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HYBRID INDICATORS FOR THE SWEDISH ECONOMY BASED ON NOISY STATISTICAL DATA AND THE BUSINESS TENDENCY SURVEY

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The lack of relevant data, not of theory,
is the greatest obstacle to research.

Nobel laureate R. W. Fogel

Abstract. Noise in Statistical Time Series (*STS*) is often overlooked when selecting the best forecasting model by looking at forecast errors. An "error" implies that one knows the true (noise-free) outcome. For noisy *STS* we instead search for Business Tendency Survey (*BTS*) data whose low frequency component has high coherence with its *STS* analogue. An extended Kalman filter, incorporating exponential smoothing, is used to build smooth indicators that can be regarded as hybrids of *STS* and *BTS* data. A special trigger is found in the joint behavior of model generated forecasts, by which smoothing can be switched off in sharp turns (high frequency but strong signals), and this avoids late turning point signals, due to time shift in one-sided smoothing.

Keywords: Business cycle indicators; Business Tendency Surveys; Noisy data; Exponential smoothing; the Kalman filter.

1. Introduction

The International Institute of Forecasters (IIF) was founded in the beginning of the 1980's, its main aim being to make forecasting useful for decision makers. New techniques had been developed to compete with more traditional business indicators, econometric models and simple ad hoc methods. The question *IIF* asked was, and still is: what techniques are useful in which circumstances, and does it really pay to be sophisticated?

This proved to be a highly relevant question. Several studies in the 1970's, followed by the well known M-Competition [Makridakis (1982)] cast some doubt on the efficiency of theoretically elegant methods as compared to more crude ones. More evidence was to come forth, the latest being Makridakis (1993). Strange enough, these results have had an almost negligible impact on the theoretical research, cf. Fildes and Makridakis (1994).

In judging the accuracy of forecasting techniques, certain rules were adhered to, aiming at bringing the models closer to the practitioner. Instead of just checking the fit within the observation period, forecasts were generated and the distance measured between out-of-sample forecast and outcome. This procedure mercilessly unmasked models that, though seemingly explaining the within-sample variation, were badly specified in the sense that they did not work in a real forecasting situation.

No doubt, this was an important step toward the practitioner. But, as will be shown here, it was based on a debatable metaphor: that of *aiming at an immobile target*. The practical forecaster, more often than not, works with statistical data that are all but stable and reliable. Fildes and Hastings (1994) report that one of the main reasons for bad forecasts in enterprises is poor statistics. Errors on the company level affect the aggregates reported in official statistics. Especially short term and preliminary data may not be much better than a forecast. More accurate figures may be available at a later time when they are too old to be of any help in forecasting. The reliability and up-to-datedness of the data to be forecasted also precede the problem of comparing forecast errors, as discussed in Clements and Hendry (1993)[1].

Late and blurred signals from preliminary short-period *Statistical Time*

Series (*STS*) have led forecasters to turn to indicators that are reported almost instantaneously. *Business Tendency Survey* (*BTS*) data are particularly popular with media, mainly because their meaning is so easy to understand. Researchers have been more sceptical. The way the tendencies are measured, as a distribution of answers across "lower", "same" and "higher", the result is poorly measured data, as compared to eg. a unit such as money or an index. At the most, *BTS* has been accepted as an explanatory variable in a regression, forecasting the outcome of the corresponding *STS*, ie. as a kind of auxiliary information. If, however, monthly or quarterly *STS*, especially fresh and unrevised, is known to be very shaky, the difference in respectability between *STS* and *BTS* should perhaps not be that big after all. The *STS* and *BTS* data will be discussed in Section 2.

This study is an application of well-known techniques to a real-life monitoring and forecasting problem. We postulate that the unobservable *production intensity* changes smoothly and that this intensity is a variance component, common to both *STS* and *BTS*.

We argue that, in practice, there often isn't much point in just matching a model using eg. *BTS* data to an unreliable statistical time series. Instead we look at the fairly accurate low frequency components of both series. The estimation and forecasting model is an extended Kalman filter, including exponential smoothing of the *STS*. This is presented in Section 3. Smoothing reduces the risk of false turning point warnings. However, the one-sidedness delays abrupt turning points. This effect can be eliminated in our case study by applying a rule that switches off the smoothing in sharp turns, i.e. high frequency but strong signals. The resulting indicator could be said to be a *hybrid* of *STS* and *BTS* data. For a noisy series, the hybrid may be able to distinguish and to signal turning points that couldn't even be spotted by eye. If the *STS* is smooth to start with, no smoothing may be needed, and we have the classical forecasting model. Brief examples of both categories of *STS*, plus hopelessly noisy ones are given in Section 4, reporting on the results. Section 5 concludes.

The forecasting models, using no smoothing, were first presented in Kääntä and Tallbom (1993). The Kalman agorithm is more or less the one published in Rahiala and Teräsvirta (1993)[2]. *BTS* data have been subject to intensive analysis since the pioneering study by Theil (1952). We haven't found a proper survey, so the reader is suggested to consult the references of the works mentioned in this study for further references to the voluminous literature. The first papers using filtering were Öller (1990 and 1992). In Entorf (1993) the forecasting relationship between *BTS* and *STS* is estimated using bandfiltered regression and German data, Hannan (1990, p. 457). The high coherence between Swedish *STS* and *BTS* on low frequencies was shown in Christoffersson et al. (1992). Recently, Young (1994) used a time-variable parameter model to show similarity between low frequency components of U.S. GNP and unemployment.

