course takes the expectations so to speak at face value, with constant weights (+1 and -1). Now for the reasons stated in section 2, these weights should in fact be variable.

Furthermore, by its very nature, the balance indicator has a rather smooth profile, at variance with what one can observe in the effective, quantitative evolution of industrial production indices.

Therefore, keeping in mind the future potential use of the qualitative business survey expectation indicator in quantitative econometric equations, we preferred to define a recomputed balance indicator exhibiting larger cyclical variability. In other words, we believe that better "gale warning" is more important in short-term forecasting than "middle of the road" indicators.

Let $A^*_{t-4}(+)$ and $A^*_{t-4}(-)$ be the proportions of firms expecting respectively an increase or a decline in their future production, in <u>the total number of firms having a definite opinion</u>. We only consider at this stage the subset of (+) and (-) answers, leaving the (=) aside for the time being.

We will define the majority expectation as

$$A^M_t = (\text{sign}) \max [A^*_t (+), A^*_t (-)] \qquad (3.1)$$

where (sign) is + when $A^*_t (+) > A^*_t (-)$ and - otherwise.

The minority expectation is then

$$a^m_t = (\text{sign}) (1 - A^M_t) \qquad (3.2)$$

with (sign) = (-1). sign of A^M_t.

In a similar manner, we may define the majority realisation for time t, i.e.

$$R^M_t = (\text{sign}) \max [R^*_t(+), R^*_t(-)] \qquad (3.3)$$

If our postulates are true, the "right" forecasting relations comparable to equation (2.2) should be written

$$R^M_t = \eta_t + \theta_t A^M_{t-4} + \xi_t a^m_{t-4} + \varepsilon_t \tag{3.4}$$

since, when the probability of error in the expectation formation process is great, R^M_t will in fact, be more linked to the minority expectation a^m_{t-4} than to A^M_{t-4} Hence the coefficients θ_t and ξ_t should be variable through time. The same is true for the systematic mean bias η_t.

We are now able to introduce our development concerning the Logit and Probit models since one way to make the parameters variables is to multiply them by the probability of successful forecast, as derived from the criteria listed below for the generalised Logit or standard Probit models.

The model to be estimated may be written as a two-equation system:

1. Generalised Logit model

$$R^M_t = \alpha\,(1 - P_t) + \beta\,[\,P_t.\ A^M_{t-4} + (1 - P_t)\,a^m_{t-4}] + \varepsilon_t$$

$$P_t \;=\; [1 + \exp(-\textstyle\sum_{j=1}^{N} Z_{j,t}.\ \delta_j\,]^{-\gamma} \qquad t=l, \ldots, T \tag{3.5}$$

2. Probit model

$$RMt = \alpha\,(1 - P_t) + \beta\,[\,P_t.\ A^M_{t-4} + (1 - P_t)\,a^m_{t-4}] + \varepsilon_t$$

$$Pt = \frac{1}{2\pi^{1/2}} \int_{-\infty}^{IR} e^{-1/2\ u2} du \qquad \text{with } IR = \textstyle\sum_{j=1}^{N} Z_{j,t}.\ \delta_j \qquad t=l, \ldots, T \tag{3.6}$$

where P_t are the estimates of the probability of success as derived from the sample observed frequencies and the Z_{jt} are the N criteria which are most likely to influence these probabilities.

Ideally, the explanatory variable matrix Z should include all the micro and macro bits of information that the respondents are likely to consider when they make their expectations. In practice, however, this would involve an intractable number of data series, even if we were able to solve the aggregation problem due to the sectoral nature of published data.

We will therefore postulate that part of the informational content of these economic environment variables can be represented by synthetic proxies, some being derived from the structure of the answers themselves.

The proportion of "no-change" answers is generally not taken into account in forecasting models using the standard balance indicator. The main reason is the ambiguous nature of the answers.

In principle, it should mean a forecasted zero variation in output during the following three months (after elimination of seasonal factors). In fact, when asking entrepreneurs taking part in the surveys what they really mean by "no- change", it appears that

(i) "no change" is defined as a range of values around zero where the effective variation in output is deemed insignificant by the firm;

(ii) "no-change may also be used as a substitute for the absent fourth possible answer to the Survey, i.e. "I don't know".

This results in series of "no changes" reflecting the level of uncertainty in the economic environment of the firms rather than the evolution of output itself. Since periods of high uncertainty are also associated with high risks of error in forecasting, the proportion of "no change" answers should play a role in the determination of our probability of success P_t.

One should however take into account that the subjective uncertainty introduced by the use of the so-called "no change" answers is not simply a function of the percentage amount of these answers but is also influenced by the initial distribution of answers between (+), (-) and (=).

