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A Time-Series Study of the Formation and Predictive Performance of EEC Production Survey Expectations

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This article provides an empirical analysis of manufacturers' survey responses on short-term production expectations. If such surveys provide valid anticipations of production activity in customer industries, they should be valuable information to management in supplier industries. Two major questions are considered: (a) Are survey expectations valid predictors of future production activity as reported later by the manufacturers and/or as measured by official statistics? (b) Do the expectations make efficient use of information available to the surveyed manufacturers? The research design involves univariate and multivariate time-series analysis of monthly data for five European countries in three major sectors of the manufacturing industry, using the concept of Granger causality. The main findings are that the survey expectations often make an efficient use of the information available to the surveyed manufacturers and that the anticipations Granger-cause survey-reported production levels, but that they do not Granger-cause objectively measured production levels. These results suggest that the value of such survey expectations is contingent on the way in which manufacturing activity is measured.

1. INTRODUCTION

There is a long-standing tradition in applied economics for the survey-based observation of economic agents' attitudes and expectations, in particular those of consumers, businessmen, and economic experts. Two kinds of attitudes are registered: *judgment* questions yield an assessment of the current or past status of an economic variable such as current production level; *expectations* yield an assessment of the likely future status of an economic variable, for example, next month's production level. When expectations refer to outcomes over which the respondent has no control, they are called *contingent;* if the outcome is (partly) under the respondent's control, we obtain plans or *intentional* expectations. The objectively measured levels of the economic variable are referred to as the *accounts*. (The terms "judgments" and "accounts" are not standard terminology, but they will be used throughout for ease of exposure.)

The inspiration for these surveys is often pragmatic; the results may become available earlier than the official accounts data so that they can readily be used to *forecast* economic activity such as consumer buying, manufacturers' investments, or interest rates. Whether or not the survey-based predictions are useful for forecasting depends on two factors: (a) the respondents' efficient use of information and (b) for intentional expectations, the extent to which they influence the agent's decisions; that is, are the expectations self-fulfilling?

It is important to know the value of survey expectations data, because these data are very expensive and time-consuming to collect. For example, the annual cost of gathering production expectations data for the major industries in the Common Market countries is 50 million European Currency Units. Furthermore, there is a pragmatic alternative for making economic forecasts; econometric or time-series models based on national accounts data are now commonly used. Since their forecasting accuracy is generally known, survey-based forecasts can be evaluated not only in absolute terms but also relative to other forecasts.

This article examines the forecasting value of one important class of survey expectations—those pertaining to the monthly industrial production levels in various Common Market countries. We adopt a state-of-the-art time-series perspective on this problem to answer two key questions:

1. Are the survey expectations unbiased and do they make efficient use of the available information?
2. Do the expectations contain predictive information that is not also conveyed by statistical forecasts based on official account data?

Although these questions are practical, they are embedded in a fairly rich body of literature on survey expectations, so we shall start with a brief survey of this literature, making empirical generalizations where possible and pointing to areas in which research is needed. Section 3 makes the case for a time-series research design based on the concept of Granger causality. Since production-expectations data are categorized, they must be scaled appropriately; this is discussed in Section 4. The empirical results and subsequent conclusions are presented in Sections 5 and 6.

2. BACKGROUND

Survey-based measures of economic judgments and expectations give rise to a number of research questions. Table 1 presents a simplified and structured overview of these questions in terms of bivariate relations among past and present judgments, expectations, and accounts. The table is to be read by columns, the column entry being the potential dependent variable and the row entry the potential independent variable. Studies using survey expectations published to date generally addressed one or more of the key research questions listed in Table 1, but they also differed in (a) the economic attitudes and accounts considered (e.g., consumer confidence vs. business investment spending); (b) the nature, size, and composition of the sample; and (c) the measurement properties of the data (e.g., interval vs. categorical scales, cross-sectional vs. longitudinal observations). For the purpose of this review, they are classified under forecasting-performance versus attitude-formation papers.

2.1 The Forecasting Performance of Economic-Anticipations Data

Survey anticipations are expressed either as point predictions (e.g., what do you expect next month's inflation rate to be?) or as directional statements (e.g., do you expect your production to increase, remain stable, or decrease next month?). The former allow a direct retrospective accuracy investigation by comparing the value of the prediction with that of the realization.

The forecasting accuracy of point predictions has been examined for various variables, for example, gross national product (GNP), interest rates, business investment spending, and production levels. In general, survey-based quantitative anticipations provide satisfactory forecasts, both in terms of absolute error size and in comparison with simple or more involved time-series or econometric models (e.g., Liebling, Bidwell, and Hall 1975; Rippe and Wilkinson 1974; Zarnowitz 1979). Rippe and Wilkinson (1974), for example, reported a percentage mean absolute error of 6.45, 2.65, and 1.04 for the McGraw-Hill one-year investment, sales, and capacity use anticipations (manufacturing industry) for the period 1948–1971; the corresponding figures for 1962–1971 were 4.17, 2.21, and .53. These one-year survey anticipations achieve a smaller mean squared error than autoregressive model forecasts. Leibling et al. (1975) stated that "the performance of anticipatory surveys . . . continued to show a margin of superiority (over large scale econometric model forecasts)" (p. 474). Zarnowitz (1979) reported squared correlations between forecasted and real annual GNP percentage changes of .717 and .780, respectively, for the periods 1963–1976 and 1969–1976 for the Livingston Survey forecasts; this can be compared with values of .603 and .746 for the Michigan econometric model or .689 and .669 for the Wharton model.

From these examples, it also appears that the survey forecasts improve in accuracy over time [see also Ahlers and Lakonishok (1983) for a comparison of 1947–1960, 1961–1969, and 1970–1978], which may point to learning effects or to the availability of better information. Nevertheless, anticipation data are not perfect; for example, they may be subject to systematic bias such as understating trends in economic indicators and thus a correction for bias may be useful (Ahlers and Lakonishok 1983; Modigliani and Weingartner 1958). These findings pertain to the questions discussed mainly in cells 11 and 12 in Table 1.

Directional survey anticipations are collected mainly on manufacturers' production levels and on consumer sentiment. Such data, possibly after rescaling, can be entered as regressors in econometric equations for the purpose of explaining and predicting economic phenomena. The key question then is whether or not the econometric models benefit from the inclusion of the survey data.

