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BUSINESS SURVEY DATA IN FORECASTING THE OUTPUT OF SWEDISH AND FINNISH METAL AND ENGINEERING INDUSTRIES: A KALMAN FILTER APPROACH

by

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Abstract. In this paper forecasting the production volume of the Swedish and Finnish metal and engineering industries one quarter ahead is discussed. A practical way of making use of the predictive information in the answers of the quarterly business survey is presented. It is based on the application of the Kalman filter. It turns out that the most informative questions of the business survey from the point of view of forecasting are different in the two countries. However, for both Sweden and Finland, the improvement in prediction accuracy after taking account of relevant business survey information is significant when the precision of autoprojective forecasts is used as a baseline.

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1. INTRODUCTION

The business surveys or business tests are conducted in a large number of countries on a regular basis. A typical business survey questionnaire contains a host of questions on the recent economic performance of the firm on the one hand and on its short-term plans/expectations on the other. A customary way of publishing the results of the survey is to tabulate the weighted relative shares of the alternative answers, relate them to the corresponding results from previous surveys and discuss them. Graphical comparisons of the results with time series of national accounts data may be carried out.

A question that arises is whether the predictive information (answers to questions on plans or expectations of the firms) could be quantified in such a way that each time the results are published, an output forecast for a number of branches and the manufacturing in total based on them could be given as well. Theil (1952) already devised a technique making that possible; for an overview of more recent developments see Pesaran (1987, chapter 8). The technique is based on the assumption that the firms' output changes at a given time follow a normal or some other known distribution. Knowing the relative shares of the firms planning increasing and decreasing production, respectively, for the next quarter is then sufficient to obtain a quantitative production forecast for the quarter.

Another possibility is to construct a model to link the relative shares to the output series and use that for forecasting. For instance, Teräsvirta (1986) constructed several models for predicting the output of the Finnish metal and engineering industries (SNI code 37 and 38) and reported improvements in prediction accuracy over autoprojective models. However, the performance of the models that have been in use at the Research Institute of the Finnish Economy, has slowly been deteriorating over time. Other attempts have given even more disappointing results. Batchelor (1982), using Theil's idea, found that models containing business survey variables did not yield better output forecasts than ARMA models. Hanssens and Vanden Abeele (1987) who analyzed data from five EC countries concluded that the plan/expectation information was "essentially useless" in forecasting next quarter's output. Öller (1990) focussed on turning-point prediction so that his results on Finnish forest industries are not relevant here.

In this paper we shall take another look at this problem using data on the metal and engineering (ME) industries from the Swedish and the Finnish business surveys. Compared to Teräsvirta (1986) we shall assume more structure and rely less on model selection to avoid spurious relationships. We first construct an autoprojective model for the output changes and then introduce the relevant information from the business survey as "new" information aimed at improving the autoprojective forecast. The Kalman filter with its prediction and updating steps provides a suitable framework for such an approach. The performance of the models is checked by post-sample forecasting. The results indicate that information from the business survey does have a significant impact on the accuracy of one-quarter-ahead output forecasts. The plan of the paper is as follows. In section 2 we shall discuss the data and in section 3 the Kalman filter. Sections 4 and 5 present empirical results for Sweden and Finland, respectively, and section 6 concludes.

2. THE DATA

The business surveys or business tests in Sweden and Finland are conducted quarterly. The firms give generally trichotomous answers to a set of questions concerning mostly their own activity and their expected or planned activities. The three typical alternative answers are "greater than", "no change" and "less than". Appendix 1 contains a list of questions considered in this paper. The answers of individual firms to each question are aggregated up to weighted relative shares. The annual turnover figures of the firms are used as weights. We shall use time series of these shares in our study.

Many questions in the Swedish and Finnish business surveys are similar. However, the Finnish survey explicitly defines the interval for "no change" (±2 %) whereas the Swedish survey does not. This difference is of importance in quantifying the relative shares, i.e., transforming them into growth rates as discussed above but does not play a critical role in this paper. Both surveys ask the respondents to ignore seasonal variation in their answers. This may make answering the questions more difficult because, as we shall see, the production series we are going to analyze contain strong seasonal variation.

The Swedish survey is larger than the Finnish one because the industrial sector in Sweden is larger than in Finland. The number of Swedish firms participating in the survey is over 1800. The corresponding figure in Finland is 560. In both countries, all the largest firms participate every quarter, the rest are selected by stratified sampling.

We focus on forecasting the output of the ME industries in the two countries. In Sweden, this branch accounts for almost one half of the total value added in manufacturing. About 55 % of this value added is exported. In Finland the value added of the ME industries is almost 30 % of the total in manufacturing. For Sweden, the definition of the ME industries used in this paper basically covers the industries under SNI code 38. There is one exception:

the shipyards, SNI 3841, are excluded, because the corresponding industrial production index in the national accounts does not contain their value added. However, that was only 4 % of the total value added in ME industries in 1987. As to Finland, we also have to include the basic metal industry, SNI 37, because the corresponding index of production measures the production of both SNI 37 and 38. Despite these differences, we shall use the term ME industries for both countries for simplicity.

The variables to be predicted are the production volume indices of the ME industries. Because our goal is to forecast the next quarter's figure, we use seasonally unadjusted series. For Sweden, we use data from 1970(1) to 1990(4) whereas for Finland we have data from 1976(1) to 1990(4). The effects of the industrial action in 1980(2) on the Swedish production series have been eliminated by interpolation. As the questions in the business survey concern realized or planned/expected changes during a quarter, it is appropriate to use first differences of the logarithmed industrial production indices as data in the models. The time series of these differences appear in Figures 1 and 2 where seasonality is clearly apparent.

