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FORECASTING THE OUTPUT OF THE FINNISH METAL INDUSTRY USING BUSINESS SURVEY DATA*

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Forecasting the output of the Finnish metal industry using business survey data

Abstract. In this paper short-term forecasting of the output of the Finnish metal industry using business survey data is considered. Models for predicting the output are based on several business survey variables, not only those concerning the actual and expected output. The weighted relative shares of "increases" and "decreases" answers are treated as separate variables. Since the number of potential predictors is large as compared to the number of observations and the risk of finding spurious relationships thus considerable, a hierarchic statistical model building procedure is suggested and applied. For the same reasons, the prediction performance of the specified and estimated models is checked outside the period of estimation. The results indicate that business survey variables contain useful information about the future output of the metal industry. The models based on business survey data yield more accurate predictions than pure autoprojective models.

Keywords: autoprojective model, business survey data, causality testing, model selection, predictive checks.

1. Introduction

The quantitative use of the results of business surveys for forecasting has been discussed for several decades. A typical business survey question has three alternative answers: "increases", "no change", and "decreases". The bounds of the "no change" interval may vary from one survey to another or may not even be indicated in the questionnaire at all. The answers of the firms are aggregated into relative shares by weighting them for instance by the turnover or the number of employees. By assuming that the weighted change represented by a survey variable is normally distributed and the limits of the "no change" interval are known or can be estimated, the categorical data may be quantified, see Theil (1952). This idea has been widely used for quantifying price expectations, cf. e.g. Knöbl (1974), Carlson and Parkin (1975), and de Menil and Bhalla (1975), but it has been applied to output expectations as well, cf. Batchelor (1982). In another variant of the same technique, a quantified expectation of output is obtained by first quantifying the aggregated response on the question concerning the actual output of the firm. An example of this approach is Abou and Szpiro (1984). In their paper, the underlying normality assumption has been replaced by a log-normality one.

Another way of representing aggregated information in the business surveys are the balances, i.e., simply the differences between the relative shares of "increases" and "decreases" answers. The temporally smoothed balances have routinely been used as elements in economic indicators constructed for predicting turning points in the business cycle; for a discussion of such indicators see e.g. Granger (1980, Chapter 7) and Klein and Moore (1983). Recently, the use of balances in econometric models and quantitative forecasting has also been considered; cf. e.g. Biørn (1982), Devilliers (1983) and Dramais (1983). Naggl (1983) reports on an econometric short-term forecasting model of the West-German economy containing 60 anticipations variables from business surveys, all of them balances.

This paper differs from the above-mentioned ones in several respects. First, a maintained hypothesis is that not only the answers to questions concerning production may contain information useful in predicting the output. It is assumed that other questions may also have predictive value. Second, balances are not accepted as the most convenient form of representing aggregated answers. In fact, the results indicate that it is much better to treat the relative shares of "increases" and "decreases" as separate variables. The firms may sometimes be less reluctant and more truthful in anticipating a decrease, say, than an increase. The share of "decreases" is then a more sensitive and reliable leading indicator than the share of "increases" or the balance. Batchelor (1982) offers some possible reasons for this kind of behaviour. Third, the purpose of this research is to build short-term prediction models for the output of the Finnish metal industry and not merely to quantify the answers according to a rule fixed in advance.[1)]

The most useful business survey variables in forecasting the output of the Finnish metal industry are an anticipated change in idle production capacity of the firms, realised decreases in their inventories and exports, and an anticipated deterioration of the business climate of the branch. A model based on these variables predicts the production volume by far more accurately than the autoprojective models based on the past values of the volume only. A model based exclusively on the anticipated increase of output also does less well than the model mentioned above.

2. Data

The data used in this work originate from the business surveys of the Confederation of the Finnish Industries (CFI, 1973-83) and cover the quarters 1973(i) - 1983(iv). In the beginning of 1973 the number of firms participating in the survey was increased and the questionnaire completed by some new questions. The earlier observations have been excluded from the data set as less reliable. The predictand in the models will be the logarithmic production volume of the metal industry, subsequently denoted by y_t at time t.