For instance, if we compare two distributions of answers Dl and D2 with

	Dl	D2
$A_t(+)$	0.3	0.1
$A_t(=)$	0.7	0.7
$A_t(-)$	0.0	0.2

the proportion of "no change" is equal to 0.7 in both cases, although it seems intuitively evident that the distribution (0.3, 0.8, 0.0) is more indicative of a slight "increase" realisation than the (0.1, 0.8, 0.2) distribution.

We have therefore used two explanatory variables:

$$I_t = A_{t-4}(=) \qquad (3.7)$$

the original proportion of "no change" answers in the survey; and

$$U_t = 1 - |A_{t-4}(+) - A_{t-4}(-)| \qquad (3.8),$$

an indication of the spread between (+) and (-), given I_t.

U_t will be equal to one, either when there are no increase" or "decrease" answers (i.e. all enterprises expect their production to remain constant), or when the proportion of enterprises who expect their production to increase is exactly the same as the percentage of enterprises who expect their production to decrease. The former case may be called maximum absolute uncertainty, the latter being a maximum relative uncertainty, both given I_t.

U_t will be equal to zero (minimum uncertainty) when all enterprises answer either that their production is going to increase, or that it will decrease ($A_{t-4}(+)=l$ and $A_{t-4}(-)=0$, or $A_{t-4}(+)=0$ and $A_{t-4}(-)=l$).

One may of course argue that a 100 percent proportion of "no change" answers should be defined as "maximum certainty" (of no growth) rather than uncertainty, but in fact given the ambiguous nature of $A_t(=)$ (caused itself by the absence of an "I don't know" answer)) this 100 percent proportion would really mean that anything might happen and therefore that any forecast based on these survey answers would have a low probability of success.

The next criterion that will be considered is more concrete, and represents the position in which the anticipator stands with respect to the last turning point in the business cycle.

Indeed, it appears that errors in expectations are maximal at both ends of the cycle phase. This over-projection of past trends is well known, and is liable to increase with the length, persistence and continuity of these economic phases. If we call 2m the length (in months) of a full cycle, the evolution of the probabilities of success of the expectations (all other things being equal) may be linked to the variable:

$$LC_t = [\frac{n_t - \mathrm{m}_{t*}}{2m}]^2 \qquad (3.9)$$

where nt is the number of months separating period t from the last turning point m_{t*}. Division by 2m has no meaning except as a normalisation factor. The dating and the average length of the business cycle has been extracted from the 1980-2002 monthly deseasonalised industrial production index, using the Bry-Boschan (1971) procedure.

Finally, the model should include the observed autocorrelation of residuals in models (3.5) and (3.6). Part of this autocorrelation is in some sense technical: since firms are giving on a <u>monthly</u> basis a forecast for the next <u>three months</u>, one may expect the residuals ε_t to show autocorrelation of first and second order with coefficients 2/3 and 1/3 respectively.

Furthermore, since answers on realisation and expectations are coming in a qualitative way from the same respondents, both survey variables are submitted to measurement errors which are themselves likely to be correlated.

Indeed, preliminary tests of models (3.5) and (3.6) in a purely static formulation did show that the a priori elimination of the first and second order autocorrelation quoted above still leaves autocorrelated residuals. We have therefore introduced as last explanatory variable the prediction error of the preceding month:

$$CP_t = (R^M_{t-1} - (\alpha\,(1 - P_{t-1}) + \beta\,[\,P_{t-1}.\,A^M_{t-5} + (1 - P_{t-1})\,a^m_{t-5}])) \qquad (3.10)$$

The estimation of models (3.5) and (3.6) was made with the WINRATS ver. 5.0 econometric software package, using FIML procedures.

The test for $\gamma=1$ in model (3.5) will be done by likelihood-ratio procedures, but following Poirier (1980), we also used the Lagrange Multiplier (LM) testing procedure since it can be applied with information immediately available from the computation of the parameters by the standard computer programs for Logit models.

4. *EMPIRICAL APPLICATION*

In order to test the validity of the approach, we applied it to the business survey data coming from the harmonised business survey data published by the Directorate General for Economic and Financial Affairs of the Commission of the European Communities.

The data used are related to the industrial production indices. All methodological aspects being described in European Commission (2000), we will simply say here that all the qualitative answers of the firms are collected monthly, weighted by the average turnover of each firm and aggregated first by sector and then by country.

When the estimation was done, the available sample covered the period January 1985 to March 2003, i.e. 220 observations of which 215 only are usable owing to the time lags in the explanatory variables. Given the short time available, the pilot study was made on the Euro-area aggregated data. It will be extended to Member countries in the near future.