The forecasting performance of the Wharton model of the U.S. economy was found to improve with the inclusion of business survey anticipations (business investment, housing starts) and, to a lesser extent, consumer-sentiment data (Adams and Duggal 1974; Adams and Klein 1972). Adams and Duggal (1974) showed an increase in the squared correlation between real and forecasted percentage changes between the standard version of the Wharton model and an adapted version incorporating exogenous survey anticipations, from .69 to .79 for real personal-consumption expenditures on automobiles and from .38 to .68 for real nonresidential fixed investment. On the other hand, consumer-sentiment data reportedly contributed only marginally to the fit of econometric models (Juster and Wachtel 1972) and failed to improve their forecasting accuracy (Shapiro 1972). Juster and Wachtel (1972), for example, found that adding survey anticipations to single-equation models for real automobile expenditures increased the squared multiple correlation coefficient from .931 to .943 in the 1953–1971 period. These negative experiences have led to the termination of the collection of purchase intentions data in the United States (McNeil 1974). European consumer survey data, however, have been found to be more useful in forecasting consumer expenditures. Praet and Vuchelen (1984), for example, compared standard econometric models of the consumption function with the same models including survey judgments and anticipations. They reported an average percent forecast root mean squared error of .365 versus .604 for France, 1.265 versus .482 for Germany, .921 versus 1.584 for Italy, and 1.577 versus .993

Table 1. Overview of Research Questions Concerning Survey-Based Economic Attitudes

	Dependent variable*		
Explanation	*Current judgment*	*Current expectation*	*Current accounts*
Current judgment		Does current expectation depend on current judgment? (#6)	Same as #2
Current expectation	Do current judgment and expectation measure a common underlying factor? (#1)		Not applicable
Current accounts	How accurately do judgments and current accounts correspond? (#2)	Do current expectations depend on current accounts? (#7)	
Past judgment	Is current judgment explained by its own past? (#3)	Do current expectations depend on past judgment? (#8)	How well are current accounts predicted by past judgment? (#10)
Past expectation	How well do past expectations predict current judgment? (#4)	How well are current expectations explained by their own past? (#9)	Are current accounts predicted by their past expectations? (#11)
Past accounts	Do current judgments depend on the history of past accounts? (#5)	Do current expectations depend on past accounts? (#7)	Do present accounts depend on their own past? (#12)

NOTE: Cell numbers (in parentheses following the questions) are referred to in the text.
*Current judgment and current expectation (the expectation of a future event, formulated today) are survey-based variables. Current accounts are objectively measured variables—for example, from national statistics.

for the United Kingdom. Overall then, the evidence on the value of directional anticipations is mixed. These findings pertain to the issues corresponding to cells 10, 11, and 12 in Table 1.

It should be noted that the conclusions so far are derived almost exclusively from studies on aggregate time-series data. Cross-sectional studies on the predictive performance of survey expectations are an exception. One such study in the consumer sector reported a significant but modest explanatory fitting power of consumer-sentiment data for subsequent durable goods spending; Dunkelberg (1972) found that consumer attitudes are a significant regressor in the explanation of car-buying-plan fulfillments although they explain only 3% of the variance. In the business sector, Nerlove (1983) studied the relationship between short-term anticipation (demand, prices) and the subsequent judgments for a German and French sample of firms (evidence pertaining to Table 1, cell 4). The marginal distribution of anticipations and of subsequent judgments are found to differ, so the forecasts may have to be made conditional on the distribution of the anticipations. The conditional distribution of judgments, given their prior anticipation, is temporally unstable for one sample, however. These results indicate that in evaluating anticipations as forecasts for subsequent judgments, a temporally variable correction for bias may be needed.

2.2 The Formation of Attitudes

Research on the formation of economic agents' attitudes and expectations has focused on two questions: (a) Can these variables be predicted from their own past? (b) Are they formed rationally? Rationality of expectations in the Muthian sense assumes that economic agents have expectations that are optimal forecasts using all available information (Mishkin 1981). This implies that the forecast error of the expectations should be uncorrelated with the set of available information.

There is substantial evidence that survey expectations are extrapolative; that is, they can be predicted from their own past or from the past of other relevant series (issues pertaining to Table 1, cells 7 and 9). Nerlove (1983) found that a simple extrapolative (error-learning) model explains demand and price expectations "surprisingly well" (Goodman–Kruskall gamma for a log-linear probability model of .808 and .673 for German data and of .534 and .727 for French data). Carlson and Parkins (1975) found that inflationary expectations for the United Kingdom are explained exhaustively by their own past and by past inflation rates. Praet (1984a) found high R-squared values (.90 and above) for autoregressive models on consumer-sentiment data. All of these results confirm that anticipations or judgments evolve rather smoothly and can be well fitted from their own past. Challenging evidence, however, was provided by Dramais and Waelbroeck-Rocha (1985), showing that autoregressive moving average models fitted to manufacturers' production-level judgments are inferior in forecasting to econometric models based on anticipations, and by Praet (1984b), who showed that acceptable autoregressive integrated moving average models for consumer sentiment data could be found for Germany and France but not for the United Kingdom and Italy.

Various tests of the rationality of expectations have been performed. From the literature, it appears that anticipations will generally fail to pass one or more of the tests of unbiasedness, efficiency, consistency, and orthogonality of forecast errors (Ahlers and Lakonishok 1983; Friedman 1980; etc.). That survey-based expectations fail a rationality test does not imply that they are irrational, however. The good forecasting performance, for example, of point forecasts, discussed previously, suggests that rationality violations may be only mild. Nerlove (1983) stated that the more stringent rationality tests (e.g., those in which expectations are formed in a way that is stochastically consistent with the behavior of the realized values of the variables in question) may be unreasonable. He proposed a weaker rationality criterion "that there is no pattern of systematic error" in the forecasts (p. 1255). He argued further that "in the absence of structural change, the final form of an econometric model leads under fairly general conditions to univariate relations between the current value of a variable and its own past values" (p. 1255). Such "quasi-rational" expectations should satisfy the minimal requirements of rationality—that is, being unbiased forecasts of the realized future values and having no systematic components in the forecast errors.