The list of questions is in Appendix 1. Certain questions of the survey have been omitted from consideration *a priori*. Changes in investments (other than inventories) are rather loosely related to the production in the short run and are therefore not considered. Changes in the number of employees rather lag behind changes in output than lead them; they are omitted as well.

As was already mentioned, there are generally three alternative answers to each question. An exception is Question 3 to which the possible answers are simply "yes" and "no". The limits of the "no change" interval in the other answers are indicated in the questionnaire and are $\pm$ 2 per cent. The respondents are asked to provide "seasonally adjusted" answers.

Figure 1 depicts the four-quarter logarithmic changes in the production volume of the metal industry from 1973(i) till 1983(iv). It also contains the balances of the answers to the question 1B concerning the four-quarter change in the firms' volume of production. The time series of the four-quarter volume changes fluctuates more than that of the balances. For instance, in the first two quarters of 1982 there is a boomlet in production without any equivalent peak in the production changes as reported by the firms. Either the measurement scale of the answers is too crude or the coverage of the survey insufficient for capturing all short-term movements in the output. This should obviously advise us to be rather cautious in our demands for accuracy in short-term predictions from models based exclusively on business survey data.

3. Model selection problem

We want to find out whether and how information published in CFI (1973-83) can be utilized in making quantitative short-term forecasts for the production volume of the Finnish metal industry. An important feature of the problem is that the number of potential business survey variables is large as compared to that of observations. This is so partially because the shares of "increases" and "decreases" answers are separate variables. Thus the selection of variables into models becomes a crucial problem in this work. There are also two other reasons enhancing the importance of model selection:

(i) There is neither appropriate theory nor adequate previous experience to tell us *a priori* which of the remaining survey variables should not be included in prediction models.

(ii) The models will be dynamic, and the lag structures of neither the dependent nor the independent variables can be assumed to be completely specified in advance.

There is a risk of overfitting and finding spurious relationships in this situation. Model building has to be careful and systematic enough to avoid spurious models. Straightforward stepwise regression procedures are not to be recommended. Instead, we have devised a hierarchic model selection procedure which consists of five different phases. They are the following:

(i) Choice of the family of prediction functions and linear transformation of the logarithmic output.

(ii) Omission of predictors not correlating with the output and specification of the significant lags of each useful predictor one predictor at a time.

(iii) Construction of models with remaining related[2] predictors and lags, and omission of redundant predictors and lags.

(iv) Combination of remaining variables and lags into a single model, and omission of redundant predictors and lags.

(v) Checking of the forecasting accuracy of the final model outside the period of estimation.

Next we shall describe these phases in more detail and discuss the results of the procedure.

4. Transforming the dependent variable

The problem of choosing the form of the prediction function is solved by settling for models which are linear in parameters. Two factors have influenced this decision. First, the number of degrees of freedom is too low so as to allow us to specify elaborate nonlinear models and fit them to data. Second, the predictors are mainly trichotomous variables. This scale of measurements restricts the model builder to simple structures.

Another problem is that the relative shares used as predictors vary between zero and one. On the other hand, the output in the Finnish metal industry is positively trending during the observation period. A transformation of the logarithmic production volume has to be considered in order to render the dependent variable compatible with the potential independent variables.

This problem may be handled by starting from the the survey variables. The majority of them are based on questions concerning the direction of an actual or anticipated change between two subsequent quarters. Thus they resemble first differences. It would be natural to difference the predictand once so that both sides of the linear equation would be in first differences. However, there is also a question (6B) asking the firms to compare the present inventories to those of four quarters ago. The last question (11) does not specify the time span of the change accurately, see Appendix 1.

Another possibility would be to start by trying to stationarise the dependent variable by differencing. Figure 2 shows that then the first differences do not work. The autocorrelation function (acf) of the four-quarter differences resembles more an acf of a stationary series than that of first differences. Furthermore, the four-quarter differences have an appreciably lower standard deviation of the two series. Four-term moving sums of most survey variables are kind of four-quarter differences because the variables themselves resemble first differences. Moving sums would thus be a way of reducing the number of parameters in the model when four-quarter differences of the volume are used.

