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Abstract

Information from the business tendency survey is used in a Kalman filter to forecast the Swedish business cycle, as represented by industrial production, net value added, exports of manufactured goods and the numbers of hours worked. Two kinds of forecasts are considered. First, by using the answers of the business survey, the values of the business cycle variables for the first unobserved quarter is forecasted (a coincident forecast). Secondly, by introducing the *predictive* information of the survey answers, forecasts are made of the variables for the next quarter. The results show that both some ex post and some ex ante answers of the business survey contain information that can improve the precision of the forecasts as well as the ability to detect turning points in comparison to results obtained using an autoprojective model.

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1. Introduction

Forecasts are dependent upon the access of reliable statistical data illustrating the outcome up to or as close to the specific period as possible. One task of the National Institute of Economic Research (NIER) is to contribute to the quality improvement of the economic statistics.

In forecasting the Swedish business cycle, manufacturing statistics is one of the main sources. Fortunately, in Sweden there is a rich variety of data on industrial activity. The National Central Bureau of Statistics (Swedish acronym: SCB) reports industrial production in the form of an index (Swedish acronym: PVI) and as net value added (NVA) in the National Accounts (NA). The value of exports of manufactured goods consists of the exports reported by the customs and the most important indicator concerning employment is the Labour Force Survey (AKU, acronym in Swedish) together with the Industrial Statistics (IS). The drawbacks of these quantitative statistics are twofold: The first of the preliminary versions is published 2-3 months after the period has expired, and the discrepancy between the final version, published 2-3 years after the actual period, and the first preliminary version can be substantial.

Another source that can be used for illustrating the direction of the industrial cycle is the *Business Tendency Survey* (BTS). Its big advantage as an indicator is that it covers a wide range of variables, it is not revised and that the results from the survey are available in the proper quarter and it contains expectations. A special feature of the BTS is that it only indicates the general perception among entrepreneurs concerning tendencies. The problem is how this information can systematically be transformed into a quantitative form and introduced into the forecasting procedures at the NIER. Henceforth, in contrast to the "qualitative" BTS data, the statistical time series will jointly be called "quantitative data".

The Economic Council has initiated several studies on the Swedish BTS. In Bergström (1992) it is shown that the information of the BTS can be used to make short-term forecasts. Cristoffersson et al. (1992) find a relationship between the BTS series "volume of production" and PVI on the business cycles frequencies. Öller (1992) discusses which of the alternative answers of the BTS, or tranformations of them, extracts the information contained in the BTS, especially at turning points. Finally, Rahiala and Teräsvirta (1993) successfully quantify BTS data using a Kalman filter approach. The work presented in this paper is a direct continuation of the approach of Rahiala and Teräsvirta. It is extended to cover more variables and puts more emphasis on *coincident forecasts*. Using BTS data, we construct state-space models, alias the Kalman Filter (KF), see eg. Harvey (1989), that produce estimates of the yet unobserved coincident quarter and forecasts of the next quarter. The study is more focussed on the present quarter.

In order to convey the results and the use of the models to a broader circle of users, it has been judged necessary to put a great effort into building user-friendly models. The models are programmed in GAUSS.

Two aspects of forecast accuracy have been studied:

1. How close are they to the final, revised figures?
2. Do they signal "real" turning points in the business cycle and disregard temporary fluctuations of non-business cycle nature?

Forecasts generated by univariate autoregressive models have been used as bench marks.

This paper starts with a presentation of the BTS conducted in Sweden (Section 2) and moves on to a short account of the methods used in calculating and revising the various quantitative time series (Section 3). These sections form the basis for a discussion about the quality of the data and the relationship between survey data and quantitative data (Section 4). The subsequent sections contain: a description of KF consisting of a more theoretical presentation (Section 5). The presentation of the results obtained in Section 6 starts off with some practical aspects concerning the project. In Section 7 we draw conlusions and comment on the results of the project.

2. The Business Tendency Survey - a description of the method

The Swedish BTS started in 1954. It was primarily introduced so as to meet the need for immediate and reliable information concerning the business cycle, cf. Lönnqvist (1959). Instead of directly measuring a quantity in a single figure, BTS produces a frequency distribution of answers in, usually, three classes, eg. "higher", "equal" and "lower" production. Often, the matters are simplified by just presenting the balance (% higher - % lower).

The main purpose of the survey is to provide fast and current information concerning the present situation along with the plans and expectations of firms. Hence, answering the questions must be easy and this explains why just dichotomous or trichotomous alternatives are used.

In order to further simplify the answering procedure, extensive and complex definitions are avoided and the questions asked are of a fairly general nature. In many cases this is not a problem, in particular when the terms used ought to be interpreted quite uniformly. This applies for example to questions concerning employment and production. In other cases, primarily questions concerning various types of judgements, the interpretations of the questions can clearly differ among the respondents. In these cases one has to work with the hypothesis that - apart from differences in interpretations - the firms' anwers are consistent over time and therefore the changes registered in the answers correspond to actual changes.

The BTS is made up of forty-two questions. The questions can be divided into three categories:

1. Ex-post questions regarding changes in the volume of production, production capacity, sales prices, orders received, employment and stocks during the current quarter.
2. Questions asking whether the firm fully utilizes its capacity, and concerning shortage of labour, volume of orders and stocks, and
3. Ex-ante questions regarding the next quarter. These are basically the same as those concerning the current quarter.

The survey is addressed to the management of the firms. The frequency of answering varies from 60 to 95 percent, averaging 80 percent or more when aggregating to total industry.

The BTS is based on a representative sample of approximately 2 000 firms out of a population consisting of all industrial firms with more than ten people employed. The sample is stratified according to firm size with complete coverage of companies with more than 200 employees.

The answers of the survey are processed, so that every firm's reply is weighted with regard to its size. The net value added (or fractions of it) of the firm is used as weight except for the answers concerning employment where employment data is used. These calculated weights for the different answering alternatives are then summed up across the firms of each stratum.

2.3 Adjusting for seasonal effects

In the Swedish survey adjusting for seasonal variation is left to the respondents. This is done in such a way that when asking the respondents about the change in a variable a specific quarter, he is told to disregard normal seasonal differences. However by doing so the respondent is supposed to be aware of the seasonal fluctuations of each and every variable and furthermore be able to incorporate these considerations in order to distinguish the "real" changes. For this reason, it is not surprising to find, by visual inspection as well as in various research reports, that the respondents cannot handle this problem in a satisfactory way. However, Christofferson et. al. (1992) found no serious seasonal in the BTS series "volume of production". Furthermore they have found strong resemblance between actual quantitative annual changes of the level of production and the BTS series "volume of production". The most plausible reason for this is that the respondents, when asked to adjust for seasonal effects, do this in the easiest possible way, i.e. by comparing the current quarter with the corresponding quarter one year ago. Teräsvirta (1992), supports this hypothesis, a hypothesis which is essential when trying to quantify the results of the BTS. Öller (1992) finds significant seasonal effects in a series on production expectations for the next quarter. Seasonal effects in Belgian, French and German surveys are found by Ghysels and Nerlove (1988).

3. The statistical time series

Preliminary quarterly indices are calculated in different manners depending on the branch. One of three sample based production indicators[1] is used:

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[1] It is mainly various branch organisations that supply these data.

1. Actual production
2. Hours worked
3. Delivery data

Note that *no revision* of the indicator data is carried out in the first case. SCB receives these monthly indicators one and a half months after the expiration of each month. For branches where employment data or delivery data are being used as indicators, revision of estimated quarterly production data is conducted when new data becomes available. Furthermore, new information in the form of data concerning investments in stocks is included in the revision.

Annual revisions are not due to any improvments in the statistical material concerning the current year; they are mere level alignments of current year data when more reliable statistics on previous years has become available.

A final annual index is based on a complete survey of all firms in each branch. The implication of the completeness of the survey is that large quantites of information need to be handled and as a consequence this annual statistics is published with a lag of 15-18 months after the expiration of the year in question. Finally, it should be pointed out that changing the base year implies revisions. Occasionally, general revisions of back years are carried out, where the number of years varies.