2.3 Conclusions

Our assessment of the literature differs on whether a pragmatic or a theoretic stance is adopted. Pragmatically, the conclusion is that survey-based attitude data allow good forecasts and that the survey attitudes themselves can be forecasted. On the more fundamental side, it is not clear that (or why) survey data are superior to alternatives. In particular, we do not know the relationship between economic agents' perceptions of the present (i.e., judgments), their perceptions of the future (i.e., expectations), and the objectively measured present and past (i.e., accounts). Survey expectations might well be valuable as forecasting tools only for future judgments, not for future accounts. Similarly, it is not clear whether or not judgments and expectations are simply linear combinations of accounts data.

This article addresses these issues in the context of short-term business attitudes in the Common Market. These attitudes have received little scientific treatment up to now. Methodologically, we propose to use modern time-series methods and the concept of Granger causality, which has not been used to date in survey expectations research. Time-series methods are particularly strong in disentangling lag structures in models with no a priori lag specification and in dealing with highly autocorrelated data. Both tasks are typical for time series of survey expectations. Granger causality is a natural concept to use when evaluating the incremental contribution of one variable in forecasting another. Since national accounts data are common in modern economies, we need to measure the incremental forecasting contribution of economic-survey data, which are optional and expensive.

3. TIME-SERIES METHODOLOGY

To summarize the concept known as Granger causality (Granger 1969), X is said to Granger-cause Y with respect to an information set containing X and Y if the error in forecasting Y from its own past *and* the past of X is lower than the prediction error when only the past of Y is used. This definition applies well to expectations modeling; that current production is partially predictable from previous expectations seems intuitively obvious. The critical issue, however, is whether or not this predictive quality holds over and above simple time-series extrapolation of past production data and perhaps other relevant information such as past orders. In other words, do the survey respondents know and reveal something about the future that cannot be captured by statistical analysis of production and order data? Since the collection of survey data is costly and time-consuming, it can be justified only if survey expectations Granger-cause industrial production.

The successful execution of a Granger-causal analysis depends on specifying an adequate information set and using statistical methods to disentangle the intrastructure (i.e., past of Y) and the interstructure (past of X) in the data. Our information set includes perceived production and orders, the expectations (i.e., the survey data), and the production accounts data. This is a fairly complete information set, given that accounting data on orders are not available.

Statistical methodology for separating intrastructure and interstructure was developed mainly in the 1970s. One popular method correlates the residuals of univariate Box–Jenkins analyses on the series of interest at various lags (Haugh 1976; Pierce 1977). This method is very efficient for removing intrastructure, but it is restricted to pairwise interstructure analysis, which may be dangerous. A second method collects the Box–Jenkins residuals in a multiple-regression equation called a "dynamic shock model" (Haugh and Box 1977). This is a comprehensive approach, which is used infrequently because of practical problems: The lag structures may be distorted, the findings may be sensitive to the choice of a Box–Jenkins prewhitening model, and the operation is cumbersome and time-consuming. Finally, one may use traditional least squares estimation in multiple-regression models containing the past of Y and X (e.g., Granger 1969; Sims 1972). For example, for the information set $\{Y, X\}$,

$$Y_t = d + \sum_{k=1}^{\infty} a_k Y_{t-k} + \sum_{l=1}^{\infty} b_l X_{t-l} + u_t, \quad (3.1)$$

X would Granger-cause Y if $\{b_l\}$ are statistically significant. If maximum lags K and L can be chosen without causing truncation bias and if a sufficient number of degrees of freedom are available, then these tests can be executed fairly safely. On the matter of testing the significance of $\{b_l\}$, some Monte Carlo simulation by Geweke, Meese, and Dent (1983) pointed to the superiority of Wald's chi-squared test over likelihood ratio tests.

Our tests of Granger causality of European Economic Community (EEC) production expectations will be based on this last method. Since Granger's definition implies a forecasting test, however, we will not restrict the analysis to the ex-post statistical significance of $\{b_l\}$ in (3.1). Rather, we will formally test the contribution of the expectations information in predicting production judgments and production accounts. To do this, we must execute the following steps:

1. Develop a univariate Box–Jenkins model for each of the production-judgment and production-accounts series Y. These models produce the optimal extrapolative forecasts for each series.
2. Add the expectations series at various lags to the univariate model; that is, develop a transfer-function model between production and expectations. These models produce the optimal forecasts when the past of production and expectations are taken into account.
3. Test the in-sample statistical significance of the transfer function using a chi-squared test. More important, the prediction significance is measured on a two-year holdout sample by comparing the mean squared forecast errors of the univariate and the transfer-function models.

The models must of course be estimated on stationary data, possibly after applying a stationarity-inducing transformation. Furthermore, the empirical results must be monitored for temporal stability and for behavioral plausibility; that is, the cumulative expectations effects $\{b_l\}$ must be positive.

4. DATA AND SCALING ISSUES

The empirical analysis is based on data from the European Community Business Survey (Commission of the European Communities 1984). This mail survey is carried out by national institutions in the respective EEC member countries on a monthly basis. The EEC harmonizes the questionnaires between the member countries so as to ensure the crossnational homogeneity of the measurement instrument and of the results. Each month a sample of some 20,000 enterprises is surveyed.

Five countries with sufficiently long-time series for the survey data and the national accounts data were selected for analysis. The sample includes France (from September 1968), Germany (from January 1969), Belgium (from January 1970), Italy (from January 1971), and Holland (from December 1972). In all cases the last month reported was December 1983, and a common 24-month forecasting sample (1982–1983) was set aside.

In addition to investigating five different countries, the study also considers three different sectors of the economy, the consumer-, investment-, and intermediate-goods sectors. This choice was based on the fact that the accelerator effect is likely to make the investment-goods sector more volatile than the intermediate-goods sector, which in turn should be more volatile than the consumer-goods sector. Previous studies have tended to pool economic sectors and even countries, which may create some aggregation bias in the reported findings.

Our main interest is in the "production expectations for the months ahead" question, the answers to which are recorded in a trichotomous way (up, unchanged, down). In addition, we consider the questions asking for a judgment of production trends in the last month (up, unchanged, down) and for the judgment of current order books (above normal, normal, below normal).

The data used for this study are aggregate response percentages under each response category of the trichotomy. Since the data do not mention "don't know" or "missing" categories, these percentages sum to 100 in every case. For expository convenience the percentage responses indicating an increase will be labeled "UP," a decrease "DO," and no change "EQ." These three series representing the responses to a single survey question are not orthogonal, and therefore they must be summarized in a meaningful and efficient way.