The choice between the two differences also depends on the properties of the disturbances of the models and remains an empirical question. Both alternatives have been experimented with during the course of the work.

5. Omitting redundant variables

In view of the large amount of possible variables, the next phase of the model building consists of reducing the number of potential predictors. Survey variables not correlated with the output should be found and excluded from further consideration as early as possible. Various methods are available for this purpose. One possibility are the tests of independence between the output and survey variables; for a time domain test see Haugh (1976). Another approach is the model-based method of Sims (1972) which tests both complete independence and the direction of predictability.[3)]

A third alternative is model comparison based upon a suitable model selection criterion. In fact, the technique of Sims (1972) may be regarded as a special case of this approach. The idea is as follows. A prediction model for the volume is constructed using first four (or five) lags of a single survey variable together with lags of the dependent variable. An optimal combination of lags is selected by a model selection criterion. The resulting single survey variable (SSV) model is then compared with the best autoprojective model of the differenced volume. This comparison is also carried out by a model selection criterion: we have applied SBIC (Schwarz, 1978) throughout. SBIC has the optimal property that it asymptotically selects the true model if it exists among the alternatives. However, it also often performs well in small samples as compared to many other criteria like the unbiased residual variance or the AIC, cf. Geweke and Meese (1981) and Teräsvirta and Mellin (1983).

The procedure is as follows: Suppose the best autoprojective model has a smaller SBIC value than the SSV model. Then the survey variable in question is omitted from further consideration. This comparison is repeated separately for each survey variable. Suppose the autoprojective model is nested in the SSV model. Then the minimum SBIC rule is equivalent to an F test of the hypothesis that the coefficients of the relevant lags of the survey variable equal zero, cf. e.g. Teräsvirta and Mellin (1984). Yet, due to lags of the differenced volume as predictors, the corresponding F statistic has only an asymptotic F distribution under the null hypothesis. In the non-nested case, the connection between the minimum SBIC rule and the F test ceases to exist.

6. First results

Of the three alternative methods of reducing the number of variables mentioned above, the last one has mainly been applied in this work. However, for a general interest the Haugh test was also applied but the results have not been used for model building purposes. Since the time series were short, we replaced the original test statistic by the variant suggested by Ljung and Box (1978).

The range of cross correlations of the prewhitened series (k_1,k_2) included in the statistic was generally (-4,4), except for a couple of cases where $(k_1,k_2) = (-5,5)$. The choice of (k_1,k_2) is not a straightforward matter; for a good discussion see Saikkonen (1983).

The significance level applied in testing the independence hypothesis was as high as 0.2. For all order stock variables and variables $M6B^-$, $M8B^+$, $M8C^+$ and $M11^-$ the null hypothesis cannot be rejected when $(k_1,k_2) = (-4,4)$.[4)] When $(k_1,k_2) = (-4,-1)$ the predictability of the volume by survey variables is tested for. In that case there is, however, among the above variables evidence of a relationship between the output and variables $M4B^+$, $M4B^-$, $M8B^+$ and $M11^-$.

The decisions to omit variables have been based on the comparisons between autoprojective and SSV models. They have been specified and estimated for both the first (y_t) and the four-quarter differences $(\nabla_4 y_t)$. All the models have been specified to have white noise errors. The method of estimation has then been the ordinary least squares and the validity of the white noise assumption has been checked afterwards. For this purpose a LM type statistic with an asymptotic χ^2 distribution under the hypothesis of no autocorrelation was used, cf. Harvey (1981, p. 276-7).

The estimated autoprojective models are in Appendix 2. The efficient estimation period was 1974(i) - 1981(iv). Note that in the model for the first differences of the volume, dummy variables are needed to take care of the deterministic part of the seasonal variation visible in the acf (Figure 2). Up to four lags of the dependent and independent variables are allowed for in the SSV models. Empirical results for these models when the dependent variable has been the first difference of the volume can be found in Table 1. The columns of the table contain the significant lags or the last remaining lag of the survey variable, standard deviations of the residuals, the SBIC value for the best SSV model and the value of the LM statistic testing autocorrelation up to the fourth order (and the corresponding value of the cumulative distribution function under the null hypothesis of no autocorrelation). The last column gives the values of the root means square error when the model predicts the four quarterly values of output in 1982.