A schedule of the publishing and revising of the volume of production data looks as follows:

Table 1: *Publishing and revising schedule of the quarterly indices, year t.*

Quarter of interest	Prel. vers. 1	Prel. vers. 2	Prel. vers. 3	Annual rev. 1	Annual rev. 2	Final index
1st quarter	may_t	$june_t$	-	$sept_t$	$sept_{t+1}$	$sept_{t+2}$
2nd quarter	aug_t	-	-	$sept_t$	$sept_{t+1}$	$sept_{t+2}$
3rd quarter	nov_t	dec_t	mar_{t+1}	$sept_{t+1}$	-	$sept_{t+2}$
4th quarter	feb_{t+1}	mar_{t+1}	$june_{t+1}$	$sept_{t+1}$	-	$sept_{t+2}$

3.2 Net value added[2]

The NVA is estimated and published by SCB and is an integral part of the National Accounts (NA). It is defined as the value of production minus costs.

The foundation of the calculations is the same as that of the PVI, i.e. the annual industrial statistics, which is a complete survey of the industry. When estimating the NVA, the value of production is measured as goods delivered. Costs are raw materials, packing, transports[3], etc. Fixed price production is calculated as a Laspeyres index.

The way to go about all this is different when it comes to estimating quarterly data, prior to the availability of the annual statistics. Preliminary quarterly data, in much the same way as its counterpart of the PVI, are based on indicators gathered from a sample of firms in each branch.

3.3 Exports of manufactured goods

The Customs Department registers the value of the merchandise that leaves the country. The value is given as f o b price at the moment of customs processing.

A new reporting system was introduced in December 1991. A central computer now receives information on exports directly from all customs offices in Sweden. This computer puts together what is called the *fast statistics* published approximately two weeks after the expiration of a month. These monthly exports data of a particular quarter are added in order to get a quarterly value.

Exports are not adjusted for the number of working days. This may introduce a calendar effect in the data, not present in the BTS data.

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[2] Based on a telephone interview with Bertil Klang of SCB, 2 March, 1993. Any errors can only be due to the authors.

[3] Wages and employment taxes are included in the costs of transports.

3.4 Hours worked

All employment in the manufacturing industry is essentially included in this variable. The preliminary estimation of the value is based on the monthly Labour Force Survey (AKU) complemented by Short period Employment Statistics (KPS). The preliminary values are revised according to the results obtained in the Industrial Statistics (IS) and the tax base.

4. The BTS versus quantitative data

The most important shortcomings of the quantitative statistics are a considerably delay in publication and that it may falsely indicate turning points. In spite of this there is a great demand for this sort of statistics and (too?) high confidence in its quality.

The BTS is carried out in the last month of a quarter and the final compilation into indicators is done before the beginning of the next quarter. The results are thus published 2-3 months before a first (and often shaky) version of its quantitative counterpart.

The survey also covers more than conventional statistics. It reflects the general mood among entrepreneurs concerning orderbooks and stocks, plus variables indicating deviations from desired course, eg. various supply and demand shortages. Furthermore, it is unique in the sense that it contains questions on expectations.

However, the BTS method has also been criticized. The criticism can be divided into two parts: drawbacks as compared to quantitative statistics, and that it may not always measure the right thing. Objections are also raised about the fact that the inquiry in itself is too "naive". This is, however, more a problem concerning the standing of the BTS rather than of its applicability. Concerning the coherence of the BTS and the quantitative series, Christofferson et al (1992) show that the BTS series of "volume of production" leads the production series by half a quarter.

The major difficulty concerning the BTS is how to systematically implement its information content in traditional forecasting procedures. To do so a "translation" of the tendency statistics of the BTS into a conventional quantitative form is needed. Attempts in this direction have been made, however with little success, see for instance Virin (1968).

Other obstacles limiting the possibilities to systematically use the information of the BTS are the lack of definitions and the firms' difficulties in predicting turning points. An example of a problem of definition is when entrepreneurs are asked about 'production', while the corresponding statistical variable is 'value added'. The results produced by the BTS concerning the expired quarter has been shown to be a satisfactory coincident indicator of turning points. But experience also shows that firms often are incapable of *predicting* major future changes of the cycle while at times in between, they manage fairly well to form an adaquate opinion about the near future. Today, the BTS is mostly being used as a tool for assessing the *present* situation rather than for forecasts based on expectations.

4.1 Possible sources of statistical errors

Perhaps the most important quality of an economic time series, which is supposed to illustrate the business cycle, is that it should not falsely indicate changes in the direction of the economy. The quantitative economic quarterly statistics sometimes displays temporary increases and decreases that do not seem to be due to any changes in the activity level of the firms. Changes in the volume of production may eg. be caused by the difference in the number of working-days between quarters. The SCB endeavours to correct for such errors by publishing adjusted series; more about this in the next section.

4.2 Adjusting for the number of working-days

For the PVI, a working-month is assumed to be composed of 21 working-days in branches using a five-day week. Should a month contain only 20 working-days a proportional adjustment is done and branch figures are aggregated to form total manufacturing production. The monthly values are also summed up over time to get a quarterly value. Similar adjustments are done in the National Accounts, but directly on quarterly figures, using the average number of working hours per quarter for the period 1970-1981. The length of the working-week depends on the branch. In the processing industry, where production runs non stop, assumptions about working time are made separately for each branch.

Problems are associated with this mechanical working-day adjustments, especially in the case of working-days wedged in between a holiday and a weekend. Often, a firm decides to make up for one or a few of these days. The period of compensating work-days will then exhibit an increase in production, due to more overtime. When the days off are transformed into vacancy, it will result in a decline in production. This effect is less serious in quarterly data than in monthly time series. It is not possible to discern any pattern in the firms' ways of handling days of this kind. Moreover, their behaviour is probably inconsistent over time. Wandering holidays as Easter holidays constitute a related problem as they fall on different quarters depending on the year. The Christmas holidays, too, fall on different days of the week, as do summer holidays, spread across both the second and the third quarter.

Consequently, even the final figures of quantitative statistics contain a non-negligable error component that seems to be impossible to model. BTS are much smoother, eg. changes of sign are more infrequent and generally signal a turning point. This could be due to the fact that entrepreneurs are directly reporting the average tendency of activity, not being disturbed by number of working-days, etc.

These sources of error should be kept in mind when evaluating the ability of survey data of emulating "true" quantitative statistics.

A section in which the KF is described, in form of an illustration of how it is used, follows below. The theoretical parts are to a large extent collected from Olbjer (1985). For anyone interested in a more detailed presentation, we recommend Harvey (1989). The method used in this paper is almost the same as the one introduced by Rahiala and Teräsvirta (1993).

5. The Kalman filter

Suppose that we are at the end of a quarter, denoted $T+1$. There is as yet no quantitative statistics for this quarter; it will be published in another 2.5 months. However, we have access to the latest BTS figures, covering the quarter $T+1$ and also including expectations and plans for $T+2$.

First we want to estimate the quantitative variable for $T+1$ using BTS. Secondly, we want to make a forecast of the quantitative variable for the next quarter $T+2$ by using the answers of the forward looking questions of the survey.

We let x_t denote the annual logaritmic change in a quantitative, quarterly variable z at time t:

$$x_t = \ln(z_t) - \ln(z_{t-4}).$$

An autoregressive (AR) process of the quantitative series is estimated through T. This univariate AR(j) process can be expressed as a vector autoregressive, VAR(1) process:[4]

$$\begin{pmatrix} x_t \\ x_{t-1} \\ x_{t-2} \\ \vdots \\ \vdots \\ x_{t-j+1} \\ 1 \end{pmatrix} = \begin{pmatrix} \alpha_1 & \alpha_2 & \cdots & \cdots & \alpha_j & \mu \\ 1 & 0 & \cdots & & \cdots & 0 \\ 0 & 1 & 0 & \cdots & \cdots & 0 \\ \vdots & & \ddots & & & \vdots \\ \vdots & & & 1 & 0 & 0 \\ 0 & \cdots & & \cdots & 0 & 1 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ \vdots \\ \vdots \\ x_{t-j} \\ 1 \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ 0 \\ \vdots \\ \\ \\ \vdots \\ 0 \end{pmatrix},$$

or in matrix notations:

(1) $$X(t) = A\,X(t-1) + e_1(t) \quad , \text{for } t \leq T.$$

X denotes the vector composed of values of the quantitative variable, x_t, and in this particular case, an intercept. This vector is also called the state vector. The first row of the matrix A constitutes the actual AR(j) equation. The rest of the matrix updates the X vector one period. $e(t)$ is an error term which is assumed to have expected value zero and to be uncorrelated with the X vector through time t-1 and with zero autocorrelation for all lags. Expression (1) is called the *transition equation*.