Figure 1. First differences of the logarithmed production volume index of Swedish ME industries, 1971(1)-1990(4)

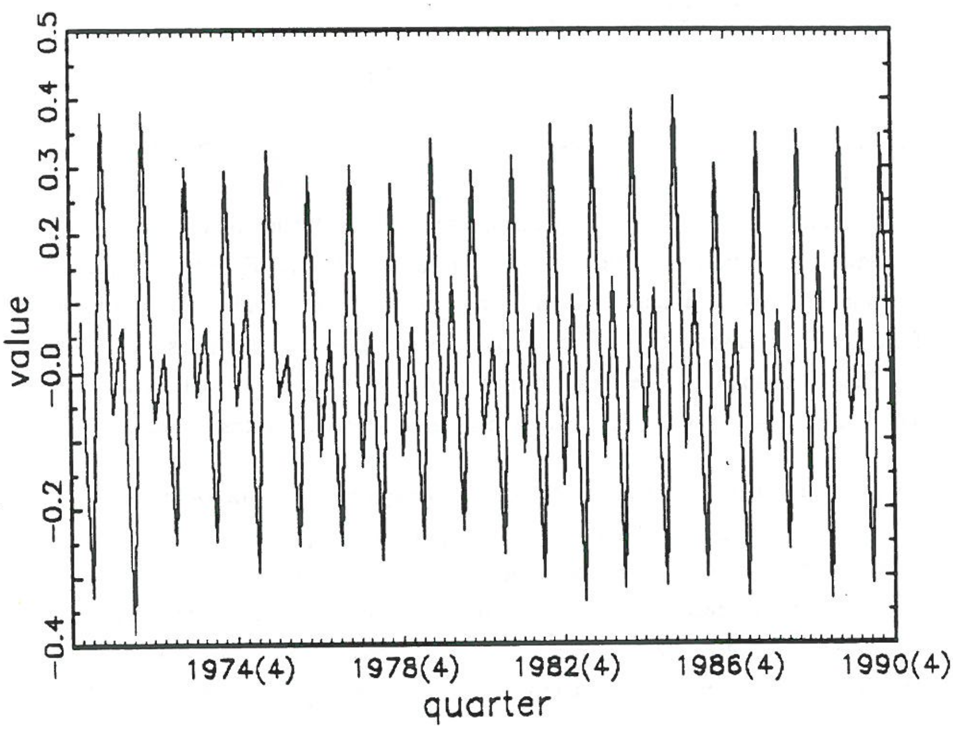
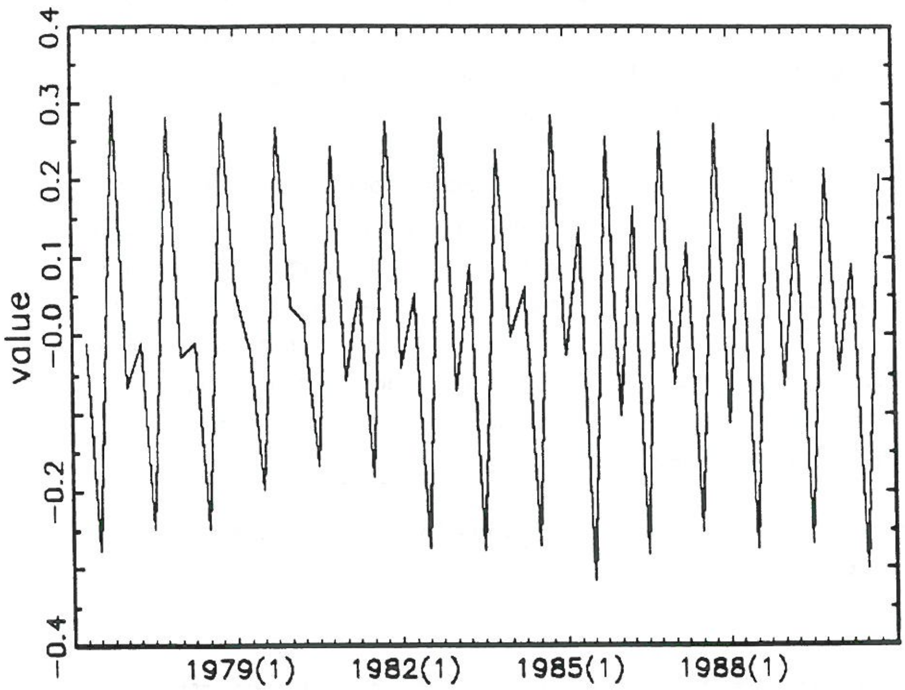


Figure 2. First differences of the logarithmed production volume index of Finnish ME industries, 1976(2)-1990(4)



3. THE MODEL

The forecasting framework is based on the idea of improving autoprojective predictions using information from the business survey. Suppose that at time t-1 we want to forecast y_t, the logarithmic difference of the volume of industrial production of a branch. Assume that we have information available until t-1: the information set $F_{t-1}=\{y_{t-1}, y_{t-2},..., y_0\}$. In addition, as "new information" we shall observe g_t, a vector which contains information from the business survey. This vector has as its elements relative shares of "greater than" and "less than" answers. The question of choosing the elements of g_t will be discussed later. The issue is how to use the information in g_t to improve the forecast based solely on F_{t-1}.

We propose that this be done by applying the state space framework. Define the state vector $\alpha_t = (y_t, y_{t-1},...,y_{t-k+1}, 1, d_{1t}, d_{2t}, d_{3t}, d_{4t}, \hat{v}_{t-1}, \hat{v}_{t-2})'$ where d_{jt}, j=1,2,3,4, are the four seasonal dummy variables and $\hat{v}_{t-j}$, j=1,2, are lagged residuals of a row in the measurement equation. They are included because of autocorrelation in the residuals of that equation and will be discussed later. The state vector contains the unobservable (at time t-1) y_t we want to forecast. The movements of the state vector are governed by the transition equation

$$\alpha_t = T_t\alpha_{t-1} + Ru_t. \tag{3.1}$$

The transition matrix T_t is dependent on t because of the lagged residuals mentioned above and has the form

$$T_t = \left[\begin{array}{cccccccc}
\varphi_1\ \varphi_2\ \cdots\ \varphi_k & \mu & \delta_1 & \delta_2 & \delta_3 & 0 & 0 & 0 \\
I_{k-1} & 0 & & & & 0 & & \\
 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
 & \hat{v}_{t-1} & 0 & 0 & 0 & 0 & 0 & 0 \\
 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{array}\right].$$

Furthermore, $R = (1,0,..,0)'$, because only the first element in α_t is not observed at t-1. The measurement equation describing how the business survey variables g_t depend on the actual production y_t is

$$x_t = Z\alpha_t + Sv_t \tag{3.2}$$

where

$$x_t = (y_{t-1}, g'_t)',$$

$$Z = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & \ldots & 0 & 0 & 0 & 0 \\ z_{21} & z_{22} & & \ldots & z_{2,p-2} & 0 & z_{2,p-1} & z_{2p} \end{bmatrix}$$

$$S = \begin{bmatrix} 0 \\ I_d \end{bmatrix}, \quad d = \dim(z_2)$$

and

$$\begin{bmatrix} u_t \\ v_t \end{bmatrix} \sim \mathrm{nid}(0, \begin{bmatrix} \sigma^2 & 0 \\ 0 & H \end{bmatrix}).$$

The main idea of (3.2) is to interpret g_t as an indirect observation of y_t. In addition to g_t we also know the history of $\{y_t\}$ up to t-1, and this leads to the inclusion of y_{t-1} in x_t.