This section will be subdivided into three parts. The first will present the maximum likelihood estimators together with their asymptotic standard errors. Goodness of fit is reported with a R^2 like measure, i.e. the ratio of the explained variance to the total variance of the dependent variables. We will also show examples of the behaviour of the system around turning points in order to see whether or not our aim was fulfilled. Finally, we will assess the forecasting power of the equations by dropping the last observations and predicting them with the re-estimated system, using the root-mean-squared error (RMSE) as indicator. In order to see how the system behaves dynamically, we made the forecasting test over longer and longer periods, i.e. we dropped successively the last one, the last two, etc..., down to the last twelve observations. In that way, any build-up of forecasting errors can be detected in the "chronological" evolution of the twelve RMSE statistics.

The second section will be devoted to some statistical inferences using a set of hypotheses.

First, we tested the general acceptance of the model, without restrictions.

Next, we tested the reduced model obtained by imposing symmetry for the Logit distribution ($\gamma=1$ in equation 3.5).

In parallel, we tested the absence of bias in the forecasting process, i.e. $\alpha = 0$ and $\beta = 1$ in equation 3.5.

We also tested the combined restriction, i.e. $\alpha = 0$, $\beta = 1$ and $\gamma=1$

Finally, should $\gamma=1$ be accepted, then of course the Probit model (3.6) should be compared to the symmetric Logit. In all cases, we used the usual transformation of the likelihood ratio:

$$- r \log_e\lambda \approx \chi^2_r \tag{4.1}$$

where: $\lambda= [(L(\theta r,\theta s)/L(\theta)]$ (4.2)

with θr the r-components vector of constrained coefficients in the original set θ and L (.) the value of the likelihood function.

Finally, section 4.3 deals with some comparisons with alternative methods and is followed by the conclusions.

4.1 Estimation and forecasting results. Estimated Coefficients.

Let us recall that at this stage the model tested is:

$$R^M_t = \alpha (1 - P_t) + \beta [P_t . A^M_{t-1} + (1 - P_t) a^m_{t-1}] + \varepsilon_t$$

$$P_t \;=\; [1 + \exp(- \sum_{j=1}^{N} Z_{j,t} . \delta_j]^{-\gamma} \qquad j=1,\ldots,4 \qquad t=1, ..., T \tag{4.3}$$

We have thus eight parameters, i.e. α, β , γ, δ_0, δ_1, δ_2, δ_3, δ_4 with δ_0 a constant term and the other four, the coefficients of explanatory variables I_t, U_t, LC_t and CP_t, in that order. Asymptotic standard errors are given beside the coefficients.

Table 1. Estimation results. Generalised Logit model

Variable	Coefficient	Std errors	T-statistics
	-0.2146	0.0187	11.442
	0.9556	0.0192	49.703
δ_0	2.050	0.6415	3.196
δ_1	-1.474	0.0886	16.629
δ_2	-2.562	0.5364	4.775
δ_3	-0.088	0.0246	3.568
δ_4	0.259	0.0457	5.667
γ	0. 260	0.028	9.286
Pseudo-R^2	0.931		

Results proved extremely satisfactory since, in all cases, coefficients are significantly different from zero and the general fit is quite good.

Also, at first glance, leaving aside formal tests for section 4.2 below, it does seem that expectations are biased ($\alpha \neq 0$ and/or $\beta \neq 1$) and that the hypothesis of symmetric distribution is not supported.

Dynamic behaviour

If we now look towards the behaviour of computed values around turning points, we see the following facts:

The R^M_t sample contains 16 signs reversals, of which 14 are perfectly reproduced by the equations. The two exceptions are located in 1987-3 where the reversal from (-) to (+) in R^M_t appears only in 1987-4 in the computed series. Conversely, the sign reversal in 1999-4 is anticipated by one month in the computed values.

We have, for instance, from 2001-1 to 2001-7

Observed R^M_t -0.50 +0.56 +0.54 +0.62 –0.57 –0.50 –0.56

Computed R^M_t -0.41 +0.69 +0.61 +0.57 –0.54 –0.47 –0.50

This in-sample capacity to follow sign variation needs, however confirmation from out-of-sample tests. As explained at the beginning of this section, we re-estimated the model over shorter and shorter samples in order to predict out of sample the missing observations. In all these tests, the absolute values of the coefficients did not vary by more than two to five percent with respect to the full-sample estimates.

The procedure was applied to the last twelve months of the sample, giving thus twelve predictions on an increasing horizon, i.e. April 2003 predicted from March 2003 down to March predicted from March 2002. This gives us twelve RMSE, the average of which is 0.0173, whereas the same concepts, when computed on the estimated residuals in the full sample exercises is 0.0167. Their dynamic behaviour is as follows

Horizon	1	2	3	4	5	6	7	8	9	10	11	12	Aver
RMSE	0.016	0.018	0.017	0.015	0.015	0.016	0.017	0.018	0.018	0.019	0.018	0.019	0.017

No pathological behaviour seems in evidence in Table 2. However, above average RMSE are more concentrated in the more-than-six-month-horizon period than in the less-than-six month period, but divergences between sub-means are not striking (0.0165 for the first six months and 0.0181 for the next six).