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[4] **The model can easily be expanded with seasonal dummies as well as MA-error terms, however, in order to achieve simplicity we have not introduced these terms. How such a model would look like is described in Rahiala et al (1993).**

A BTS series, y_t, for time t is estimated as a function of *the quantitative series*. Any number of BTS series can be estimated jointly in a vector, but only one series is needed. The regression function can then be written as:[5]

$$y_t = \begin{pmatrix} \beta_1 & \beta_2 & \cdots & \cdots & \beta_m & \gamma \end{pmatrix} \begin{pmatrix} x_t \\ x_{t-1} \\ x_{t-2} \\ \vdots \\ \vdots \\ x_{t-j+1} \\ 1 \end{pmatrix} + e_{2,t} \ ,$$

or by using matrix notation:

(2) $$y(t) = B\,X(t) + e_2(t) \quad , \text{ for } t \leq T.$$

This equation is in the literature usually referred to as *the measurement equation*. It should be noted that the first element in X is the value of the quantitative series for the *same period* as that of the BTS to be predicted.

5.1 Coincident forecasting

By using transition equation (1), a value of the quantitative variable for the latest quarter, $T+1$ is forecasted. This VAR model forecast is based on information available at time $T+1$, i.e. values of the series itself through time T. According to (1):[6]

$$\begin{pmatrix} \hat{x}_{T+1|T} \\ x_T \\ x_{T-1} \\ \vdots \\ \vdots \\ x_{T-j+2} \\ 1 \end{pmatrix} = \begin{pmatrix} \alpha_1 & \alpha_2 & \cdots & \cdots & \alpha_j & \delta \\ 1 & 0 & \cdots & & \cdots & 0 \\ 0 & 1 & 0 & \cdots & \cdots & 0 \\ \vdots & & \ddots & & & \vdots \\ \vdots & & & 1 & 0 & 0 \\ 0 & \cdots & & \cdots & 0 & 1 \end{pmatrix} \begin{pmatrix} x_T \\ x_{T-1} \\ x_{T-2} \\ \vdots \\ \vdots \\ x_{T-j+1} \\ 1 \end{pmatrix} ,$$

[5] Rahiala et al (1993) uses a vector of y in order to distinguish that several BTS values can be used.

[6] $\hat{x}(T+k|T)$ denotes a forecast for $T+k$, $k=1,2,3,\ldots$ based on information up to time T.

or:

$$\hat{X}(T+1|T) = A\,X(T).$$

The measurement equation is used in much the same way to forecast a BTS for the same period, $T+1$, namely $\hat{y}_{T+1|T}$, based on the VAR prediction $\hat{X}(T+1|T)$, according to (2):

$$\hat{y}_{T+1|T} = (\beta_1\ \beta_2\ \cdots\ \cdots\ \beta_m\ \gamma)\begin{pmatrix}\hat{x}_{T+1|T}\\ x_T\\ x_{T-1}\\ \vdots\\ \vdots\\ x_{T-j+2}\\ 1\end{pmatrix},$$

i.e.:

$$\hat{y}(T+1|T) = B\,\hat{X}(T+1|T).$$

But as already mentioned, at time $T+1$ we have an actual observation of BTS, y_{T+1}. Any discrepancy between the forecast of BTS, $\hat{y}_{T+1|T}$ and the outcome of the BTS, y_{T+1} would imply that the last observation deviates from the estimated historical pattern, described by the measurement equation. Then the quantitative series, x_t should also diverge from its estimated pattern, since both estimations are essentially based on the same history (of x). For this reason, if the two BTS values differ, an adjustment of the VAR forecast of $\hat{X}_{T+1|T}$ is called for. This correction is done by calculating the *optimal reconstructor* in the following manner:

(3) $$X^*(T+1|T+1) = \hat{X}(T+1|T) + K(T+1)[y(T+1) - \hat{y}(T+1|T)].$$

Since only the first element of the X vector to be forecasted is affected by the adjustment, (3) can be written in a scalar form:

$$x^*_{T+1|T+1} = \hat{x}_{T+1|T} + K(T+1)[\,y_{T+1} - \hat{y}_{T+1|T}\,]$$

This value, x^*_{T+1}, is later on refered to as *the Kalman filtered coincident forecast* of the period. K(T+1) is the gain matrix and its value depends on the variances of the forecasts obtained by the transition equation as well as those of the measurement equation, according to:

$$K(T+1) = V_{xx}(T+1|T)B'V_{yy}^{-1}(T+1|T).$$

V_{xx} and V_{yy} are one step ahead forecasting variances of X and y, respectively.[7] This gain can be said to be determined in size by the historical correlation between the BTS series and the quantitative variable. If the series display a low degree of correlation or if the forecast variances are large, the gain will be close to zero, regardless of the discrepancy between the BTS outcome and the forecasted BTS value. The gain will also be small if the forecasted BTS value approaches its observed value, because this would imply that the observed BTS value can be accurately determined by historical values of x. Therefore, the value of x should be correctly forecasted and no adjustment of the VAR forecast (3) would be needed.

5.2 Forecasting

We will now explain how to use *the BTS data in forecasting the quantitative variable for* $T+2$. This is done in much the same way as when forecasting the coincident x_{T+1}. Two values, not available at the time $T+1$, are needed: x_{T+1} and y_{T+2}.

The first value can be replaced by the KF value obtained from (3). This value is used in the transition equation (1) to produce a VAR forecast of x_{T+2}:

$$(1') \qquad \hat{X}(T+2|T+1) = A\,X^{*}(T+1|T+1).$$

The missing value of a BTS series for the coming period $T+2$ can be substituted by forward-

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[7] These can be updated as follows:

$$V_{xx}(T+1|T) = V[e_1(T)]$$

$$V_{yy}(T+1|T) = B(T)V[e_1(T)]B'(T) + V[e_2(T+1)]$$

The variance of the reconstructed value for the period $T+1$ is obtained by:

$$V_{xx}(T+1|T+1) = V_{xx}(T+1|T) - K(T+1)V_{yy}(T+1|T)K'(T+1)$$

looking information in the survey. There are questions concerning expectations for $T+2$ in the survey, $y(T+2|T+1)$ and there may also be such information in variables concerning $T+1$, $Y(T+1|T+1)$, here Y denotes a vector of BTS series. A forward-looking link is added to the KF that produces a *forecast* of the BTS series, $\check{y}(T+2|T+1)$ according to:

$$\check{y}(T+2|T+1) = h\ [\ y(T+2|T+1),\ Y(T+1|T+1)\ ].$$

Technically, the procedure is analoguous to the one applied for coincident forecasts. The measurement equation, cf. (2) is[8]

$$\hat{y}(T+2|T+1) = B\ \hat{X}(T+2|T+1).$$

The VAR forecast for $T+2$ is then adjusted:

$$X^{*}(T+2|T+2) = \hat{X}(T+2|T+1) + K(T+2)[y(T+2|T+1) - \hat{y}(T+2|T+1)].$$

In the adjusting term our estimated BTS value, $\check{y}$ replaces the actual outcome y. The first element in the resulting X^{*} vector is the *KF foreward-looking forecast* of the quantitative series for $T+2$.

[8] For the sake of convenience, we have chosen to use the measurement equation estimated for the BTS outcome, instead of estimating a new measurement equation for this 'estimated' BTS outcome. We are aware of the fact that this is not 'correct', however it simplifies the model.