The forecasting is carried out as follows. At time t-1 the relevant information in F_{t-1} appears in a_{t-1}, the estimate of α_{t-1}. In this case, α_{t-1} is observed directly, i.e., $\alpha_{t-1} \equiv a_{t-1}$. Thus $P_{t-1} = \mathrm{cov}(a_{t-1}) = 0$. From the transition equation (3.1) we obtain the forecast $a_{t|t-1} = T_t a_{t-1}$. The covariance matrix of the prediction error $e_t = a_{t|t-1} - \alpha_{t-1}$ is

$$\mathrm{cov}(e_t) = P_{t|t-1} = \sigma^2 TP_{t-1}T' + \sigma^2 RR' = \sigma^2 RR'.$$

The autoprojective forecast $a_{t|t-1}$ is updated by incorporating the information in x_t (Harvey, 1981, p. 110). The updating equation for α_t is

$$a_t = a_{t|t-1} + P_{t|t-1} Z' F^- (x_t - Z a_{t|t-1})$$

where

$$F = ZP_{t|t-1}Z' + SHS' = \sigma^2 ZRR'Z' + SHS' = \mathrm{diag}\,(0, F_2)$$

and

$$F^- = \mathrm{diag}\,(0, F_2^{-1}).$$

In practice, Z, σ^2, and H are replaced by their estimates. The correction to $a_{t|t-1}$ is a function of the prediction error made in forecasting x_t using the information in F_{t-1}. The first element of a_t is the forecast for y_t.

So far we have assumed that g_t is available and can be used in forecasting y_t. As the business surveys in Sweden and Finland are conducted just before the end of each quarter (t) and the results made public right after the quarter is over, the above framework is suitable for obtaining the first estimate of y_t. If we want to apply it to forecasting y_t at the end of quarter t-1, then we have to construct a separate prediction equation for forecasting g_t. This can be done by taking the answers to some of the plan/expectation questions in the business survey that become available at the end of quarter t-1. Their relative shares can be used to predict the relative shares of the answers to realization or judgment questions appearing in x_t. These predictions are used in x_t in place of g_t when the autoprojective forecast is updated. The prediction equation is separate from the Kalman filter, because it does not seem possible to incorporate it in our state space formulation in a useful way. It may also be worth noting that we cannot make use of a Kalman model formulation along the lines in (3.1) in predicting

g_t. The reason is that the plan/expectation variables cannot be interpreted as indirect observations of g_t. Such an attempt would produce an anticipatory measurement equation.

4. FORECASTING THE OUTPUT OF SWEDISH ME INDUSTRIES

4.1. Constructing the model

To build a state-space type forecasting framework for the Swedish ME industries the data were divided into two parts. The observations from 1970(1) until 1987(4) were used for estimating the parameters of our equations. The data from 1988(1) to 1990(4) were saved for out-of-sample forecasting to investigate the prediction performance of the system.

As mentioned above, selecting the variables for g_t was an open question. We restricted ourselves to questions related to the observed performance of the firm (the realization or judgmental questions). The question concerning the output of the firm was of course the one that could be expected to be the most important one, but other questions were investigated as well. The list of the questions considered is in Appendix 1. The selection of variables was carried out in two stages as follows. First, the realization questions considered were added into the autoprojective equation for y_t. The ones that seemed to have explanatory power were selected. In making the choice we also used AIC which is a rather generous criterion, for discussion see e.g. Teräsvirta and Mellin (1986), but at this stage we did not want to be very restrictive. At the second stage the Kalman filter was applied and post-sample forecasts were made using these variables in the measurement equation. The ones that did not seem to affect the prediction accuracy during the test period 1988-1990 were omitted from consideration.

After the first stage, five variables seemed important. First of all, there were the relative shares of "greater than" and "less than" answers to the question of change in output (question 1.01), pr^+_t and pr^-_t, respectively. An F-test suggested that the balance, $pr_t = pr^+_t - pr^-_t$, was the appropriate variable to use. The other two variables with explanatory power were ep^-_t, the relative share of the firms reporting decreasing prices for their exports (question 1.04) and nod^+_t and nox^+_t, increase in domestic and export orders (questions 1.05 and 1.06), respectively. The hypothesis that the two could be combined to $(nod^+_t + nox^+_t)$ was not rejected. However, later on it turned out that in 1988-1990 neither of these two variables contributed to the precision of the one-quarter-ahead predictions. Thus the only remaining variable was pr_t, which is hardly surprising. In the following we shall only report results based on defining $g_t = pr_t$.

The autoprojective equation estimated for y_t from the data 1972(2)-1987(4) was

$$y_t = -0.36\, y_{t-1} + 0.22\, y_{t-2} + 0.15\, y_{t-3} + 0.24\, y_{t-4}$$
$$\quad (0.13) \qquad (0.13) \qquad (0.13) \qquad (0.12)$$

$$+\ 0.14\ -\ 0.054\, d_{1t} - 0.14\, d_{2t} - 0.35\, d_{3t} + \hat{u}_t \tag{4.1}$$
$$(0.047)\ (0.080) \quad (0.064) \quad (0.075)$$

$s_L = 0.0314$, LB(12-4) = 13.2 (0.10), ML(2) = 8.2 (0.016),

sk = 0.096, ek = -0.83, JB = 1.9 (0.38)

where the figures below the parameter estimates are estimated standard deviations, s_L is the residual standard error, LB is the Ljung and Box (1978) test of no error autocorrelation, ML is the McLeod and Li (1983) test of no autoregressive conditional heteroskedasticity (ARCH), sk is skewness, ek excess kurtosis and JB the test of normality by Lomnicki (1961) and Jarque and Bera (1980). The figures in parentheses after the values of the test statistics are p-values. The ones below the coefficient estimates are estimated standard deviations.