In passing we may notice that the conclusions concerning predictability are quite different from the results of the independence tests. Judged by SBIC, all order stock variables, $M4A^+$, $M4A^-$, $M4B^+$ and $M4B^-$, do have predictive power. One the other hand, all export variables except $M8A^-$ seem to be useless in predicting the production volume of the metal industry. $M6A^-$ (decreasing inventories) is not a useful variable either: according to the independence tests its relationship with the volume is mainly contemporaneous. It may appear surprising that the anticipated decrease in the volume, $M2A^-$, does not contribute significantly to the fit of the model. A middle ("no change") category which is symmetric around zero may not be a very fortunate choice when the volume has a clearly positive trend. Its counterpart $M2A^+$ is a more promising predictor of the two. We do not report results on building models for $\nabla_4 y_t$ as the models were less successful than those built for ∇y_t.

There are several reasons for the discrepancy between the results of the independence tests and the model-based approach. The alternative hypothesis in independence tests is very general, and the power of the test may vary considerably in different parts of the set of alternatives. In the SSV models, the set of alternatives is rather limited. In fact, it is even dependent of an outcome of a model selection procedure: unnecessary lags are eliminated before comparing the resulting model to the autoprojective one. Another noteworthy point is that the true significance levels of the procedures are not equal so that the procedures are not directly comparable.

If it were our primary task just to investigate relationships between the variables of the CFI business survey and the output of the metal industry, these conflicting outcomes could be rather confusing. However, we have insisted on specifying and estimating prediction models for the production volume. Therefore, it is natural to build on the results of the model-based approach. This means excluding from further considerations those variables and lags which have not significantly contributed to the estimated SSV models.

7. Final results

The purpose of the specification and estimation of SSV models was twofold: (i) to find and exclude the unimportant predictors and (ii) to fix the lag structure of each predictor. The set of alternative variables is reduced further by adopting a hierarchic approach. All the remaining variables and lags will not immediately be combined into a single model. Instead, individual models are built using sets of related predictors with the lag structures from SSV models. This is stage (iii) of the model building procedure. Examples of such sets are the order stock variables or the set of remaining inventories variables $M6A^+$, $M6B^+$ and $M6B^-$. After a first estimation of such a model, a number of redundant lags of these variables may again be deleted by applying SBIC. This step is followed by an estimation of the parameters of the respecified model.

The remaining variables and lags will finally be brought together in one model. Like the earlier models, it is originally specified to include a full set of lags (five) of the independent variable. Their number as well as that of lagged predictors is then reduced by omitting the unimportant lags. To conserve space, the details of the hierarchic specification procedure are not discussed. It can be mentioned, however, that the specification of the lag structure may also involve other types of reductions in the number of lags than mere omissions of certain lags. For instance, differencing a survey variable may come into question as a way of replacing two subsequent lags by a single variable.

We proceed to the final model for the first differences of the volume. Its estimated equation (the efficient estimation period is 1974(i) - 1981(iv)) is

$$
\begin{aligned}
\nabla y_t = {} & \underset{(0.016)}{0.26} - \underset{(0.040)}{0.29} d_t^1 - \underset{(0.025)}{0.094} d_t^2 - \underset{(0.034)}{0.32} d_t^3 - \underset{(0.071)}{0.43} \nabla y_{t-1} - \underset{(0.063)}{0.64} \nabla y_{t-2} \\
& - \underset{(0.075)}{0.34} \nabla y_{t-3} + \underset{(0.071)}{0.17} \nabla y_{t-5} - \underset{(0.022)}{0.13} \nabla M3B_{t-3} + \underset{(0.028)}{0.16} \nabla M6B_{t-1}^- \\
& - \underset{(0.023)}{0.13} M8A_{t-4}^- - \underset{(0.012)}{0.10} M11_{t-2}^- + e_t
\end{aligned}
\tag{7.1}
$$