6. Results

The results presented are those of the total of the manufacturing industry (ISIC 3)[9]. Time series of quarterly data starting at 1970:1 are used, except in the case of the PVI where time series back to 1968:1 are available. Since all variables examined are affected by the labour market conflict in the second quarter of 1980, a dummy variable for this quarter has been introduced[10]. Throughout, *balances* of the BTS data have been employed. All models have been estimated up to 1987:4. Results obtained for the period 1988:1 - 1993:1 with the coincident model are accounted for and results of the foreward-looking model for the period 1988:2 - 1993:2 are presented. One reason to use such a relatively long out of sample period is that the values of the variables for 1991 - 1992 are not finally revised. Including the years 1988 - 1990 makes it possible to make comparisons with final figures.

The accuracy of the forecasts is measured in RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). Large errors affect RMSE more than MAE. In order to examine whether the BTS data in a KF improve on the AR model forecasts, we employ *the Granger Newbold (GN) test*[11], cf. Appendix. The working-day problem mentioned in 4.2 can affect forecast accuracy. To eliminate this sort of error, calendar year forecasts are also examined.

When the models are run, the most recent version of the time series available has been used. Coincident and forward-looking forecasts have been generated for, say 1989:1, all observations preceding this quarter that are *'available today'* have been used.

Since the main purpose of these models is to monitor and forecast the business cycle, we have also looked at how well they forecast business cycle turning points. The last turning point lies outside the estimation period.

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[9] International Standard Industrial Classification of all economic activities, third revision, 1968.

[10] The measurement equations do not contain a dummy-variable for the quarter of the labour market conflict, since the respondents of the survey are expected to have disregarded from the effects of the conflict.

[11] Granger-Newbold (1986), pp 278-279.

Turning points are here defined as follows[12]:

1. Shifts from a positive (negative) to a negative (positive) change as compared to the corresponding quarter the previous year.
2. The change must persist for at least three consequtive quarters.
3. A small change, but one whose sign changes, is considered in the following manner:
   a) If it is followed by at least two values of the same sign, it is considered a turning point.
   b) If the surrounding changes are both of the opposite sign and larger in absolute values, it is not regarded as a turning point.

6.1 The index of industrial production

Differences of the quantitative variable are regressed on the BTS series "volume of production, y^P ".

Table 2: The VAR transition equation for the INDEX OF INDUSTRIAL PRODUCTION.

lags	$\Delta_1 x_{t-1}$	const	d1	d2	d3	d80:2
coeff	-.37	.17	-.41	-.12	-.14	-.08
t-value	-3.52	6.26	-11.62	-5.60	-2.46	-3.42
	s	LB(8-1)	ML(2)	sk	ek	JB
value	.024	21.10	2.99	.04	.72	1.57
probab.		.01	.68			.46
	R^2	ill-cond				
value	.99	49.7				

The symbols in the lower part are: *s* is the standard error of residuals, *LB* is the test according to Ljung and Box of no autocorrelation, *ML* is the McLeod and Li test of no autoregressive conditional heteroscedasticity (ARCH), *sk* stands for skewness, *ek* is excess kurtosis (subtracted by 3, which implies no ek if the value is close to zero) and *JB* is the test of normality by Jarque

12 For a general discussion on turning points in Sweden, see Sundberg (1992).

and Bera. We also give the probability of the null hypothesis. *The index of ill-conditioning*[13] is a measure of multicollinearity. A high value of the index means a greater uncertainty whether the obtained results are the proper ones which is the same as saying that rounding off errors or small changes in the input data have a large impact on the resulting estimated values.[14]

Table 3: The measurement equation for INDEX OF INDUSTRIAL PRODUCTION.

lags	$\Delta_4 x_t$	$\Delta_4 x_{t-1}$	$\Delta_4 x_{t-2}$	$\Delta_4 x_{t-3}$	$\Delta_4 x_{t-4}$	$\Delta_4 x_{t-5}$	$\Delta_4 x_{t-6}$	const
coeff	2.40	3.05	3.03	2.44	.01	-.68	-.53	.02
t-value	7.97	9.56	9.64	10.26	.03	-2.21	-1.80	2.06
	s	LB(8)	ML(2)	sk	ek	JB	R^2	ill-cond
value	.07	21.17	.77	-.14	-.18	.34		55.2
probability		.01	.68			.84		

Table 4: The equation for estimating a value of the BTS series: production volume, for t+1 at time t.

variables	y^{P+}_t	y^P_t	total order stock at *t*	d80:2			
coeff	.59	.15	.31	-.28			
t-value	8.05	1.85	4.90	-5.36			
	s	LB(8)	ML(2)	sk	ek	JB	ill-cond
value	.05	14.67	4.34	-.10	-.04	.12	3.8
probab.		.07	.11			.94	

From Table 2 it can be seen that both equations exhibit strong autocorrelation. For the transition equation we can conclude, from tests not presented here, that most of it originates from lag 2, but the introduction of an AR(2) term did not help: neither was the parameter significant nor was the forecasting ability improved. Graphical inspection of the residuals

13 Golub & van Loan (1989), p 223.

14 There is no real threshold value telling us when an equation is ill-conditioned. However, the index does give an indication of when the risk of such a situation might be present. If the index approaches 40-50, we have further examined the equation by introducing disturbances in order to find their impacts on the results. In the case of the PVI the results of these exercises are that, even for high index value, the results are stable, i e they do not produce any excessive changes in the resulting parameters.

revealed that the autocorrelation is concentrated to the period 1975 through 1982. In the second quarter of 1982 SCB changed the base year from 1968 to 1980.[15] We tested the hypothesis of parameter constancy against the alternative of smooth structural change in the VAR model, using the tests in Lin and Teräsvirta (1991). The test results are that parameter constancy over the period is rejected. This is the same result obtained by Rahiala and Teräsvirta (1992) for the Swedish metal and engineering industry. They concluded that the seasonality of the series in 1976-1980 was different from that outside this period. The change in seasonality may be due to the changes in the official statistics (remark of the authors of this paper). Using the same mean to overcome this problem as in ibid. i.e. by re-estimate the VAR model starting in 1980, results in a much lower forecasting precision compared to the VAR model estimated on the larger sample. Another approach is to scale down the values of 1975-1982 by a factor of 0.5, say. Then the null hypothesis of no autocorrelation cannot be rejected on the 10 % level, but to the price of a lower precision of the VAR predictions.

The autocorrelation of the residuals when estimating the measurement equation, Table 3, are of first and second order. By introducing MA(1) and MA(2) errors into our state vector both orders of autocorrelation clearly diminish. The parameters of the two terms are significant and the value of LB becomes 5.8. However, the forecasting ability of a model including MA errors is not improved and therefore the MA terms are not included in the final model. By visual examination of the residuals, when estimating the equation, it is obvious that the problem of autocorrelation dates back to the first ten years of the estimating period. This would explain why the forecasting precision is not improved by the MA error terms.

The residuals of the estimation of the equation, for estimating a value of the BTS one period ahead, are almost significantly autocorrelated as is seen in Table 4. The equation already contains an AR(1) term, so we have tested the inclusion of a MA(1) to absorb autocorrelation on lag one. This does no change the significance of autocorrelation.

It is evident, from looking at table 5 that the KF, when predicting quarterly data, produces smaller errors tha the VAR model. The coincident KF forecasts are more accurate than

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[15] Statistical Reports I 1983: 3.10 (in Swedish) published by SCB.