Table 1. Results of testing the hypothesis of parameter constancy against the alternative of smooth structural change in the Swedish autoprojective model (4.1) using the tests in Lin and Teräsvirta (1991)

Model	Test	Value	p-value
(4.1)	LM_1	F(8,47) = 0.99	0.45
	LM_2	F(16,39) = 1.78	0.072
	LM_3	F(24,31) = 2.77	0.0041
	$LM_{2\|3}$	F(8,31) = 3.17	0.0096

The first sign of trouble in (4.1) is that the McLeod-Li test rejects the null hypothesis of no ARCH at the conventional 5 % significance level. Next we performed the three parameter constancy tests of Lin and Teräsvirta (1991). The alternative hypotheses in these tests are parameterized and may be estimated if the null hypothesis is rejected. The test results are in Table 1. In LM_1 the alternative is monotonic change over time. In LM_2 it is a change which is nonmonotonic but symmetric about a time-point, whereas the alternative in LM_3

accommodates even more general nonmonotonic parameter change. It is seen from Table 1 that while LM_1 and LM_2 do not reject parameter constancy at conventional levels of significance, LM_3 does it very strongly. The specification test $LM_{2|3}$ shows that the third-order terms cannot be removed from the model. This lends support to the model that constituted the nonlinear alternative in LM_3. Following Lin and Teräsvirta (1991) we estimated this model. The result is

$$
\begin{aligned}
y_t = {} & \underset{(0.10)}{0.32}\, y_{t-2} + \underset{(0.21)}{0.52}\, y_{t-3} - \underset{(0.24)}{0.62}\, y_{t-4} + \underset{(0.080)}{0.53} - \underset{(0.12)}{0.68}\, d_{1t} - \underset{(0.065)}{0.37}\, d_{2t} - \underset{(0.17)}{1.06}\, d_{3t} \\
& +(-\underset{(0.11)}{0.48}\, y_{t-1} - \underset{(0.21)}{0.52}\, y_{t-3} + \underset{(0.24)}{0.62}\, y_{t-4} - \underset{(0.17)}{0.36} + \underset{(0.12)}{0.68}\, d_{1t} \\
& + \underset{(0.051)}{0.14}\, d_{2t} + \underset{(0.17)}{0.67}\, d_{3t})\, \hat{F}(t^*) + \hat{u}_t ,\ t = 1,\ldots,n;\ t^* = t/n \qquad (4.2)
\end{aligned}
$$

where

$$
F(t^*) = (1+\exp\{-\underset{(125)}{77}(t^{*3} + \underset{(2.5)}{5.2}t^{*2} - \underset{(2.1)}{4.8}t^* + \underset{(0.36)}{0.88})\})^{-1} \qquad (4.3)
$$

and

$s = 0.0268$, $s^2/s_L2 = 0.73$, $LB(4) = 6.5$, $ML(2) = 3.2\ (0.21)$,

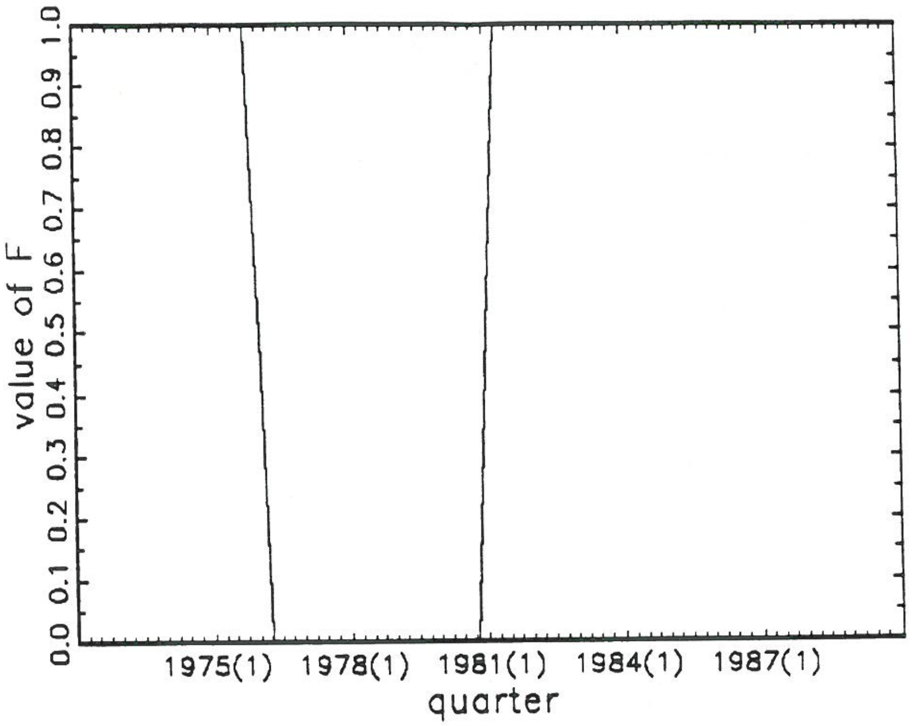
$sk = -0.27$, $ek = 0.93$, $JB = 3.0\ (0.22)$.

The residual variance of (4.2) is 73 % of the residual variance of (4.1), a considerable decrease. The null hypothesis of no ARCH is no longer rejected. The restrictions on the coefficients of y_{t-3}, y_{t-4} and d_{1t} are supported by the data. The large standard deviation of the scale parameter in (4.3) reflects the fact that any large value of the parameter would give about the same F. The estimated transition function (4.3) is graphed in Figure 3. It indicates the existence of two regimes, one between 1976 and 1980 ($\hat{F}=0$) and the other outside this period ($\hat{F}=1$). Interpreting the estimated coefficients of (4.2) is not straightforward but it may seem that the seasonality of the series in 1976-1980 is different from what it is before 1976 and after 1980.

To proceed, an obvious possibility is to take the regime corresponding to $\hat{F}=1$, the value of the transition function at the end of the sample, and use that for forecasting. The regime is

$$
y_t = -\,0.48\, y_{t-1} + 0.32\, y_{t-2} + 0.17 + 0.0001\, d_{1t} - 0.24\, d_{2t} - 0.39\, d_{3t} + \hat{u}_t \qquad (4.4)
$$

Figure 3. Graph of estimated transition function (4.3)



Another possibility is to discard the sample until 1980 and begin by estimating an autoprojective model for y_t from the data 1980(1) to 1987(4). The estimated model is

$$y_t = -\underset{(0.11)}{0.39}\, y_{t-1} + \underset{(0.11)}{0.22}\, y_{t-2} + \underset{(.031)}{0.21} - \underset{(0.068)}{0.12}\, d_{1t} - \underset{(0.041)}{0.23}\, d_{2t} - \underset{(0.041)}{0.45}\, d_{3t} + \hat{u}_t \qquad (4.5)$$

s = 0.0181, LB(8-4) = 7.3 (0.12), ML(2) = 4.9 (0.086)

sk = -0.24, ek= -0,48, JB =0.63 (0.73).