The simplest way to summarize the survey responses is by using one or two of the percentage series. UP and DO are series indicative of a direction and are substantially correlated (see Table 2), so either one of them may be selected as a regressor. Alternatively, they may be combined in the commonly used balance transformation BAL = UP − DO, which is equivalent to a linear transformation of the responses UP = 1, EQ = 0, DO = −1. Either choice may be complemented by the nondirectional EQ series as a second variable, for example to represent the degree of respondents' uncertainty about the direction of future changes.

Another popular transformation is the fraction of positive answers in the total of directional answers: POS = UP/(UP + DO). The POS series is theoretically independent of the EQ series, but it is insensitive to the size of the balance between UP and DO (e.g., 2% UP and 1% DO give the same POS value as 20% UP and 10% DO). An extension to POS is the "majority"

Table 2. Correlation Matrix of Expectations Series

Country	Sector	Correlation UP-EQ	Correlation UP-DO	Correlation EQ-DO	Mean percentage UP	Mean percentage EQ	Mean percentage DO
Belgium	Consumer	−.25	−.76	−.43	.19	.57	.23
	Investment	.16	−.74	−.78	.15	.58	.26
	Intermediate	.15	−.76	−.76	.15	.60	.25
France	Consumer	−.62	−.76	−.05	.28	.60	.12
	Investment	−.27	−.77	−.41	.25	.59	.16
	Intermediate	−.17	−.78	−.48	.21	.64	.15
Germany	Consumer	−.48	−.63	−.38	.14	.74	.12
	Investment	−.12	−.75	−.57	.13	.75	.12
	Intermediate	−.14	−.65	−.66	.13	.74	.13
Holland	Consumer	−.61	−.35	−.53	.14	.77	.10
	Investment	−.56	−.28	−.63	.10	.78	.12
	Intermediate	−.58	−.42	−.50	.17	.71	.12
Italy	Consumer	−.38	−.62	−.48	.20	.62	.17
	Investment	−.53	−.69	−.25	.18	.66	.16
	Intermediate	−.29	−.65	−.54	.18	.67	.16

variable proposed by Dramais and Waelbroeck-Rocha (1985)—Majority = POS if POS > .5, otherwise Majority = POS − 1. This transformation behaves as a more polarized variable, as it ranges from −1 to 1 but excludes the −.5 to .5 interval.

The preceding transformations have a limited range, making them less suitable as dependent variables in a regression. Nonlinear transformations based on the assumption of a continuous latent variable circumvent this problem (Bechtel 1981; Carlson and Parkins 1975). Let x_{it} present the interval-scaled attitude of individual i at time t, with $f_t(x)$ the density of x_t over the population and $F_t(x)$ the corresponding cumulative density. Let the discriminal process be such that there are two cutoff points X_{DO} and X_{UP} ($X_{\mathrm{DO}} < X_{\mathrm{UP}}$) on the attitude continuum and that a DO response occurs if $x_t \le X_{\mathrm{DO}}$, an UP response occurs if $x_t > X_{\mathrm{UP}}$, and an EQ response occurs if $X_{\mathrm{DO}} < x_t \le X_{\mathrm{UP}}$. If the attitude continuum is interval scaled, we can arbitrarily set $X_{\mathrm{DO}} = 0$ and $X_{\mathrm{UP}} = 1$ and write

$$\mathrm{DO}_t = F(0) \tag{4.1}$$

and

$$\mathrm{DO}_t + \mathrm{EQ}_t = F(1). \tag{4.2}$$

Since DO, EQ, and UP provide two independent information elements, a two-parameter function $f_t(x)$ or $F_t(x)$ can be inferred. The logit relationship

$$F_t(x) = [1 + e^{\alpha_t - \beta_t x}]^{-1} \tag{4.3}$$

is an attractive formulation. Its parameters α_t, β_t can easily be inferred from the DO, EQ, and UP data using (4.1) and (4.2). The central tendency of f_t is located at x_{ct} such that $F_t(x_c) = .50$, namely $x_{ct} = \alpha_t/\beta_t$. The slope of $F_t(x)$ at x_c serves as a measure of concentration of $f_t(x)$ around x_{ct} and equals $\beta_t/4$. Although these measures of central tendency and of concentration (denoted by *Central* and *Agree* for the next section) are independent in principle, empirical correlations between them cannot be ruled out.

The previous discussion shows that various indicators can be suggested to represent multichotomous survey responses. Some empirical results are helpful to reduce the complexity of the problem. These results are based on a study of correlations between the variables UP, DO, EQ, BAL, POS, Majority, Central, and Agree for the question on production expectations as measured for three industrial sectors and five countries. Since all of these correlations are based on more than 100 observations in general, they are fairly reliable. The findings are as follows:

1. The correlations between BAL and Central range from .97 to .999.
2. The correlations between BAL and POS range from .91 to .99 with an average of .97. These results indicate that one should be indifferent between BAL, Central, or POS.
3. The correlations between BAL and Majority range between .74 and .92, with an average correlation of .87. Although BAL and Majority are substantially correlated, they are not virtually identical. This may be due to the fact that they contain different systematic information; we suggest that it may also be the result of the downgrading of information in the Majority transformation.
4. Two nondirectional measures, EQ and Agree, have been investigated. When choosing either one to complement BAL or Majority, one will most likely select the least collinear complementary variable. The correlations show EQ to be less collinear in general with either BAL or Majority. The correlations of EQ with BAL range between .04 and .57 in absolute value, with an average (absolute value) of about .2; the correlations of EQ with Majority range between .01 and .39 with an average of about .15.