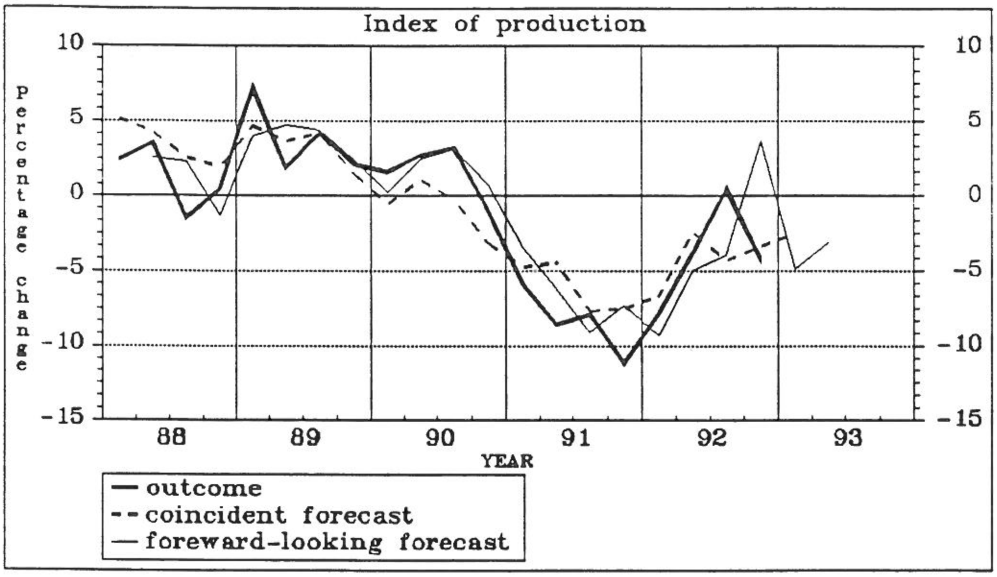
foreward-looking ones. The RMSE, MAE and errors on a yearly basis are relative measures of error. Granger Newbold's test (GN) states the *probability* for the null hypothesis that the errors obtained with the KF model are *not* smaller than those of a VAR model.

Table 5: The index of industrial production. VAR och KF models estimated on differenced data. BTS variable: 101 volume of production.

Period of estimation 1970:2 - 1987:4				
	COINCIDENT FORECAST 1988:1 - 1992:4		FORWARD-LOOKING FORECAST 1988:2 - 1992:4	
	AR	KF	AR	KF
RMSE	0.0347	0.0242	0.0390	0.0284
MAE	0.0282	0.0202	0.0307	0.0215
GN	0.0355		0.0018	
	ANNUAL ERRORS			
1988	0.0045	0.0216	0.0187	0.0003
1989	0.0040	0.0035	0.0040	0.0009
1990	0.0057	-0.0233	0.0135	0.0000
1991	0.0404	0.0228	0.0381	0.0191
1992	0.0189	0.0012	0.0183	0.0049

Looking at annual errors, the KF model is in many cases less accurate than the AR model. Looking at 1988 we see that BTS data overestimate production. For this year, BTS data indicate a substantial increase in production, and this does not show up in official figures, in spite of a period of high overall activity in the Swedish economy. As a whole, the annual forward-looking KF forecast errors are very small for the period 1988-1990 outperforming the coincident forecasts. However, it should be pointed out that, in this case, the statistics for the period 1988-1989 will be revised.

Figure 1 shows the outcome, the coincident and the foreward-looking forecasts of the production for the same period. The coincident forecasts overestimate all four quarters in 1988 and underestimate all four quarters in 1990. The coincident forecast leads the outcome at the end of the period, whereas the foreward-looking forecast lags by a quarter during the same period and moves strongly in the wrong direction in the last quarter of 1992. The coincident



Figur 1: Graphs of the annual change in outcome, the coincident and the foreward-looking forecasts of the index of production.

forecast is smoother than the outcome, but not the forward-looking forecast.

The capability of detecting turning points is summerized in Table 6. Note that the AR models as well as their KF counterparts pin-point the three first turning points. For the last down turn only the coincident KF forecast signals an early warning - all the other forecasts are late. Also it is the only model to signal in advance the up turn in 1978.[16]

[16] We consider an early indication of a turning point by a model as something good, if it is *one* period earlier, and as useless if it is earlier than that. This distinction is based on the assumption that in times of changes, occuring at the end of a period, the survey answers, probably, are more a reflection of this later change rather than an average recollection of the entire period. So, a late change during a quarter could produce a survey result signalling a change, whereas the statistics would produce an average number, for the entire period, indicating no change.

Table 6: Observed turning points in the outcome of the PVI and the corresponding forcasts generated by VAR and KF models. Period: 1978:1 - 1992:4.

	outcome	AR coincident	KF coincident	AR forw-look	KF forw-look
up	1978:4	1978:4	1978:3	1978:4	1978:4
down	1980:2	1980:2	1980:2	1980:2	1980:2
up	1983:1	1983:1	1983:1	1983:1	1983:1
down	1990:4	1991:1	1990:3	1991:1	1991:1

6.2 Net value added

Annual (seasonal) differences of the NVA have been employed. The BTS series is the same as for PVI.

Table 7: The VAR transition equation for NET VALUE ADDED.

lags	$\Delta_4 x_{t-1}$	$\Delta_4 x_{t-2}$	$\Delta_4 x_{t-3}$	$\Delta_4 x_{t-4}$	const	d80:2
coeff	.46	.52	.25	-.56	.70	-3.37
t-value	4.65	4.80	2.28	-5.82	1.99	-3.42
	s	LB(8-4)	ML(2)	sk	ek	JB
value	.025	4.36	4.25	-.57	-.09	3.23
probab.		.36	.12			.20
	R^2	ill-cond				
value	.78	14.5				

Table 8: The measurement equation for NET VALUE ADDED.

lags	$\Delta_4 x_{t-1}$						
coeff	2.44						
t-value	10.87						
	s	LB(8)	ML(2)	sk	ek	JB	ill-cond
value	.09	16.93	.60	-.05	-.29	.24	1.0
probab.		.03	.74			.89	

Significant autocorrelation is present in the measurement equation, Table 8. By introducing MA(1) and MA(2) error terms these autocorrelations disappear and the LB statistical value decreases to 3.64. But as in the case of PVI, the forecasts are not improved when using these error terms, and they are not included in the model.

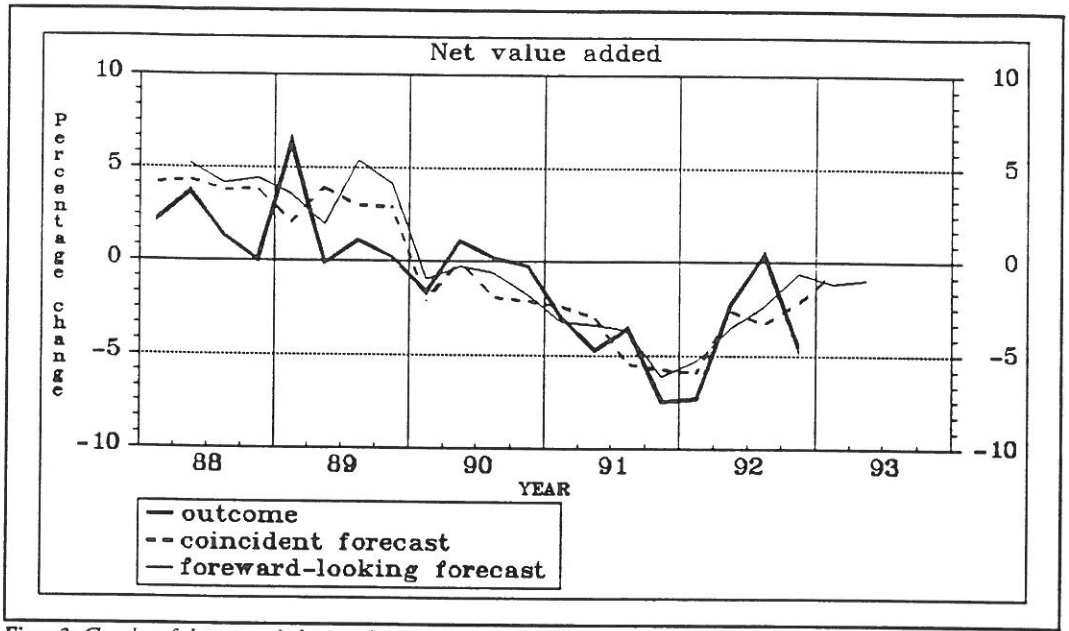
From Table 9 it can be established that the RMSE and the MAE measures for both KF models are of the same size as in the case of PVI. Note that the GN test is close to being significant only for coincident forecasts, so that strictly speaking the KF model does not outperform the VAR model in the foreward-looking case.