Note the similarity between (4.4) and (4.5). We took the latter road and estimated the model for pr_t needed in the measurement equation using the same estimation period, 1980(1) to 1987(4). However, the residuals of the model displayed strong positive first and second-order autocorrelation. Re-estimation by exact maximum likelihood assuming MA(2) errors yielded the following model:

$$pr_t = 266\ y_t + 226\ y_{t-1} + 205\ y_{t-2} + 73\ y_{t-3}$$
$$\quad (58) \quad (73) \quad (63) \quad (47)$$
$$- 26 + 37\ d_{1t} - 12\ d_{2t} + 94\ d_{3t} + \hat{v}_{1t} + 0.47\ \hat{v}_{t-1} + 0.53\ \hat{v}_{t-2}$$
$$(17)\ (28) \quad (22) \quad (35) \qquad (0.18) \quad (0.17) \tag{4.6}$$

$s = 7.31$, $LB(4) = 0.26$, $ML(2) = 0.039\ (0.98)$, $sk = 1.0$,

$ek = 0.79$, $JB = 6.3\ (0.042)$.

The skewness is mainly due to a single large residual in 1985(4). Note that (4.6) also contains lags of y_t: this may at least partly be due to strong seasonality in y_t. To make the Kalman filter work, the two MA error terms in (4.6) have to be included in the state vector α_t. We have taken this into account in section 3. However, in forecasting one step ahead without re-estimating the model after each step we shall assume $\hat{v}_{n+j} \equiv 0$ for $j > 0$, $n = 1987(4)$.

As discussed above, to make a one-quarter-ahead forecast for y_t we also need a model to obtain a forecast for g_t. A natural plan/expectation variable when $g_t=pr_t$ is the corresponding production plan variable pre_t (question 3.01). We considered other variables as well, and AIC was used to help find an appropriate specification. The final choice is seen in the estimated equation

$$pr_t = -10 + 0.32\ pr_{t-1} + 0.71\ pre_{t|t-1} + 0.52\ node^{+}_{t|t-1} + \hat{w}_t \tag{4.7}$$
$$(5.4)\ (0.13) \qquad (0.15) \qquad (0.21)$$

$s = 8.50$, $LB(4) = 4.0$, $ML(2) = 1.2\ (0.54)$, $sk = -0.80$,

$ek = 1.79$, $JB = 7.7\ (0.021)$.

Not unexpectedly, the balance of the "greater than" and "less than" answers to the question about next quarter's output appears in (4.7). In addition, expected increase in domestic orders next quarter, $node^{+}_t$ (question 3.05), seems important in predicting pr_t. The negative skewness is largely due to a single residual in 1980(2). This is the quarter with the industrial action mentioned in section 2 which disrupted the production plans of the firms. We experimented with a dummy variable for that quarter. Because it did not have any positive effect on the precision of the post-sample forecasts, it is not included in (4.7).

4.2. Forecasting with the model

Having obtained all the ingredients needed in applying the Kalman filter to forecasting we now consider the output forecasts for the period 1988(1) to 1990(4). The forecasts are one-quarter-ahead forecasts that have been computed without re-estimating the model. Thus the parameter estimates are those appearing in equations of section 4.1. The period is rather difficult to forecast with autoprojective models, because the annual growth rates fluctuate widely. By the end of 1990, the growth rate sinks to -9 %. The period should then constitute an informative test in assessing the value of the business survey information in predicting industrial production.

The RMSEs of the forecasts are in Table 2. The RMSE of the autoprojective model (4.5) is about 3.9 %. This may be compared to the residual standard error of (4.5) which is about 1.8 % confirming that the period 1988-1990 has not been an easy one to predict. It is seen

Table 2. The root mean square errors (RMSE) and median of absolute errors (MAE) for the forecasts of the output of Swedish ME industries in 1988(1)-1990(4) from autoprojective models (4.5) and (4.1) (AP) and the Kalman filter (KF)

Autoprojective model	Prediction method		
	AP	KF: g_t known	g_t predicted
	RMSE:		
(4.5)	0.0414	0.0258	0.0270
(4.5)*	0.0414	0.0257	0.0276
(4.1)	0.0391	0.0273	0.0319
	MAE:		
(4.5)	0.0267	0.0123	0.0200
(4.5)*	0.0267	0.0133	0.0180
(4.1)	0.0327	0.0175	0.0243

Note: (4.5)* represents a Kalman filter in which (4.6) is replaced by an equation estimated by assuming that the errors are white noise.

that if we know pr_t at the time of forecasting, the RMSE decreases to 2.5 %. Having to predict pr_t using plan/expectation variables causes a minor increase in the RMSE to 2.7 %. Table 2 also contains the median absolute errors of the forecasts. Measured in them, the differences between the autoprojective and Kalman filter predictions appear larger than if we use RMSE as our precision measure. The corresponding precision measures obtained by using the whole observation period from 1972(2) to 1987(4) are also available. In that case the parameters have been estimated ignoring the structural change problem and dropping the assumption of MA(2) errors in (4.6). The autoprojective model is thus (4.1). A comparison shows that for the autoprojective forecasts there is no essential difference in RMSE whereas MAE of forecasts from (4.1) is somewhat higher than that of forecasts from (4.5). Nevertheless, omitting the observations from 1970s becomes more important when predictive business survey information is used. Finally, parameterizing the error structure in (4.6) only has a tiny effect on the precision of the forecasts.

To assess the significance of the differences in RMSE we tested the hypothesis that the mean square errors (MSE) of the forecasts with and without business survey information are equal against the alternative that the forecasts obtained using business survey information have the lower MSE of the two. This was done using the test in Granger and Newbold (1986, pp. 278-279). The p-values of the test statistic appear in Table 3. The business survey information does seem to increase the accuracy of the forecasts at least in the case of the short estimation period 1980(1)-1987(4).