Table 3. Univariate Production Judgment Models

Country	*Sector*	*Model*	*Q(12)**	*Q(24)**
Belgium	Consumer	$(1 - .70L)(1 - .21L^{12})P_t = .11 + (1 - .26L + .24L^5)a_t$	3.3	26.4
	Investment	$(1 - .80L)(1 - .13L^{12})P_t = .08 + (1 - .47L + .17L^5)a_t$	8.5	22.2
	Intermediate	$(1 - .78L)(1 - .23L^{12})P_t = .08 + (1 - .27L + .18L^5)a_t$	11.2	24.4
France	Consumer	$(1 - .90L)P_t = .07 + (1 + .15L)a_t$	8.5	18.4
	Investment	$(1 - .90L)P_t = .06 + (1 + .11L + .20L^2)a_t$	11.7	18.7
	Intermediate	$(1 - .89L)P_t = .06 + (1 + .17L + .27L^2 + .14L^4)a_t$	4.3	9.7
Germany	Consumer	$(1 - .79L)(1 - .97L^{12})P_t = .0 + (1 - .34L + .31L^6)(1 - .72L^{12})a_t$	7.0	17.3
	Investment	$(1 - .87L)(1 - .61L^{12})P_t = .02 + (1 - .27L + .19L^7 - .18L^{10})a_t$	13.7	20.2
	Intermediate	$(1 - .87L)(1 - .58L^{12})P_t = .02 + (1 - .32L + .27L^{15})a_t$	14.5	23.5
Holland	Consumer	$(1 - .72L)(1 - .27L^{12})P_t = .09 + (1 - .36L)a_t$	5.6	12.5
	Investment	$(1 - .26L)(1 - .13L^{12})P_t = .29 + (1 - .11L + .50L^5 + .32L^6)a_t$	9.3	26.0
	Intermediate	$(1 - .42L)(1 + .03L^{12})P_t = .29 + (1 - .09L)a_t$	5.6	16.2
Italy	Consumer	$(1 - .86L)(1 - .47L^{12})P_t = .02 + (1 - .22L)a_t$	16.3	30.1
	Investment	$(1 - .78L)(1 - .54L^{12})P_t = .03 + (1 + .10L)a_t$	10.6	19.9
	Intermediate	$(1 - .86L)(1 - .34L^{12})P_t = .02 + (1 - .18L - .34L^{15})(1 + .15L^4)a_t$	6.4	22.5

* Ljung–Box chi-squared statistic $Q(k)$ at lag k.

The empirical data indicate that there is no clear evidence in favor of the particular set of variables or transformations. The practice of using the BAL series to indicate direction, eventually supplemented by the EQ series as nondirectional data, is certainly not worse than any other approach and has the advantage of remaining close to the meaning of the original survey data. Because our work also uses attitudinal data as independent variables, we prefer the central tendency transform, which is not constrained in range and is almost perfectly correlated with balance data.

5. EMPIRICAL RESULTS

5.1 Forecasting Production Judgments

The first criterion for establishing the usefulness of survey expectations is that they must predict next period's production judgments. These predictions must be better than those obtained from straight extrapolation of past production judgments data. The available information set to test Granger causality includes three variables from the survey reports—production judgments, order judgments, and production expectations. Thus we test the forecasting performance of the univariate model,

$$\text{current production judgment} = f(\text{past production judgments}),$$

against the model with survey expectations,

$$\text{current production judgment} = g(\text{past production judgments}, \text{past order judgments}, \text{past expectations}).$$

The inclusion of past orders in the information set is justified, because orders are logically related to future production. Since this information can only be obtained via the survey, this variable is treated in the same way as the expectations.

Following the results of the scaling investigation, the survey results were transformed to an overall sentiment level (central tendency) and a sentiment homogeneity (agreement) score. The logit-derived central tendency was used because it is not range constrained, and thus it is more appropriate in a regression context than the balance data. The sentiment homogeneity variable was initially included in the models, but it never contributed significantly to the results. In addition, this variable causes collinearity problems, presumably because it lacks variance over time. For example, the percentage of "status quo" opinions in Germany centers on 74, with a very small standard deviation. Therefore, all opinion variables are measured with one instrument, the central tendency of the sentiment.

The univariate time-series models for the 15 production judgment series are reported in Tables 3 and 4. All series are stationary and exhibit a first-order autoregressive pattern and one or more moving-average effects. Furthermore, all but the French judgment series have a mild seasonal autoregression of lag 12, even though the survey requests seasonally adjusted opinions. The wording of the questions with respect to deseasonalization is not identical across the investigated countries, however.

The transfer functions relating production judgments to expectations and orders are added to the univariate processes as follows: The three most recent lags of expectations were included on a priori grounds, and the survey expectations are reported for the next quarter. Thus up to three lagged expectations could be related to current production. [Alternatively, Dramais and Waelbroeck-Rocha (1985) replaced the production series by three-month moving averages. We found that approach to be problematic when time-series methods are used.] Likewise, one lag for orders was included, because that question invites a month-by-month comparison of ordering activity. The adequacy of the transfer functions was verified using the least-squares

Table 4. Univariate Production Account Models

Country	Sector	Model	Q(12)*	Q(24)*
Belgium	Consumer	$(1 - .91L)(1 - .35L^3)\nabla^{12}A_t = 1.00 + (1 - .62L)(1 - .57L^{12})a_t$	10.7	30.9
	Investment	$(1 - .94L)(1 - .16L^3)\nabla^{12}A_t = .51 + (1 - .65L)(1 - .59L^{12})a_t$	9.4	20.1
	Intermediate	$(1 - .92L)(1 - .13L^2)\nabla^{12}A_t = 1.05 + (1 - .46L)(1 - .69L^{12})a_t$	11.3	22.0
France	Consumer	$(1 - .98L)\nabla^{12}A_t = .52 + (1 - 1.05L + .24L^2)(1 - .43L^{12})a_t$	9.8	19.1
	Investment	$(1 - .95L)\nabla^{12}A_t = 1.67 + (1 - .57L + .08L^2)(1 - .56L^{12})a_t$	11.1	27.1
	Intermediate	$(1 - .93L)\nabla^{12}A_t = 1.10 + (1 - 23L + .18L^2)(1 - .63L^{12})a_t$	6.9	26.0
Germany	Consumer	$(1 - .85L)(1 - .09L^3)\nabla^{12}A_t = 2.48 + (1 - .65L + .18L^9)(1 - .56L^{12})a_t$	12.0	28.5
	Investment	$(1 - .93L)(1 - .12L^3)\nabla^{12}A_t = 1.14 + (1 - .67L)(1 - .56L^{12})a_t$	9.9	25.6
	Intermediate	$(1 - .92L)(1 - .08L^3)\nabla^{12}A_t = .96 + (1 - .18L)(1 - .61L^{12})a_t$	9.5	28.7
Holland	Consumer	$\nabla^{12}A_t = 2.06 + (1 + .11L^6 + .22L^9 - .15L^{11} - .41L^{12})a_t$	11.0	26.6
	Investment	$(1 - .93L)\nabla^{12}A_t = .14 + (1 - .56L)(1 - .56L^{12})a_t$	10.8	24.8
	Intermediate	$(1 - .84L)\nabla^{12}A_t = .03 + (1 - .18L)(1 - .54L^{12})a_t$	5.1	24.1
Italy	Consumer	$(1 - .88L)\nabla^{12}A_t = 5.40 + (1 - .50L)(1 - .68L^{12})a_t$	5.0	9.5
	Investment	$(1 - .84L)\nabla^{12}A_t = 6.16 + (1 - .61L)(1 - .72L^{12})a_t$	3.1	11.6
	Interemdiate	$(1 - .90L)\nabla^{12}A_t = 2.27 + (1 - .68L)(1 - .73L^{12})a_t$	1.0	6.2