Table 9: The net value added of the total industry. The VAR and the KF models are estimated on seasonally differenced data. BTS variable: 101 volume of production.

Period of estimation 1973:1 - 1987:4				
	COINCIDENT FORECAST 1988:1 - 1992:4		FORWARD-LOOKING FORECAST 1988:2 - 1992:4	
	AR	KF	AR	KF
RMSE	0.0307	0.0238	0.0286	0.0247
MAE	0.0256	0.0206	0.0239	0.0207
GN	0.0525		0.1277	
	ERRORS ON A YEARLY BASIS			
1988	0.0115	0.0228	0.0107	0.0227
1989	0.0034	0.0118	0.0114	0.0248
1990	-0.0013	-0.0132	-0.0024	-0.0077
1991	0.0307	0.0067	0.0287	0.0061
1992	0.0098	0.0006	0.0085	0.0058

The coincident KF forecast overestimates the years 1988 and 1989 and underestimates 1990. For the last two years the KF models produce small annual errors. The foreward-looking KF forecast indicates much the same development of the NVA as the coinciding KF forecasts.

Comparing Figures 1 and 2 we see that the outcome for 1989 is below that of the PVI. The outcome does not indicate any definite point of downturn in 1990, somewhat arbitrarily we chose 1990:4, applying the rules 1-3 on p. 16.



Figur 2: Graphs of the annual changes in outcome, the coincident and the foreward-looking forecasts of the net value added.

Table 10 shows how the models perform at turning points. The KF forecasts are never late but both are early in two cases, whereas the AR forecasts are late in the last down turn.

Table 10: Observed turning points in the outcome of the NVA and the corresponding for the VAR and the KF models when forecasting. Period: 1978:1 - 1992:4.

	outcome	AR coincident	KF coincident	AR forw-look	KF forw-look
up	1978:4	1978:4	1978:4	1978:4	1978:3
down	1980:2	1980:2	1980:2	1980:2	1980:2
up	1983:1	1982:3	1982:4	1981:4	1983:1
down	1990:4	1991:2	1990:1	1991:2	1990:1

6.3 Exports of manufactured goods

Seasonally differenced exports along with the BTS series "order stock for exports, *y_eo*" is the combination best fitted for forecasting the exports. The BTS series was introduced as a fixed distributed lag function: $\tilde{y}^{E}_{t} = 0.85y^{E}_{t} + 0.15y^{E}_{t-1}$ reflecting the delay between order and delivery. The one period ahead forecast of this variable is obtained as a regression on the equivalent expectations concerning the next quarter, y^{E+}_{t} and domestic orders, y^{D+}_{t}.

Table 11: The VAR transition equation for EXPORTS.

lag	Δ_4x_{t-1}	Δ_4x_{t-2}	Δ_4x_{t-3}	Δ_4x_{t-4}	Δ_4x_{t-5}	Δ_4x_{t-6}	Δ_4x_{t-7}	Δ_4x_{t-8}	const	d80:2
coeff	.358	.429	.092	-.579	.136	.247	.121	-.441	.034	-.167
t-val	3.50	3.99	.79	-5.04	1.28	2.13	1.13	-4.38	3.65	-3.84
	s	LB	ML	sk	ek	JB	R^2	ill-cond		
value	.042	5.47	2.04	-.79	2.31	19.19	.67	30.34		
prob.			.36			.00				

Table 12: The measurement equation for EXPORTS.

lags	Δ_4x_t	Δ_4x_{t-1}	Δ_4x_{t-2}	Δ_4x_{t-3}			
coeff	1.62	.91	-.01	-.85			
t-value	5.23	2.86	-.01	-2.92			
	s	LB(8)	ML(2)	sk	ek	JB	ill-cond
value	.14	32.21	10.23	-1.05	.96	13.09	3.3
probab.		.00	.01			.00	

Table 13: The equation for estimating a value of the BTS series: exports orders, for t+1 at time t.

variables	$\tilde{y}^{E}_{t}$	$\tilde{y}^{E+}_{t}$	y^{E+}_{t}	const	d80:2		
coeff	.68	.70	-.65	-.05	.19		
t-value	5.78	3.79	-2.82	-2.43	1.73		
	s	LB(8-4)	ML(2)	sk	ek	JB	ill-cond
value	.11	11.43	.07	-.26	.38	1.25	20.2
p-value		.18	.97			.54	

From Table 11 it can be seen that according to *sk*, the distribution of the residuals of the VAR equation is platykurtic (flatter).

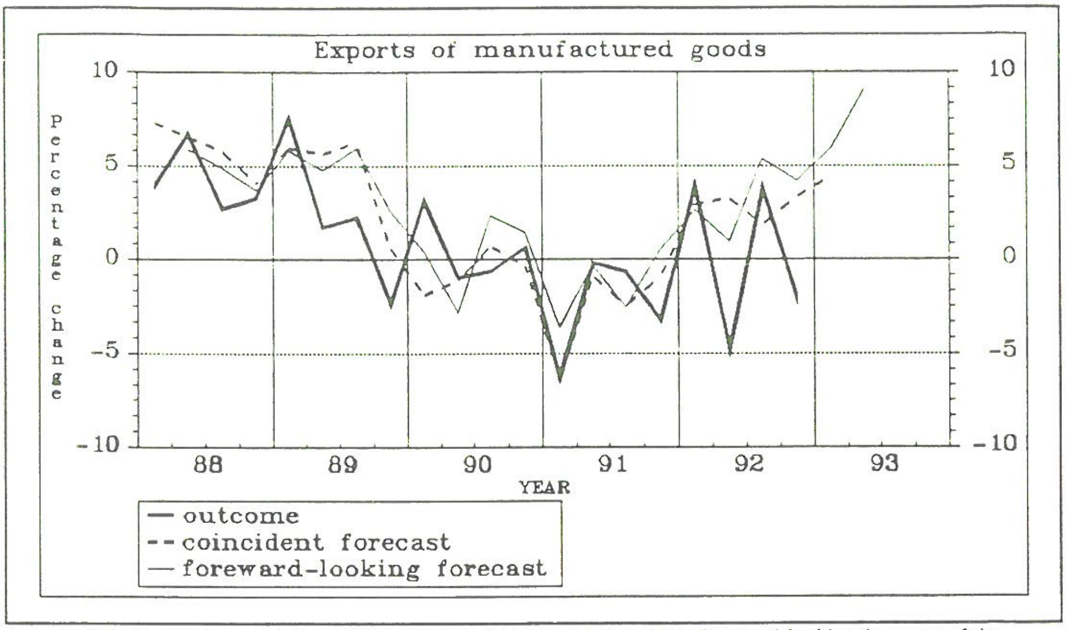
The high autocorrelation of the measurement equation, Table 12, is of the first order. The values of ML and JB are lowered to 0.75 and 0.93 respectively when an MA(1) error term is introduced, LB, however, is still as high as 21.6. The KF forecasts are not improved. The problem of autocorrelation originates from the 1970's. By re-estimating the measurement equation starting with 1980, the LB decreases to 8.0, with a p-value of 0.09. But in this case the forecasting precision of the KF is not improving on the VAR forecast.

Table 14 shows that in nine cases out of ten the KF model generates more accurate annual forecasts.