$s = 0.013$, $df = 20$, $LM(4) = 0.96\ (0.08)$, $SBIC = -251.0$

where s is the unbiased standard deviation of residuals and df is the number of degrees of freedom. Furthermore, LM(k) is an LM test statistic for testing residual autocorrelation up to order k mentioned above, with the corresponding cdf value under the null hypothesis in parentheses. Finally, d_t^j is a seasonal dummy variable which takes value one at the jth quarter and zero elsewhere. Model (7.1) contains quite a few parameters and the number of degrees of freedom is only 20. The risk of overfitting is obvious; we shall discuss the predictive performance of (7.1) and other models in the next section.

The residuals bear no trace of autocorrelation in disturbances, and the residual standard deviation is very low as compared to the corresponding values of the SSV models. It may be interesting to notice that the share of an anticipated increase in production, $M2A^+$, is not included in (7.1). The information it carries about future output is obviously already contained in other business survey variables. On the other hand, a more general anticipatory variable

$M11^-$, the deteriorating future prospects in the branch, is present in (7.1). The decreases in inventories and idle capacity also seem important in predicting the volume. Variable $M6B^-$ is a four-quarter difference; it is therefore rather natural that it appears differenced in the model. The same is true for M3B which does not as such indicate a change but rather a level. As a curiosity note that the independence between $M6B^-$ and the volume of production could be rejected by using the Haugh cross correlation test and significance level 0.2.

For comparison, we have specified and estimated another model by just choosing three best individual predictors of ∇y_t. The criterion has been their ability to predict the quarters of the year 1982, as measured by the RMSE. They are $M2A^+$, M3B and $M8B^+$, see Table 1. After deleting the redundant $M8B^+$ the estimated model (the efficient estimation period is 1974(i) - 1981(iv)) is

$$\begin{aligned}\nabla y_t = {} & \underset{(0.035)}{0.077} - \underset{(0.071)}{0.14}d_t^1 - \underset{(0.068)}{0.17}d_t^2 - \underset{(0.15)}{0.41}\nabla y_{t-1} - \underset{(0.12)}{0.56}\nabla y_{t-2} - \underset{(0.14)}{0.29}\nabla y_{t-3} \\ & - \underset{(0.11)}{0.30}\, y_{t-4} + \underset{(0.043)}{0.10}M2A_{t-2}^+ - \underset{(0.046)}{0.14}\, M3B_{t-3} + e_t \end{aligned} \tag{7.2}$$

$s = 0.025$, $df = 23$, $LM(4) = 5.17$ (0.73), SBIC = -216.1.

Model (7.2) does not fit the data as well as (7.1). Nevertheless, if its predictive properties are better than those of (7.1), then the hierarchical model building approach is apparently not worth very much. In (7.2), the coefficient estimate of $M2A_{t-2}$ is significant. Note, however, the lag length which is two quarters, one more than expected. Since M3B appears lagged by three quarters, (7.2) can be used for forecasting two quarters ahead.

8. Checking the predictive performance

To reduce the risk of spurious relationships, it is important to check the predictive power of the estimated models. The autoprojective models may conveniently serve as a yardstick here. Any business survey variable model has to predict better than the autoprojective models in order to be deemed useful. The estimated autoprojective models are in Appendix 2.

The checking is performed by predicting first the quarters of 1982 using the models estimated till 1981(iv) and observed values of survey variables in 1982. The check is completed by taking the same model, re-estimating the parameters using data till 1980(iv) (and 1982(iv)) and forecasting the quarters of 1981 (and 1983). The results are summarised in Table 2 by three different statistics. They are the median of the prediction errors (MPE) and the absolute prediction errors (MAPE), and the root mean square error (RMSE) of prediction. The MPE is an indicator of bias in the forecasts while the other two describe the dispersion of predictions around the realized output. Of these, MAPE gives less weight to large prediction errors and completes the picture conveyed by RMSE.