*Ljung–Box chi-squared statistic $Q(k)$ at lag k.

identification method of Liu and Hanssens (1982). In conclusion, the models were estimated as follows: The univariate estimate is

$$\phi_1(L)P_t = \theta_1(L)a_t, \tag{5.1}$$

and the multivariate estimate is

$$P_t = \beta_0 + (\gamma_1 L + \gamma_2 L^2 + \gamma_3 L^3)E_t + \delta_1 L\, O_t + \phi_2^{-1}(L)\theta_2(L)e_t, \tag{5.2}$$

where P_t = central tendency of production judgment; E_t = central tendency of production expectations; O_t = central tendency of order judgments; ϕ_1, ϕ_2, θ_1, and θ_2 are autoregressive and moving-average parameter polynomials; and a_t and e_t are white-noise residuals. The transfer-function parameters γ_1, γ_2, γ_3, and δ_1 for each country and sector are listed in Table 5.

The in-sample tests of Granger causality between production judgments and expectations are reported in Table 6. The results are strongly in favor of rejecting the null hypothesis of no causality: Wald's chi-squared test is significant at $p < .01$ in 14 out of 15 cases, the exception being in the German consumer sector.

The forecasting test sheds further light on the value of production expectations. Using 24 one-step forecasts on the holdout sample (1982–1983), Table 7 compares the performance of the univariate and the transfer function models in terms of one-step squared forecast errors. In 13 cases, the multivariate model outperforms the univariate model. [It is difficult to develop formal hypothesis tests of Granger causality on out-of-sample data; see Ashley, Granger, and Schmalensee (1980).] The exceptions occur in the German consumer sector, confirming the in-sample results, and in the Dutch con-

Table 5. Transfer-Function Parameters: Production Judgments

Country	Variable	Consumer sector	Investment sector	Intermediate sector
Belgium	$E(t-1)$	.54 (.09)	.13 (.09)	.57 (.10)
	$E(t-2)$	−.27 (.22)	−.01 (.14)	−.02 (.21)
	$E(t-3)$	.06 (.10)	.14 (.12)	−.12 (.11)
	$O(t-1)$	−.02 (.08)	−.08 (.04)	−.12 (.07)
France	$E(t-1)$	.25 (.07)	.26 (.06)	.32 (.07)
	$E(t-2)$	.18 (.09)	−.03 (.09)	.08 (.10)
	$E(t-3)$	−.07 (.08)	.18 (.08)	.02 (.09)
	$O(t-1)$	.10 (.05)	.03 (.04)	.02 (.03)
Germany	$E(t-1)$	.72 (.09)	.63 (.09)	.57 (.10)
	$E(t-2)$	−.30 (.17)	.20 (.18)	−.18 (.18)
	$E(t-3)$	−.28 (.10)	−.10 (.10)	−.21 (.11)
	$O(t-1)$	.00 (.03)	−.15 (.06)	−.03 (.02)
Holland	$E(t-1)$	.24 (.12)	.12 (.07)	.48 (.11)
	$E(t-2)$	−.08 (.15)	−.06 (.07)	.55 (.15)
	$E(t-3)$	.28 (.12)	.13 (.07)	.30 (.11)
	$O(t-1)$	.04 (.13)	.15 (.13)	.12 (.09)
Italy	$E(t-1)$	.24 (.09)	.24 (.08)	.35 (.09)
	$E(t-2)$	−.09 (.13)	.22 (.10)	−.01 (.13)
	$E(t-3)$	.15 (.10)	−.01 (.09)	−.05 (.10)
	$O(t-1)$	−.08 (.07)	−.14 (.05)	−.11 (.05)

NOTE: The table entries are the transfer-function parameters with standard errors in parentheses.

Table 6. In-Sample Tests

Country	Variable	Univariate model R squared	Univariate model RSS	Univariate model N	Multivariate model R squared	Multivariate model RSS	Multivariate model N	Wald's chi-squared test
Belgium	Cons. judgments	.36	1.65	131	.53	1.21	131	47.64*
	Inv. judgments	.40	1.06	131	.52	.84	131	34.31*
	Int. judgments	.41	2.20	131	.63	1.39	131	74.86*
	Cons. accounts	.88	277.43	128	.89	247.91	128	15.24*
	Inv. accounts	.91	141.30	128	.92	133.00	128	7.99
	Int. accounts	.89	232.15	128	.90	207.81	128	14.99*
France	Cons. judgments	.86	1.05	159	.93	.56	157	139.12*
	Inv. judgments	.89	.62	159	.93	.39	157	93.77*
	Int. judgments	.91	1.10	159	.95	.55	157	159.00*
	Cons. accounts	.94	364.45	147	.94	349.56	147	6.26
	Inv. accounts	.98	173.03	147	.98	164.73	147	7.41
	Int. accounts	.98	80.50	147	.98	76.83	147	16.54*
Germany	Cons. judgments	.69	1.09	143	.70	1.03	143	8.33
	Inv. judgments	.72	.71	143	.80	.51	143	56.08*
	Int. judgments	.63	1.94	143	.75	1.31	143	68.77*
	Cons. accounts	.89	240.95	140	.90	223.88	140	10.67
	Inv. accounts	.91	180.67	140	.92	171.14	140	7.80
	Int. accounts	.95	97.59	140	.95	82.21	140	8.82
Holland	Cons. judgments	.33	1.12	96	.43	.97	96	14.85*
	Inv. judgments	.42	1.94	96	.43	1.90	96	31.56*
	Int. judgments	.18	2.00	96	.38	1.51	96	31.15*
	Cons. accounts	.84	2.45	97	.86	2.21	97	10.75
	Inv. accounts	.93	.72	96	.94	.76	96	10.34
	Int. accounts	.92	1.51	96	.93	1.49	96	3.29
Italy	Cons. judgments	.47	1.75	119	.55	1.49	119	20.77*
	Inv. judgments	.59	1.31	119	.70	.96	119	43.39*
	Int. judgments	.73	1.23	119	.78	.98	119	30.36*
	Cons. accounts	.86	1,146.75	119	.87	1,062.08	119	9.49
	Inv. accounts	.83	1,078.10	119	.84	1,001.08	119	9.16
	Int. accounts	.80	902.08	119	.81	827.59	119	10.71