*Table 14: Exports of manufactured goods. The VAR and the KF models are estimated on seasonally differenced data. BTS variable: 106 order stock (exports market) (85%*t + 15%*(t1)).*

Period of estimation 1973:1 - 1987:4				
	COINCIDENT FORECAST 1988:1 - 1992:4		FORWARD-LOOKING FORECAST 1988:2 - 1992:4	
	AR	KF	AR	KF
RMSE	0.0404	0.0322	0.0397	0.0309
MAE	0.0341	0.0249	0.0334	0.0258
GN	0.0574		0.0163	
	ERRORS ON A YEARLY BASIS			
1988	0.0138	0.0177	0.0108	0.0039
1989	0.0324	0.0239	0.0513	0.0342
1990	0.0194	0.0131	0.0186	0.0032
1991	0.0353	0.0005	0.0320	0.0124
1992	0.0326	0.0287	0.0385	0.0323

The accuracy of the KF model forecasts is further demonstrated in Figure 3. Strong oscillations in the outcome in 1992 raises doubts that there are errors in the statistics. Occasional large shipments, as well as working-day variation (no adjustment) may also have contributed to these irregularities. Further explanations could be the general turbulence on the foreign exchange



Figur 3: Graphs of the annual changes in outcome, the coincident and the foreward-looking forecasts of the exports of manufactured goods.

markets in 1992 and changes in the customs reporting system in the beginning of 1992. If quarterly exports would look like this for periods to come, it would probably be impossible to make sensible forecast using BTS data where no corresponding variation can be traced.

The turning point comparison in Table 15 offers little help in disriminating between the models. The KF models signal an upturn that is not materialized.

Table 15: Observed turning points in the outcome of the exports of manufactured goods and the corresponding for the VAR and the KF models when forecasting. Period: 1978:1 - 1992:4.

	outcome	AR coincident	KF coincident	AR forw-look	KF forw-look
down	1980:2	1980:2	1980:2	1980:2	1980:2
up	1981:4	1981:4	1981:4	1981:4	1981:4
down	1990:2	none	1990:1	none	1991:1
up	?	none	1992:1	none	1991:4

6.4 Hours worked

This variable has been seasonally differenced. The BTS does not contain any question naturally linked to this variable. We used a weighted sum of the answers to questions regarding *the number of employed* and *the number of employees*, the weights being 0.75 and 0.25 respectively. The new BTS series is denoted y^L_t. The one period ahead forecast of this variable is obtained by regressing on its value for the current quarter, firms' plans for same variable one quarter ahead, y^{L+}_t and the current *total order stock*, y^S_t.

Table 16: The VAR transition equation for HOURS WORKED.

lags	$\Delta_4 x_{t-1}$	$\Delta_4 x_{t-2}$	$\Delta_4 x_{t-3}$	$\Delta_4 x_{t-4}$	d80:2	
coeff	.52	.58	.20	-.64	-.05	
t-value	4.72	4.99	1.68	-5.18	-3.04	
	s	LB(8-4)	ML(2)	sk	ek	JB
value	.09	1.82	.92	.09	-.08	.10
probab.		.77	.63			.95
	R^2	ill-cond				
value	.73	9.55				

Table 17: The measurement equation for HOURS WORKED.

lags	$\Delta_4 x_t$	$\Delta_4 x_{t-1}$					
coeff	2.42	1.31					
t-value	5.40	2.94					
	s	LB(8)	ML(2)	sk	ek	JB	ill-cond
value	.07	42.57	6.80	.02	-.48	.58	2.4
probab.		.00	.03			.75	

Table 18: The equation for estimating a value of $\hat{y}$_emp, for t+1 at time t.

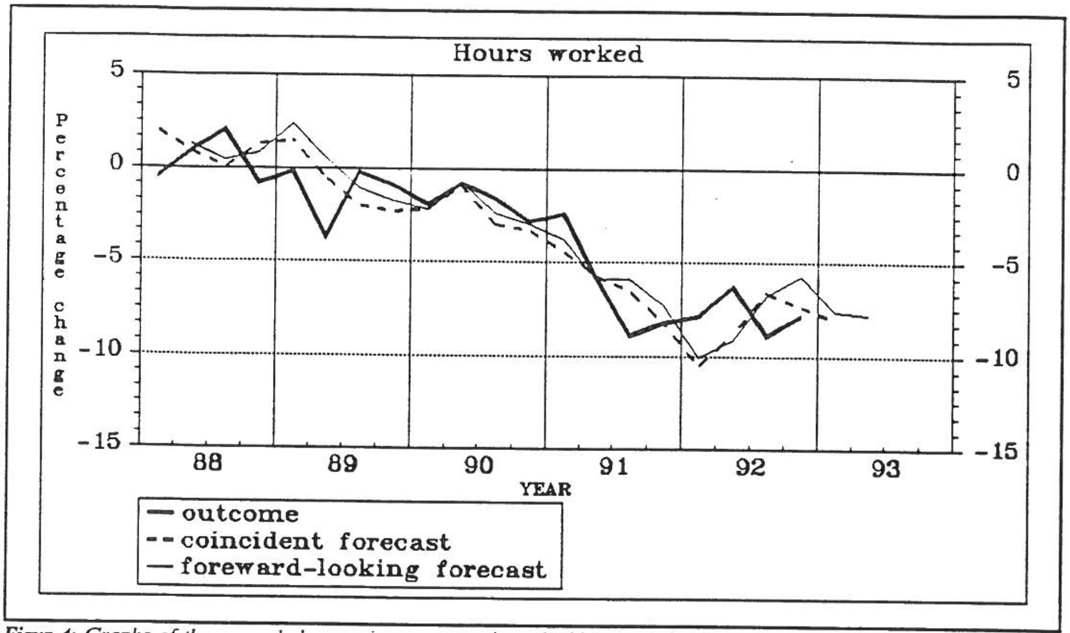
variables	y^{L}_{t}	y^{L+}_{t}	y^{S}_{t}	const			
coeff	.52	.24	.18	-.08			
t-value	4.92	2.60	5.20	-1.44			
	s	LB(8)	ML(2)	sk	ek	JB	ill-cond
value	.04	7.37	5.56	-.24	.77	2.48	5.3
probab.		.50	.06			.29	

Introducing MA(1) and MA(2) error terms in the measurement equation, Table 17, lowers the ML to 2.75 and the LB to 15.56 with a p-value of 5.0, but the KF forecasts lose some precision compared to the case of no error terms.

Again the KF model forecasts are more accurate if we just consider RMSE and MAE, as seen in Table 19. But the GN test is on the limit of being significant and if we look at the annual results, the KF forecasts are more accurate in only half of the cases.

Table 19: Hours worked. The VAR and the KF models are estimated on seasonally differenced data. BTS variable: 204 number of workers employed (75%) and 205 number of employees (25%).

Period of estimation 1973:1 - 1987:4				
	COINCIDENT FORECAST 1988:1 - 1992:4		FORWARD-LOOKING FORECAST 1988:2 - 1992:4	
	AR	KF	AR	KF
RMSE	0.0221	0.0173	0.0220	0.0179
MAE	0.0190	0.0142	0.0182	0.0142
GN	0.0639		0.0401	
	ERRORS ON A YEARLY BASIS			
1988	0.0044	0.0080	0.0017	0.0018
1989	0.0027	0.0052	0.0120	0.0183
1990	0.0091	0.0051	0.0048	0.0029
1991	0.0224	0.0002	0.0223	0.0046
1992	0.0074	0.0074	0.0043	-0.0033



Figur 4: Graphs of the annual changes in outcome, the coincident and the foreward-looking forecasts of the number of hours worked.

From Figure 4 one can see, that as before the model forecasts are smoother than the actual outcome. For hours worked the two KF model forecasts lie close to each other. The BTS and the statistics on 1988-89 disagree on the turning point.

Turning to Table 20, the history of turning points offers few clues for how to select the best model.

Table 20: Observed turning points in the outcome of the hours worked and the corresponding for the VAR and the KF models when forecasting. Period: 1978:1 - 1992:4.

	outcome	AR coincident	KF coincident	AR forw-look	KF forw-look
up	1979:4	1979:3	1979:3	1979:3	1979:3
down	1981:1	1981:1	1981:1	1981:1	1980:4
up	1984:1	1984:2	1984:1	1984:2	1984:2
down	none	1985:4	1985:4	1985:4	1985:4
up	none	1987:2	1987:2	1987:2	1987:2
downturn	1988:4	1989:2	1989:2	1989:3	1989:3

7. Conclusions

The results show that BTS data in a Kalman filter approach produces more accurate coincident as well as foreward-looking forecasts than an AR forecast. The reduction in RMSE and MAE is significant or close to significance according to the test by Granger and Newbold. Only the foreward-looking KF forecasts of the net value added can be considered as a non-significant improvment. The errors on a calendar year basis show tendencies to over estimate production 1988 and 1989. For the not yet finally revised years of 1991 and 1992, the errors are in general small (except for exports). This could be due to the fact that the preliminary figures (contrary to final statistics) is based on a similar sample structure as that applied in BTS.