Table 3. The p-values of the Granger and Newbold test for testing that the mean square error of forecasts from two models for output in Swedish ME industries are equal

Autoprojective (AP) model	Testing AP vs.	
	g_t known	g_t predicted
(4.5)	0.031	0.026
(4.5)*	0.0061	0.0078
(4.1)	0.047	0.093

Note: (4.5)* represents a Kalman filter in which (4.6) is replaced by an equation estimated by assuming that the errors are white noise.

5. FORECASTING THE OUTPUT OF FINNISH ME INDUSTRIES

5.1. Constructing the model

We begin with the autoprojective model for y_t estimated from the observations 1976(2)-1987(4). Its equation is

$$y_t = -\underset{(0.13)}{0.23}\, y_{t-1} + \underset{(0.13)}{0.52}\, y_{t-4} + \underset{(0.041)}{0.075} - \underset{(0.068)}{0.033}\, d_{1t} - \underset{(0.037)}{0.051}\, d_{2t} - \underset{(0.069)}{0.18}\, d_{3t} + \hat{u}_t \qquad (5.1)$$

$s_L = 0.0372$, LB(8-4) = 8.2 (0.081), ML(2) = 0.47 (0.79)

sk = 0.21, ek = 0.019, JB = 0.34 (0.84).

As before, we carried out the parameter constancy test discussed above. This was done having both an AR(4) model and the subset AR model (5.1) as a base. The results were somewhat sharper in the latter case and appear in Table 4. It is seen that while neither LM_2 nor LM_3 reject the null hypothesis at the 5 % level of significance, LM_1 does. The nested

Table 4. Results of testing the hypothesis of parameter constancy in the Finnish autoprojective model (5.1) against the alternative of smooth structural change using the tests in Lin and Teräsvirta (1991)

Model	Test	Value	p-value
(5.1)	LM_1	F(6,35) = 2.60	0.034
	LM_2	F(12,29) = 2.01	0.061
	LM_3	F(18,23) = 2.05	0.053
	$LM_{2\|3}$	F(6,23) = 1.62	0.19
	$LM_{1\|2}$	F(6,29) = 1.45	0.23
AR(4) + seasonals	LM_1	F(8,31) = 2.18	0.058
	LM_2	F(16,23) = 1.32	0.27
	LM_3	F(24,15) = 1.72	0.14
	$LM_{2\|3}$	F(8,15) = 1.81	0.15
	$LM_{1\|2}$	F(8,23) = 0.84	0.58

specification tests also indicate that monotonic change seems to be the relevant alternative; see Lin and Teräsvirta (1991) for discussion.

The estimation of the alternative yields

$$\begin{aligned} y_t = \underset{(0.013)}{0.29} - \underset{(0.017)}{0.29}\, d_{1t} - \underset{(0.023)}{0.30}\, d_{2t} - \underset{(0.020)}{0.51}\, d_{3t} \\ + (\underset{(0.20)}{-0.41}\, y_{t-1} - \underset{(0.063)}{0.14} + \underset{(0.11)}{0.19}\, d_{1t} + \underset{(0.065)}{0.26}\, d_{2t} + \underset{(0.093)}{0.13}\, d_{3t})\, \hat{F}_1(t^*) + \hat{u}_t \end{aligned} \qquad (5.2)$$

where

$$\hat{F}_1(t^*) = (1 + \exp\{\underset{(4.5)}{-9.5}\,(t^* - \underset{(0.059)}{0.52})\})^{-1} \qquad (5.3)$$

$s = 0.0334$, $s^2/s_L2 = 0.81$, $LB(4) = 4.2$, $ML(2) = 6.0\ (0.049)$, $sk = 0.35$, $ek = -0.41$, $JB = 1.3\ (0.52)$.

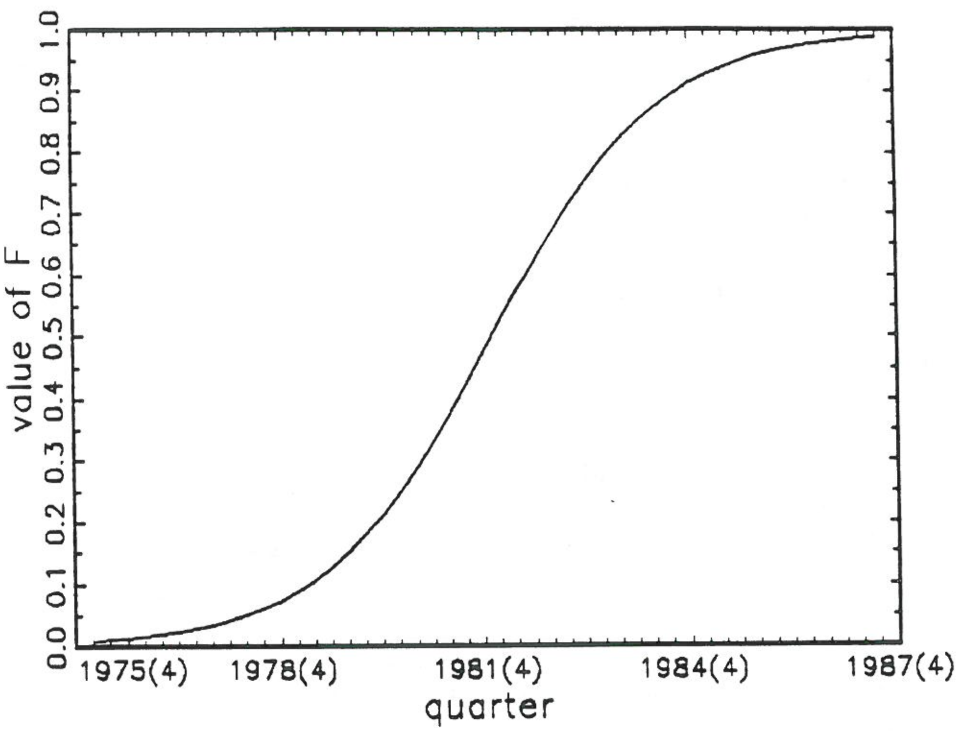
It is seen from (5.2) that the seasonality changes from purely deterministic towards more stochastic. The graph of transition function (5.3) is in Figure 4. The change in seasonality is smooth and extends over the whole estimation period. The regime corresponding to $\hat{F}_1 = 1$ equals

$$y_t = -0.41\, y_{t-1} + 0.15 - 0.10\, d_{1t} - 0.039\, d_{2t} - 0.38\, d_{3t} + \hat{u}_t \qquad (5.4)$$

Equation (5.4) will be used in post-sample one-step-ahead forecasting for quarters 1988(1) to 1990(4).