*Significant at $p < .01$.

sumer sector. They seem to be caused largely by a poor multivariate forecast in one single period. The range of forecasting improvement for the 13 cases is from 2% to 64%, averaging about 20%. These results support the notion that expectations data are of some value in predicting production judgments.

In conclusion, there is empirical evidence of internal consistency of the survey data: manufacturers' *current* judgments of orders and current production expectations are generally useful in predicting *next* period's production judgments. Moreover, the role of the expectations is stronger than that of the orders—the expectations parameters and their t ratios are generally higher (both series have about equal means and variances).

5.2 Forecasting Production Accounts

If manufacturers' assessments of production activities are accurate and if the survey sample is adequate, the results of the analysis so far should apply to objectively measured production data. It is not obvious that such will be the case, however, because there may be systematic bias in the surveys over time. For example, a manufacturer may report increased production because he recalls reporting an optimistic expectation last month and does not want to appear inconsistent. Thus a replication of the models on a different data source is in order.

National accounts production data were obtained in the form of a time series of indexes for the same sectors and countries in which December 1975 is scaled as a base index 100 (Commission of the European Communities 1984). Although seasonally adjusted data were also available, the analysis is done on raw numbers. It is preferable to analyze the time-series properties of these raw data and, if necessary, to use an appropriate transformation. The results of multivariate modeling may be substantially different between original and seasonally adjusted data (e.g., Feige and Pearce 1979).

The production indexes exhibit strong seasonal behavior as expected, so seasonal differencing was necessary to achieve stationarity. The transformed series were correlated with the production-judgment data to obtain a first crude idea of the correspondence between the two. As illustrated in Table 8, the correlations are generally positive and significant, but they average only about .43. Production judgments and production accounts are not equivalent measures of economic activity; thus the additional test on the value of production expectations is not trivial.

Table 7. Residual Sums of Squares for the Forecasting Sample (1982–1983)

Country	Sector	Univariate model	Multivariate model	Percent improvement*
Belgium	Consumer judgments	.351	.314	10.5
	Investment judgments	.122	.108	11.5
	Intermediate judgments	.280	.253	9.6
	Consumer accounts	36.576	38.097	−4.2
	Investment accounts	19.963	20.758	−4.0
	Intermediate accounts	44.976	48.361	−7.5
France	Consumer judgments	.136	.126	7.4
	Investment judgments	.088	.077	12.5
	Intermediate judgments	.339	.264	22.1
	Consumer accounts	75.055	73.802	1.7
	Investment accounts	21.529	29.569	−37.3
	Intermediate accounts	9.461	10.086	−6.6
Germany	Consumer judgments	.117	.284	−142.7
	Investment judgments	.230	.226	1.7
	Intermediate judgments	.275	.189	31.3
	Consumer accounts	43.610	34.612	20.6
	Investment accounts	23.230	23.850	−2.7
	Intermediate accounts	15.688	14.470	7.8
Holland	Consumer judgments	.091	.133	−46.2
	Investment judgments	.212	.076	64.2
	Intermediate judgments	.294	.197	33.0
	Consumer accounts	77.288	72.879	5.7
	Investment accounts	22.798	40.149	76.1
	Intermediate accounts	42.336	42.367	−.1
Italy	Consumer judgments	.226	.181	19.9
	Investment judgments	.301	.226	24.9
	Intermediate judgments	.205	.171	16.6
	Consumer accounts	112.740	95.541	15.3
	Investment accounts	96.648	169.700	−75.6
	Intermediate accounts	57.232	127.620	−123.0

*Forecasting improvement calculated as a percentage of the univariate residual sums of squares.

The design of the Granger test on production-accounts data is similar to the one used in the survey analysis. The in-sample tests, summarized in Table 6, reveal that only 20% of the cases (3 out of 15) confirm the effect of production expectations on production accounts at $p < .01$. Furthermore, only 5 cases show a contribution of production expectations in the 24-period forecasting sample (Table 7). The conclusion is that Granger causality cannot be established when economic activity is measured by production accounts; that is, the expectations series do not systematically contribute to production forecasting beyond what can be achieved from simple time-series extrapolation.

5.3 The Formation of Survey Expectations

Since the results on the predictive value of survey expectations are mixed, it is of interest to examine the formation of these anticipations in more detail. The most prevalent question that arises is whether or not the expectations are formed rationally. This is usually determined by comparing the expectations to the actual outcomes, for example, interest rates versus their point forecasts (Friedman 1980). Straight comparisons are not possible in the present context, however, because the survey-reported production expectations are only directional.

The logit-derived "central tendency" transformation proposed earlier allows for a limited investigation of rationality, because it is interval scaled between $-\infty$ and ∞. First, we may compare the average expectation tendencies to the subsequent production judgments and determine if European manufacturers are, on the whole, too optimistic or too pessimistic. Table 9 lists the results along with t tests for differences between

Table 8. Correlations Between Production Judgment and Accounts Data

	Belgium (N = 156)	France (N = 172)	Germany (N = 168)	Holland (N = 121)	Italy (N = 142)
Consumer sector	.28[a]	.19[b]	.30[a]	.15	.60[a]
Investment sector	.44[a]	.42[a]	.41[a]	.26[a]	.28[a]
Intermediate sector	.53[a]	.85[a]	.64[a]	.37[a]	.72[a]

NOTE: The accounts data are seasonally differenced to achieve stationarity.
[a]Significant at $p < .01$.
[b]Significant at $p < .05$.