In Table 2 it is seen that prediction biases both in model (7.1) and (7.2) are small. Although there are large short-term fluctuations in the volume in 1981-1983, its trend has not changed very much. Thus the inherent weakness of autoprojective models in predicting turning-points does not become evident. For comparison, Table 2 also contains predictions from a model containing only the variable $M2A^{+}$. The equation of the estimated model (A2.3) is in Appendix 2.

The two autoprojective models have rather similar predictive power. Measured in RMSE, (A2.1) is consistently slightly more accurate than (A2.2) but in terms of MAPE the systematic difference disappears. Model (A2.3) fails in 1983 which has been an easy year to predict by autoprojective models. Model (7.1) is clearly best: the predictions are more accurate each year than those from (7.2) or (A2.3).

The autoprojective models do have a lower RMSE in 1983 than (7.1). This is due to a large prediction error of model (7.1) on 1983(ii). In fact, all models underestimate the volume of the second quarter of 1983. The other quarters are very well forecast by (7.1) as indicated by the MAPE. An obvious conclusion is that the hierarchic model building procedure has paid off.

The results from models with $\nabla_4 y_t$ as the dependent variable are not as good as the previous ones and their properties are omitted from discussion here.

9. On prediction accuracy

Summing up, an average RMSE of prediction from model (7.1) is about two and a half per cent. It is about 0.01 less than the corresponding figure (0.035) of an autoprojective model so that the gain is substantial. It is doubtful whether this figure can be decreased very much by additional fine-tuning of the model. Two things speak against large improvements. First, the variables are mainly based on trichotomous answers. The inaccuracy of the measurement scale is itself a source of error and affects the outcome of the model building procedure. Second, if the firms for some reason seriously fail in anticipating their own future, this is reflected in the predictions. There is no reason to expect that not to happen every now and then. The model building procedure has no doubt detected and deleted those anticipatory variables which are based on systematically inaccurate answers. Nevertheless, random inaccuracies, for instance due to rapidly changing circumstances, may always occur in variables like $M11^{-}$. They may lead to single large prediction errors showing in the RMSE of prediction. However, even as things are now, business survey variables appear to be a useful source of information in forecasting the output of the Finnish metal industry.

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Footnotes

1) This research is a part of a larger project aiming at predicting the total output of the Finnish industries using business survey data.

2) This concept will be explained later.

3) It has been suggested that the term "causality" often used in this context be replaced by "predictability". The suggestion has been followed as "causality" is an unfortunate concept here; the business survey variables do not cause industrial production but may help to predict it.

4) Superscript "+" indicates that the variable is a relative share of increases, whereas "-" corresponds to a relative share of decreases. M3A and M3B are relative shares of "yes" answers.

Appendix 1. The questions of the Finnish business survey used in this paper

1A	volume of production as compared to the preceding quarter
1B	volume of production as compared to four quarters ago
2A	anticipated volume of production next quarter as compared to now
3A	idle production capacity now
3B	idle production capacity six months from now
4A	order stock as compared to the preceding quarter
4B	anticipated order stock next quarter as compared to now
6A	inventories as compared to the preceding quarter
6B	inventories as compared to four quarters ago
8A	volume of exports as compared to the preceding quarter
8B	anticipated volume of exports next quarter as compared to now
8C	anticipated volume of exports two quarters ahead as compared to the next quarter
11	future economic prospects (business climate) of the branch

Appendix 2. Estimated equations of two autoprojective models and a model using M2A$^+$ as the only predictor

The efficient estimation period of these models is 1974(i)-1981(iv).

Autoprojective models:

$$\nabla_4 y_t = \underset{(0.0087)}{0.013} + \underset{(0.11)}{0.76}\ \nabla_4 y_{t-1} + e_t \tag{A2.1}$$

s = 0.035, LM(4) = 1.69 (0.22), SBIC = -210.3,

and

$$\nabla y_t = \underset{(0.046)}{0.14} - \underset{(0.046)}{0.15} d_t^1 - \underset{(0.050)}{0.13} d_t^2 - \underset{(0.082)}{0.25} d_t^3 + \underset{(0.13)}{0.50}\ \nabla y_{t-4} + e_t \tag{A2.2}$$

s = 0.032, LM(4) = 3.30 (0.49), SBIC = -209.1.