Next we have to consider the choice of variables in g_t. The two business survey variables that seem to contribute to the explanation of y_t are no^+_t, the share of firms whose incoming orders have increased (question 4a), and e^+_t, the share of firms whose exports have increased (question 8a). A surprising fact is that the output variables pr^+_t and pr^-_t play no role in this context. This result is strikingly different from the Swedish one and was checked in several ways. We have no plausible explanation as to why the business surveys of two countries are so drastically different in this respect. The exclusion of shipyards from the Swedish output series and the inclusion of basic metal industry in the Finnish one hardly offer a sufficient explanation.

Figure 4. Graph of estimated transition function (5.3)



Construct first a model for no^+_t. The residuals of a model with four lags of y_t, the intercept and the seasonal dummies are heavily autocorrelated at lags 1 and 2. This again suggests estimating the model with MA(2) errors. The estimated model is

$$no^+_t = \underset{(32)}{113}\, S_4y_t + \underset{(2.6)}{24} + \hat{v}_{1t} + \underset{(0.14)}{0.49}\, \hat{v}_{1,t-1} + \underset{(0.14)}{0.35}\, \hat{v}_{1,t-2} \qquad (5.5)$$

s = 8.06, LB(4) = 7.4, ML(2) = 1.2 (0.54), sk = 0.068,

ek = -0.56, JB = 0.66 (0.72)

where S_4y_t is the sum of the first four one-quarter differences, i.e., a four-quarter difference. The restriction that the coefficients of y_t and its first three lags are equal is supported by the data.

Because of the MA error structure we did not apply a parameter constancy test to (5.5). For prediction purposes, we assume parameter constancy.

The corresponding model for the increasing exports variable is

$$\underset{}{e^{+}_{t}} = \underset{(26)}{87\, S_4 y_t} + \underset{(2.9)}{31} - \underset{(3.8)}{11\, d_{1t}} - \underset{(3.7)}{3.1\, d_{2t}} - \underset{(3.7)}{16\, d_{3t}} + \hat{v}_{2t} \tag{5.6}$$

$s = 9.14$, $LB(4) = 7.8\ (0.10)$, $ML(2) = 2.8\ (0.25)$, $sk = 0.76$,

$ek = 0.25$, $JB = 4.6\ (0.10)$.

There seems to be first-order autocorrelation left in the residuals but the estimation of the model with MA(1) errors does not yield a significant MA coefficient estimate. Thus we shall use (5.6) for forecasting without further modification.

As above, to obtain one-step-ahead forecasts for y_t we need prediction equations for no^{+}_{t} and e^{+}_{t}. The equation for the former variable is

$$no^{+}_{t} = \underset{(0.12)}{0.58\, no^{+}_{t-1}} - \underset{(0.091)}{0.21\, be^{-}_{t|t-1}} + \underset{(5.7)}{18} + \hat{w}_{1t} \tag{5.7}$$

$s = 8.04$, $LB(4) = 4.5$, $ML(2) = 2.0\ (0.36)$, $sk = -0.39$, $ek = 0.47$, $JB = 1.6\ (0.44)$.

Equation (5.7) does not contain the expected order variable noe^{+}_{t}, although this variable constitutes a direct one-quarter-ahead forecast for no^{+}_{t}. Instead, the expectation variable that seems to predict new orders is $be^{-}_{t|t-1}$, the share of firms expecting deteriorating business prospects in the near future (question 15). This variable has no counterpart in the Swedish data set because the corresponding question does not appear in the Swedish business survey. An interesting fact is that $be^{+}_{t|t-1}$ does not seem to contain any predictive information whatsoever. A possible explanation is that there has been much less variation in $be^{+}_{t|t-1}$ than $be^{-}_{t|t-1}$. The proportion of firms reporting improving business prospects has generally remained rather low. Some recent results in Ilmakunnas (1990) also reflect the propensity of Finnish firms to report negative rather than positive expectations.

The predictive equation for e^{+}_{t} has the form

$$e^{+}_{t} = \underset{(0.13)}{0.32\, e^{+}_{t-1}} + \underset{(0.17)}{0.40\, ee^{+}_{t|t-1}} - \underset{(0.077)}{0.13\, be^{-}_{t|t-1}} + \underset{(8.7)}{16} - \underset{(4.5)}{6.9\, d_{1t}} + \underset{(3.8)}{2.2\, d_{2t}} - \underset{(5.2)}{11\, d_{3t}} + \hat{w}_{2t} \tag{5.8}$$

s = 8.27, LB(4) = 0.27, ML(2) = 5.3 (0.069),

sk = 0.17, ek = -0,41, JB = 0.56 (0.76).

The estimated equation contains the planned exports variable $ee^{+}_{t|t-1}$. The equation also indicates that the firms' expectations may not be completely free from seasonality. In contrast to (5.7), the planned/expected increase in exports appears in (5.8) while $be^{-}_{t|t-1}$ still has a role to play.

5.2. Forecasting with the model

The one-quarter-ahead forecasts for the quarters 1988(1) to 1990(4) are computed in the same way as the predictions of the Swedish output series. The production volume in the Finnish ME industries in 1990 experienced a downturn similar to that in the Swedish output.

Table 5. The root mean square errors (RMSE) and medians of absolute errors (MAE) for the forecasts of the output in Finnish ME industries in 1988(1)-1990(4) from autoprojective models (5.4) and (5.1) (AP) and the Kalman filter

Autoprojective model	Prediction method		
	AP	KF: g_t known	g_t predicted
	RMSE:		
(5.4)	0.0310	0.0225	0.0244
(5.4)*	0.0310	0.0243	0.0260
(5.1)	0.0340	0.0239	0.0269
	MAE:		
(5.4)	0.0175	0.0182	0.0080
(5.4)*	0.0175	0.0182	0.0088
(5.1)	0.0214	0.0194	0.0187

Note: (5.4)* represents a Kalman filter in which (5.5) is replaced by an equation estimated by assuming that the errors are white noise.