4.2 Statistical inference

As could be expected for the estimation result, the χ^2 test confirms the goodness of fit criteria and the information contained in the asymptotic standard errors since the null hypothesis $\theta = 0$ with $\theta = \alpha, \beta, \gamma, \delta_0, \delta_1, \delta_2, \delta_3, \delta_4$ is rejected at the 0.01 significance level.

The null hypothesis $\gamma = 1$ is also rejected at the 0.01 level, This leads to the rejection of either the symmetric Logit or the Probit model.

The absence of a bias hypothesis $\alpha = 0$ and $\beta = 1$ is accepted at the 0.05 level. However, it has to be rejected at the 0.01 level.

Finally, the combined hypothesis $\alpha = 0$, $\beta = 1$ and $\gamma = 1$ is rejected at the 0.01 level

4.3 Comparison with other methods

The main question raised by this analysis is: "Is that entire computational burden and complication really worthwhile?". The answer is, of course, always a matter of opinion, but still it may be helped by some objective facts. The best-known alternative is the Theil (1966) approach, i.e. in our formulation:

$$R^M_t = a + b\, A^M_{t-4} + vt \qquad (4.4)$$

Results for equation (4.3) estimated by Generalised least Squares with first and second order autocorrelation is (standard-errors are below the coefficients)

$$R^M_t = -0.143 + 0.472\, A^M_{t-4}$$

$$(0.065)\ (0.093) \qquad R^2 = 0.161 \qquad DW = 1.796$$

Although the coefficients are all significant, it is already evident that the goodness of fit is lower than in our model (3.5).

Besides, the examination of the residuals does show the problem quoted before: sign reversals are predicted only with a lag of more than two months, together with a number of incorrectly predicted sign reversals, a problem completely absent from the probabilistic approach. This amply confirms the problems encountered by other researchers when working with the balance between plus and minus or some other direct use of the business survey data as published.

As a complement, we modified equation 4.3 in order to reproduce equation 3.4, with constant coefficients, i.e.:

$$R^M_t = -0.185 + 1.546.A^M_{t-4} + 1.867\, a^m_{t-4} \qquad (4.5)$$

$$(0.062) \quad (0.141) \qquad (0.244) \qquad R2=0.314 \quad DW=1.917$$

using the same GLS estimation technique as for (4.4.)

The results do not show much improvement in corrected R^2 with respect to 4.3 and the dynamic behaviour of 4.5 is just as unsatisfactory as the behaviour of 4.4.

Finally, we also made a comparison, this time at the forecasting level with non-causal methods (Box and Jenkins, 1970), according to the following methodology:

i) estimation of ARMA models for the majority realisation

ii) use of this ARMA model for the forecasting of R^M_t on an increasing horizon from one to twelve months;

iii) computation of RMSE for these forecasts, to be compared with those of table 2.

Results are given hereunder.

Horizon	1	2	3	4	5	6	7	8	9	10	11	12	Aver
ARMA	0.036	0.034	0.046	0.056	0.048	0.061	0.107	0.093	0.087	0.088	0.097	0.111	0.072

As can be seen, the application of non-causal methods leads to larger RMSE than our own approach. and there is a significant increase in the RMSE when the forecasting horizon goes beyond six months (first six months average 0.047, average of last six months 0.097. It does not therefore seem that ARMA methods might be a useful alternative to our probabilistic scheme.

5. CONCLUSIONS

Our probabilistic approach to the quantification of business survey data proved extremely satisfactory as far as the internal consistency of the data is concerned. In other words, a probability weighting of majority and minority expectations gives an "expectation" variable which anticipates effectively the corresponding realisation data up to and including turning points.

It also shows that the implicit hypothesis of symmetry used, so to speak, as a matter of course in the literature on discrete choice models may be misleading and should be tested.

We can also see that biases in the published expectation series are not only present as already proven, but also variable with the phase of the business cycle, and cannot therefore be properly represented by fixed coefficients in a standard regression analysis.

To conclude, we would thus say that, as far as the business data themselves are concerned, our method gives a way to relate expectations and realisations in a more efficient way. For prediction of quantitative data, results may vary from sector to sector or between kinds of goods, but where the correlation between business survey data and the evolution of the quantitative series is good, the introduction of expectations may improve significantly the quality of the forecast, especially in the vicinity of turning points in the quantitative series, which are, as we all know, the main pitfall of the forecasting job.

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