Model with M2A$^+$ as the only predictor:

$$\nabla y_t = -\underset{(0.031)}{0.074} d_t^3 - \underset{(0.13)}{0.64}\ \nabla y_{t-1} - \underset{(0.11)}{0.45}\ \nabla y_{t-2} - \underset{(0.12)}{0.42}\ \nabla y_{t-3}$$

$$+ \underset{(0.12)}{0.35}\ \nabla y_{t-4} + \underset{(0.038)}{0.18} M2A^+_{t-2} + e_t \tag{A2.3}$$

s = 0.027, LM(4) = 2.67 (0.39), SBIC = - 217.1.

Table 1. Statistics for SSV models: Residual standard deviations (s), minimum SBIC values, residual autocorrelation tests and RMSE values for 1982

Predictor	Lags	s	SBIC	LM(4)	rmse(e_t^*)
$M2A^+$	2	0.027	-217.1	2.67 (0.39)	0.025
$M2A^-$	1*	0.032	-205.6	3.52 (0.52)	0.042
M3A	1,2,4	0.025	-218.7	1.36 (0.15)	0.051
M3B	3,4	0.027	-216.0	4.38 (0.64)	0.022
$M4A^+$	1	0.024	-226.3	6.50 (0.84)	0.036
$M4A^-$	1	0.026	-214.7	5.99 (0.80)	0.040
$M4B^+$	1	0.030	-213.7	2.24 (0.31)	0.036
$M4B^-$	1	0.026	-217.3	0.58 (0.04)	0.038
$M6A^+$	3	0.031	-209.2	5.47 (0.76)	0.052
$M6A^-$	2*	0.031	-207.9	4.53 (0.66)	0.044
$M6B^+$	4	0.028	-209.3	3.81 (0.57)	0.041
$M6B^-$	1,2,4	0.026	-216.8	8.12 (0.91)	0.032
$M8A^+$	2*	0.031	-208.1	7.76 (0.90)	0.043
$M8A^-$	2	0.030	-209.2	2.01 (0.37)	0.041
$M8B^+$	3*	0.031	-207.7	4.19 (0.62)	0.023
$M8B^-$	1*	0.032	-206.5	3.04 (0.39)	0.042
$M8C^+$	3*	0.032	-206.8	4.79 (0.69)	0.034
$M8C^-$	2*	0.031	-208.6	3.40 (0.51)	0.043
$M11^+$	2*	0.031	-208.8	3.36 (0.50)	0.029
$M11^-$	2	0.026	-215.8	3.09 (0.46)	0.031
Model (A2.2)		0.032	-209.0	3.30 (0.49)	0.043

* SBIC value of the autoprojective model is smaller than the corresponding value of the SSV model.

Table 2. Medians, absolute medians and RMSE's of prediction errors e_t^* for some models of ∇y_t in 1981, 1982 and 1983

Model	$\mathrm{med}(e_t^*)$			$\mathrm{med}\lvert e_t^*\rvert$			$\mathrm{rmse}(e_t^*)$		
	1981	1982	1983	1981	1982	1983	1981	1982	1983
(7.1)	-0.017	0.007	-0.002	0.017	0.010	0.010	0.023	0.019	0.030
(7.2)	0.006	0.015	0.007	0.028	0.015	0.018	0.038	0.025	0.030
(A2.1)	-0.023	-0.011	0.002	0.023	0.035	0.022	0.040	0.041	0.022
(A2.2)	-0.014	-0.031	0.005	0.020	0.031	0.027	0.041	0.043	0.026
(A2.3)	-0.011	0.008	0.028	0.030	0.024	0.028	0.041	0.024	0.041

Figure 1. Four-quarter differences $\nabla_4 y_t$ and balances M1B in 1973(i)-1983(iv)