The RMSEs and MAEs of the forecasts are in Table 5. It contains predictions obtained both by ignoring structural change and using (5.1) as the autoprojective model and by using (5.4). It is seen that the RMSEs of the autoprojective forecasts are about the same size as the residual standard errors of the autoprojective models. Taking the structural change into account by using (5.4) causes a reduction of about 10 % in the RMSE compared to forecasts from (5.1). The gain from using business survey information seems about the same as that observed in connection with the Swedish series. In absolute terms, the RMSE are even smaller here, 2.2 % for g_t known and 2.4 % for g_t predicted. Table 6 contains the results of the Granger-Newbold MSE equality test. They leave little doubt that Finnish business survey information increases the precision of the forecasts based on AP models. In the case of predicted g_t, i.e., when (5.7) and (5.8) are applied, the evidence in favour of that claim is even stronger than in the Swedish case.

Table 6. The p-values of the Granger and Newbold test for testing that the mean square error of forecasts from two models for output in Finnish ME industries are equal

Autoprojective (AP) model	Testing AP model vs. KF:	
	g_t known	g_t predicted
(5.4)	0.013	0.0031
(5.4)*	0.026	0.0071
(5.1)	0.016	0.0064

Note: (5.4)* represents a Kalman filter in which (5.5) is replaced by an equation estimated by assuming that the errors are white noise.

6. CONCLUSIONS

The above results show that the information contained in the business survey is useful in predicting the next quarter's industrial output. In this respect they conform to the results in Teräsvirta (1986) that were, however, obtained by relatively short time series and by selecting the relevant variables from a large set of business survey variables and their lags. They were also restricted to data from a single country. The present approach, building upon the experiences from the previous one, does not relate the output indices directly to the plan/expectation variables. That is instead done by using the judgmental variables as a link. This is an important part of the present modelling strategy and works equally well for both countries.

An open question not touched upon here is whether the precision of the forecasts could be further enhanced by an appropriate transformation of the business survey data. The limited experiments conducted in connection with the present work did not give positive results. A more systematic investigation of the issue will be deferred to a later study.

In this paper we have assumed that the output figure for t-1 is available at the end of that quarter and used in forecasting the production volume at time t. In practice, that is not the case. A forecast for the output at t-1 can be obtained, however, by the Kalman filter using the judgmental business survey information for quarter t-1 as discussed in the paper. That forecast may then be used for obtaining a prediction for the output at quarter t. The autoprojective counterpart of this forecast is a prediction two quarters ahead.

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Appendix 1. The questions of the Swedish and Finnish business surveys used in this paper

A. SWEDEN

Note: The alternative answers are generally "greater than", "no change" and "less than". To question 2.03 they are "relatively large", "appropriate" and "too small". The respondents are asked to give "deviations from seasonal changes only" as answers.

1.01 Production volume this quarter compared to last quarter

1.02 Production capacity this quarter compared to last quarter

1.03 Prices of delivered products this quarter compared to last quarter (domestic prices)

1.04 Prices of delivered products this quarter compared to last quarter (export prices)

1.05 New orders this quarter compared to last quarter (domestic orders)

1.06 New orders this quarter compared to last quarter (export orders)

1.07 Value of purchases of raw materials and intermediate goods this quarter compared to last quarter

1.08 Delivery times for new orders this quarter compared to last quarter

2.03 Present order stock with respect to the level of production

2.04 Number of employees now compared to three months ago (blue collar)

2.05 Number of employees now compared to three months ago (white collar)

2.10 Inventories of raw materials and purchased intermediate goods now compared to three months ago

2.12 Inventories of finished products now compared to three months ago

3.01-08 As 1.01-1.08 but next quarter compared to this quarter

4.01 Number of employees three months from now compared to now (blue collar)

4.02 Number of employees three months from now compared to now (white collar)

4.03 Inventories of raw materials and purchased intermediate goods three months from now compared to now

4.04 Inventories of finished products three months from now compared to now

B. FINLAND

Note: The alternative answers are generally "greater than", "no change" and "less than". To question 3b they are "yes" and "no", to question 5 "large", "normal" and "small" and to question 15 "better", "the same" and "worse", respectively. The limits of the "no change" category are ± 2 %. The respondents are asked to give "seasonally adjusted" answers.

Question:

1a	Production volume this quarter compared to previous quarter
1b	Production volume this quarter compared to the same quarter last year
2a	Production volume next quarter compared to this quarter
3b	Idle production capacity six months from now
4a	Amount of new orders this quarter compared to previous quarter
4b	Amount of new orders next quarter compared to this quarter
5	Present order stock
7a	Number of employees now compared to three months ago
7c	Number of employees after next three months compared to now
8a	Exports volume this quarter compared to previous quarter
8c	Exports volume next quarter compared to this quarter
15	Business prospects in the near future

SAMMANFATTNING

Konjunkturbarometern, isynnerhet de aggregerade svarsandelarna, antas allmänt innehålla nyttig information om industriproduktionens framtida volym. Hur denna information skall utnyttjas för att få fram pålitliga kvantitativa prognoser för industriproduktionens volym ett kvartal framåt har däremot varit mindre klart. De inte alltför många rapporterade försöken för att åstadkomma detta kan anses vara mer eller mindre misslyckade. Denna uppsats återgår till problemet och anlitar då en statistisk modellram, det såkallade Kalmanfiltret, för att kombinera tillgänglig information från Konjunkturbarometern med den information, som finns i industriproduktionsseriens egen historia. Som data användes verkstadsindustrins volymserier i Sverige och Finland. Med statistiska beslutsregler väljer man ur barometern de variabler (frågor) som är mest relevanta för detta prognosproblem och använder dem som barometerinformation i prognosmodellerna. Man använder sig dock inte av nettotal, som många hittills gjort, utan behandlar andelarna av "större" och "mindre" svar som skilda variabler. En annan anmärkningsvärd detalj är, att de förväntnings/planvariabler, som användes i denna studie, inte kopplas ihop direkt med volymvariabeln. Istället sker kopplingen indirekt. Man definierar ett samband mellan plan- och realisationsvariablerna och ett annat mellan de sistnämnda och volymvariabeln. I alla parameterskattningar använder man tidsserieinformation till och med sista kvartalet 1987. De färskaste observationerna från 1988(1) framåt utnyttjas för att undersöka hur väl prognostekniken fungerar och om prognosfelet blir mindre än hos prognoser, som enbart baserar sig på produktionsvolymseriens egen historia. Det visar sig, att den föreslagna statistiska modellen är framgångsrik både för den svenska och den finska verkstadsindustrin. Det genomsnittliga prognosfelet för 1988(1)-1990(4), när man gör prognoser på produktionsvolymen ett kvartal framåt blir mindre med data från Konjunkturbarometern än utan denna information. Skillnaden är statistiskt signifikant.

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