Table 9. Average Production Expectation and Subsequent Judgment Tendencies

Country	Sector	Expectations	Judgments	Difference
Belgium	Consumer	.41	.49	−.09[a]
	Investment	.32	.46	−.13[a]
	Intermediate	.33	.46	−.14[a]
France	Consumer	.65	.65	.00
	Investment	.56	.57	−.01
	Intermediate	.54	.53	.00
Germany	Consumer	.49	.47	.02[b]
	Investment	.47	.47	.00
	Intermediate	.46	.44	.02[c]
Holland	Consumer	.54	.49	.05[a]
	Investment	.47	.47	−.00
	Intermediate	.54	.50	.04[a]
Italy	Consumer	.46	.23	.22[a]
	Investment	.47	.22	.24[a]
	Intermediate	.46	.20	.26[a]

[a]Significant at $p < .01$.
[b]Significant at $p < .1$.
[c]Significant at $p < .05$.

expectations and subsequent judgments. Some striking intercountry and intersector differences occur. Italy is very optimistic (i.e., production-expectation tendencies are systematically higher than subsequent judgments), Holland and Germany are somewhat optimistic except in the investment sector, France is neutral (but both expectations and judgments are higher than in the other countries), and Belgium is pessimistic. Thus if production expectations are used directly to assess future production judgments, a correction for bias should be used in a majority of the cases sampled.

Second, we may investigate the updating of forecast errors made by the manufacturers. The central issue is whether or not a forecast error could have been avoided by using all information available to the manufacturers at the time the prediction was made. The statistical test consists of regressing the prediction error against the previous-period information set; the lack of a statistical relation would suggest that the forecast error could not have been reduced with the available information—that is, that the manufacturers are making an optimal use of the data, and vice versa.

We performed the prediction-error test on production-judgments and production-accounts data. A direct comparison of actual and predicted production is not possible, however, because the judgments data may be subject to bias, as seen in the previous results, and the accounts data are not on the same scale. The following two-step procedure was used to circumvent this problem.

Step 1. Regress production on previous expectations, and collect the residuals:

$$P_t = a_0 + a_1 E_{t-1} + u_t \tag{5.3}$$

and

$$A_t = a_0' + a_1' E_{t-1} + u_t'. \tag{5.4}$$

Step 2. Regress the residuals against previous orders, judgments, and expectations:

$$\hat{u}_t = b_0 + b_1 P_{t-1} + b_2 O_{t-1} + b_3 E_{t-2} + v_t \tag{5.5}$$

and

$$\hat{u}_t = b_0' + b_1' P_{t-1} + b_2' O_{t-1} + b_3' E_{t-2} + v_t'. \tag{5.6}$$

Table 10. Expectations Error Models

	Production judgments			Production accounts		
Country	Consumer	Investment	Intermediate	Consumer	Investment	Intermediate
Belgium	.03	.03	.09	.08	.07	.03
	1.26	1.43	4.60[a]	3.52[a]	3.37[a]	1.23
France	.35	.50	.60	.01	.20	.32
	27.55[a]	51.60[a]	78.43[a]	.44	12.00[a]	22.55[a]
Germany	.03	.08	.01	.10	.04	.17
	1.44	4.33[a]	.25	4.96[a]	1.99	9.41[a]
Holland	.05	.04	.06	.01	.28	.16
	1.70	1.28	2.37[b]	.42	12.20[a]	6.06[a]
Italy	.20	.51	.48	.22	.01	.13
	10.68[a]	44.20[a]	38.54[a]	10.86[a]	.38	5.92[a]

NOTE: The table lists the R squared and the overall F statistic for the regression model (5.4).
[a]Significant at $p < .01$.
[b]Significant at $p < .10$.

Step 1 removes systematic bias and/or scaling differences between the expectations and the production series. The residual series capture the production component that was unanticipated by the manufacturers in the previous period. This component is explained in Step 2, in function of all information available to the manufacturers at time $(t - 1)$—that is, the order judgments, the production judgments, and the previous expectation level. Production accounts are not included in this list, because government bureaus take several months to compile and release the official statistics on economic activity.

The results are summarized in Table 10. There are several instances of imperfect use of information, most notably among French and Italian manufacturers. In many other cases, however, the forecast-error variance explained by the model is low, even though it may be statistically significant. Overall, Belgium, Germany, and to a lesser extent Holland appear to make reasonably good use of the available information, whereas France and Italy typically do not. We also note a tendency for manufacturers in the intermediate sector to make less efficient use of information.

6. CONCLUSIONS AND DISCUSSION

This article has presented an empirical evaluation of the value of survey-reported production-expectations data in the European Common Market. At the *methodological* level, we have compared various methods for scaling survey expectations, and we have introduced logit-derived central tendency and dispersion measures of producer sentiment. We have also stressed the importance of examining the time-series behavior of the survey data in developing evaluation models. In particular we have developed tests of the forecasting value of survey expectations based on the concept of Granger causality.

At the *empirical* level, we applied these methods to EEC production-survey and national-accounts data for three sectors in five member countries. Although differences exist among countries and sectors, we concluded overall that the survey expectations Granger-cause production judgments but not production accounts. Furthermore, we found several cases of bias and suboptimal use of information in the survey-reported production expectations. They explain, in part, why the use of the expectations data does not uniformly improve our ability to forecast subsequent production levels.

The apparent conflict in the results on the forecasting value of survey expectations is intriguing and important. The correlations between survey-reported and national-accounts production are modest, so the question arises as to which source of information should be used. We leave the answer open to the reader, but its implications are clear: If the level of industrial activity in a country is measured by manufacturers' opinions (production judgments), then the expectations data often make a valuable contribution in forecasting. If national accounting data are used, then the expectations are essentially useless.

Although this study is the first to use a Granger causality test on multiple measures of the economic variable to be forecast, it leaves a few areas of needed research unexplored. First, the use of a multicountry, multisector design may enhance one's statistical confidence in the results, but the choice of countries and sectors was influenced by data availability. An investigation of the poolability of the data is needed. Second, a validation of our findings on consumer-sentiment data would also be useful. Finally, we have not explored some more sophisticated modeling techniques, such as varying-coefficients models, that recognize that the predictive value of expectations may be contingent.

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