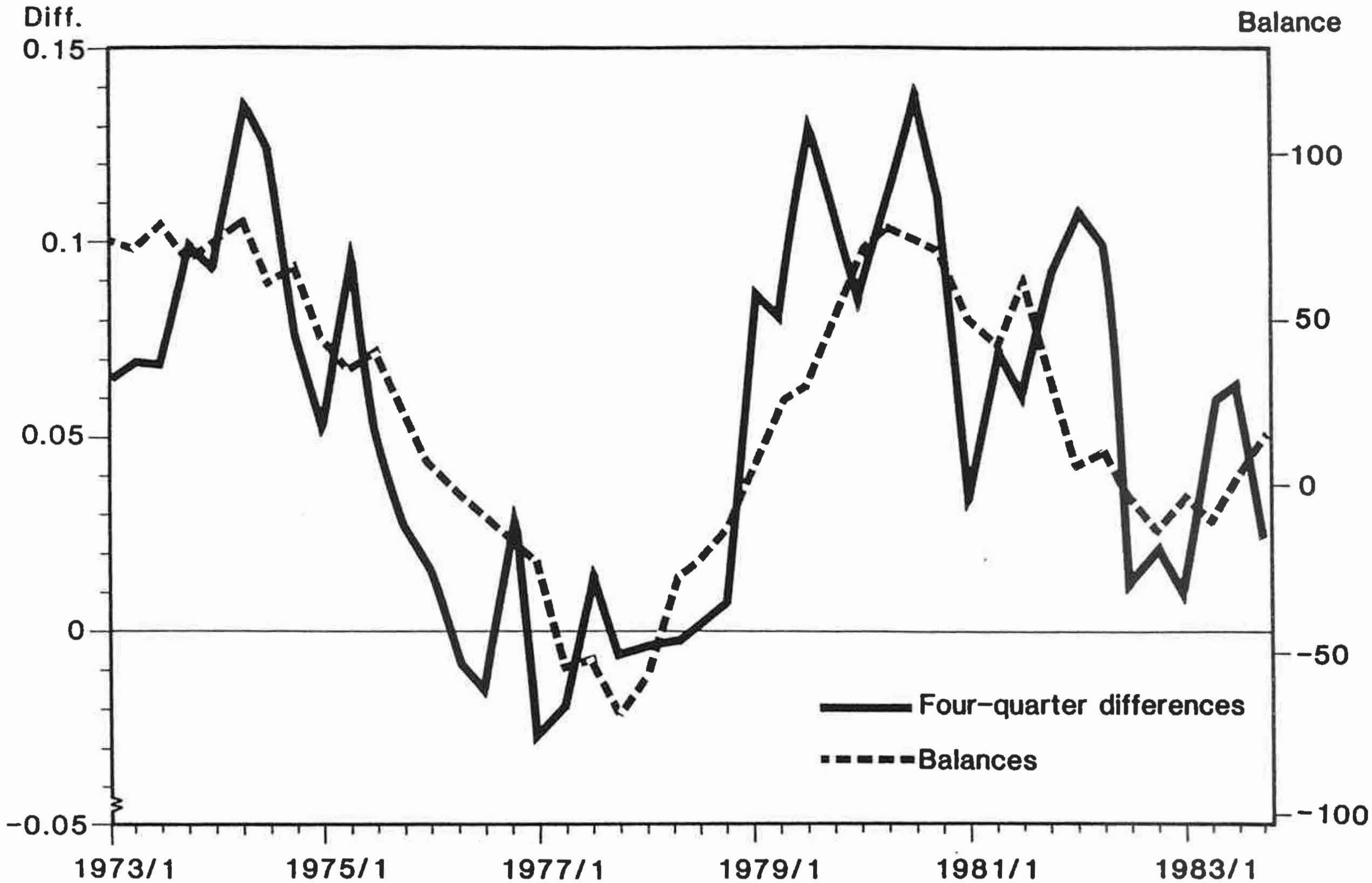

Figure 2. The autocorrelation functions of the differences ∇y_t and $\nabla_4 y_t$ of the logarithmic production volume