In the turning point analysis we find that the BTS contain useful information in indicating major changes in industrial activity. Primarily, this is true for the coincident KF model, whereas the results obtained by the foreward-looking KF model are more ambiguous. The latter model can, however, be used as an important complement to the former.

The KF program is now fully operational. Much work have been put into making the models user-friendly, also to people not familiar with the technical aspects of Kalman filtering. It has already been used in a real forecasting situation at the NIER.

Our main objective was to reproduce quantitative series using BTS data. But the quantitative data exhibit some undesired features when used for business cycle forecasting. The major drawback is temporary fluctuations, not due to changes in industrial activity. The BTS displays less volatility of this kind. As a consequence, the KF models are incapable of pin-pointing quarterly values. This is, however, not necessarily a shortcoming of the models if they produce smoother series emphasizing the underlying tendencies for the variable. This kind of information is more useful for forecasting purposes. In fact, one could argue that in many cases the approximation of a quantitative series, generated by a KF model based on survey data, is at least as good a business cycle indicator as the variable it is designed to predict. On top of that it is obtained much earlier and in some cases even produces genuine forecasts.

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Appendix: The KF computer programs

The model was imbedded into a software designed in a simple and practical fashion, keeping in mind that it is intended as a contribution to the arsenal of forecasting tools used for monitoring the business cycle. The starting point of our programs is those constructed for Rahiala and Teräsvirta (1993). Development of the initial programs have been carried out as follows:

a) Built-in optimization of the modelling structure of the transition equation based on the Akaike Criterion (AIC) and the Bayes' Criterion (BIC)[17]. The optimizing algorithm tests all lag structures, ranging from one to eight. This procedure is first conducted using seasonal dummies, then an intercept is introduced and in the final stage there are only lagged values. A restriction is that the lag structure is kept "straight", meaning that if the number of lags in an equation is found to be j, but one or a few of the parameters for lags $< j$ is/are insignificant, this/these are not dropped. Usually this does not lead to any serious differences in the AIC- and BIC-values, compared to those obtained by using the optimal lag structure in which insignificant lags have been removed. The gain is a considerable simplification in programming and a substantial speeding-up when running the program.

b) The corresponding optimization is carried out when estimating the measurement equation.

c) These "optimal" structures are saved by the program and used for the coincident and the ex ante forecasting of the chosen period to be predicted.

Hence the program is not centered around any fixed equations. This is a state space model and hence it is recursive in the sense that it is up to the user to decide the period of estimation. The reestimated (updated) equations are then used for coincident and forward-looking forecasting.

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[17] Cf e g Harvey (1989) p 78-80.

Appendix: The Granger-Newbold's test

We need a test instrument to decide whether incorporating BTS data in a KF significantly improves the predictions obtained with an AR model. We use a test according to Granger and Newbold (1986, p 279). The prediction error of an AR prediction is denoted δ_1 and the corresponding error of a KF model is denoted δ_2. Consider the two new stochastic variables: $\delta^+ = \delta_1+\delta_2$ and $\delta^- = \delta_1-\delta_2$. The expected value E of the product is:

$$E(\delta^+\delta^-) = E[\delta_1^2 + \delta_1\delta_2 - \delta_1\delta_2 - \delta_2^2] = E[\delta_1^2] - E[\delta_2^2] = \sigma_1^2 - \sigma_2^2$$

Conclusion: The variances of the errors, σ_1^2 and σ_2^2, are of equal size if and only if the new variables δ^+ and δ^- are uncorrelated.

Testing the null hypothesis that the coefficient of correlation:

$$r = \frac{\sum_{i=T+1}^{M} \delta_i^+\delta_i^-}{\left[\sum_{i=T+1}^{M} (\delta_i^+)^2 \sum_{i=T+1}^{M} (\delta_i^-)^2\right]^{1/2}}$$

is equal to zero is equivalent to testing if the KF model increases forecasting accuracy or not. It is well known that if δ^+ and δ^- can be assumed to be jointly normally distributed, in the terms of Hendry and Richard (1982), the KF model 'encompasses' the AR model,

$$t = \frac{r\sqrt{N-2}}{\sqrt{1-r^2}}$$

has student distribution with N-2 degrees of freedom.

Sammanfattning

Huvudsyftet med denna uppsats är att använda informationen i industribarometern i ett Kalmanfilter för att prognosticera ett antal variabler associerade med den svenska industrikonjunkturen: PVI, förädlingsvärde enligt NR, export av bearbetade varor samt antal arbetade timmar. Ansatsen är hämtad från Rahiala och Teräsvirta (1993) men med tyngdpunkt på "utfallsprognoser" dvs att med hjälp av barometerns utfallsdata göra en första uppskattning av den kvantitativa variabelns värde för utgående kvartal.

Den allvarligaste bristen i den kvantitativa statistiken är att den ofta kommer med en betydande eftersläpning, och kan ge felaktiga signaler om vändpunkter. I sin preliminära form publiceras kvantitativ statistik ca 2-3 månader efter mätperioden varefter den i omgångar revideras för få en slutgiltig form efter drygt 2 år. Den kvantitativa statistiken som redovisas på kvartal uppvisar också tillfälliga upp- och nedgångar som inte tycks bero på några förändringar i aktivitetsnivå hos företagen. En viktig orsak till detta torde vara en schablonmässig dagkorrigering. Konjunkturbarometern har i sin tur visat sig vara en snabb och pålitlig indikator av utvecklingen inom industrin. Den publiceras i sin slutgiltiga form i direkt anslutning till mätperioden och uppvisar endast i ett fåtal fall sådana förändringar som inte kan förklaras av det allmänna konjunkturförloppet. Dessutom innehåller barometern förväntningar och planer för den närmaste framtiden.

Två sorters prognoser undersöks: "utfallsprognoser" d v s prognoser av det senaste utfallet och prognoser av nästföljande kvartal. I det senare fallet används barometerns förväntnings- och planvärden tillsammans med utfallsdata. I båda fallen bedöms precisionen i förhållande till motsvarande autoprojektiva prognoser. Prognoserna bedöms utifrån hur väl de överensstämmer med utfallsdata samt förmågan att indikera vändpunkter.

Modellernas förmåga att indikera rätt kvartalsvärden utvärderas med hjälp av måtten RMSE, MAE och Granger-Newbold:s test. För att överbrygga eventuella problem med tillfälliga fluktuationer i kvartalsdata undersöks även sammanlagda prognosresultat över hela år.

Överlag finner vi att träffsäkerheten för kalmanfilter-prognoserna är bättre än för motsvarande

AR-prognoser. Dessutom gäller att förbättringarna är signifikanta, förutom för prognoser som avser förädlingsvärdet för nästkommande kvartal. KF-modellerna uppvisar också en positiv egenskap, om man lägger större vikt vid indikationsegenskaper än förmågan att pricka enskilda kvartal, detta eftersom modellerna ger ett jämnare kvartalsförlopp. Helårsresultaten visar att KF- modellerna, avseende produktionsvolym, överskattar 1988 och 1989. Vidare indikerar resultaten för 1991 och 1992 att barometerinformationen lämpar sig bättre för att prognosticera preliminära kvantitativa värden. En förklaring till detta torde vara att man tillämpar samma typ av företagsurval i barometern som i SCB:s preliminärstatistik.

I vändpunktsanalysen finner vi att barometerns kanske främsta tillgång är att den ger tillförlitlig information avseende förändringar i ekonomin. Främst gäller detta utfallsdata medan större osäkerhet gäller de framåtblickande prognosernas förmåga att förutsäga vändpunkter. De senare prognoserna är dock ett utmärkt komplement för konfirmera vändpunktsindikeringar i utfallsdata.

KF-modellerna har redan börjat användas i Konjunkturinstitutets löpande konjunkturbevakning.

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