The same technique has been applied on all *STS* that have an analogue in the *BTS*, but we only highlight the model for manufacturing (*ISIC 3*) [3]. Summary statistics will be given for the other *STS*: exports, hours worked and employment (all *ISIC 3*), as well as for disaggregated manufacturing (*ISIC 31, 33 - 38*). We also analyzed all survey questions for each *STS* variable, but generally, very few *BTS* questions seem to contain any relevant information for forecasting.

2. The data

2.1 The statistical time series on manufacturing

This time series (Figure 1) is measured as "value added" in industrial manufacturing and is published by Statistics Sweden. We are using the quarterly manufacturing time series, adjusted for normal numbers of working-days, but not seasonally adjusted. It is an integral part of the National Accounts. The calculations are based on the annual industrial statistics, which is a complete census of the industry sector. The total coverage implies handling huge quantities of information. This leads to a delay in publication of 7-10 quarters from the expiration of the quarter when manufacturing occured, cf. Tengblad (1992).

[Figure 1]

How suitable is quarterly manufacturing for monitoring and forecasting? Gustafson and Holmén (1993) describe how the statistics is compiled in the case of production indices, strongly resembling that of our series. The calculations of preliminary quarterly values differ among subsectors. One of three sample-based monthly production *indicators*[4] is used:

(1) actual production,

(2) hours worked, and

(3) delivery data.

Statistics Sweden publishes a first preliminary value of the quarterly manufacturing 2.5 months after the expiration of each quarter. For subsectors, where employment data or delivery data are being used as indicators, revision of estimated quarterly production data is conducted when new data on the indicator becomes available. Furthermore, new information concerning investments in stocks is included in the revision. When the actual production is used as an indicator, no revision of the indicator is carried out.

Revisions of the last few annual figures are due to improvements in the data for preceding years, i.e. they are mere level alignments. A final annual figure is based on a complete census of all firms in each branch. However, the distribution across individual quarters is basically the same as in the first preliminary figures. Finally, it should be pointed out that changing the base year leads to revisions. Occasionally, general revisions of back years are carried out, where the number of years varies.

Perhaps the most important quality of an economic time series that is supposed to illustrate the business cycle, is that it should not falsely indicate turning points. A large high frequency variance, as in the unsmoothed series of Figure 1, can be due to two factors: measurement errors, especially when the number of working-days differs from what is assumed, or real quarter-to-quarter changes in the underlying production, due to a variety of irregularities. In large aggregates, the former should be much larger than the latter ones. For the purpose of monitoring and forecasting the underlying production intensity, both factors can be regarded as meaningless noise.

In the case of the unsmoothed manufacturing series in Figure 1, a major noise factor is the mechanical calendar correction rule. As an example, the rule does not recognize a working-day wedged in between a holiday and a weekend. Often, a firm decides to make up for one or a few of these days. The preceding quarter may then exhibit an increase in production, due to compensating overtime. On the other hand, when the day off is transformed into vacation, this will result in a decline in the production figure. It is not possible to discern any pattern in the firms' ways of handling days of this kind. Moreover, their behavior is probably inconsistent over time. Wandering holidays such as Easter constitute a related problem, falling on different quarters in different years. The Christmas holidays, too, fall on different days of the week, as do Swedish summer vacations, spread across both the second and the third quarter. For all of these cases, the rules of thumb and averaging applied by statistical offices may generate considerable fluctuations, that have nothing to do with production intensity. Five working-days in a week makes 65 working-days in a normal quarter, not counting off-weekend holidays. Removing one working-day makes the *STS* deviate from the underlying production intensity by 1.5%. Compensating will distort the next observation by the same 1.5% in the opposite direction, leaving a gap of 3% between these observations, the same size or larger than the average forecast errors of Tables 5 and 6! Should we require from a model to be able to forecast this?

Statistics Sweden publishes an annual report on the quality of its data. Eklöf (1992) is a general discussion on the quality of Swedish data. Tengblad (1992) assumes that final accuracy is proportional to the amount of total revision. Comparing economic statistics he finds manufacturing to be among the least accurate.

Gustafsson (1994) compares quarterly stock-investment calculated as *production minus deliveries* with *the change in the sum of stocks of finished goods and goods in process*. He finds hardly any resemblance between the resulting series! His paper seems to suggest that the production series is very inaccurate.

The conclusion is that in the case of manufacturing, quarterly Swedish data are very noisy. Swedish economic statistics are not internationally known for being inaccurate, cf. Table 6.1 in Tengblad (1992), and the problem is international in its characteristics, cf. de Leeuw (1990) on U.S. GNP data and Treadway's (1994) work with Spanish data. Yet, the final annual figures are based on the most solid data as compared to any quarterly figures, and this would probably also apply to other countries.

2.2 BTS data in relation to STS

The National Institute of Economic Research (NIER) conducts a quarterly survey among companies in the manufacturing industry. The answers to 42 questions are returned to *NIER* within the last month of that quarter, arriving up to three months before the preliminary *STS*. The questions are both coincident and forward-looking. The *BTS* is published during the first half of the month following the expired quarter. The survey is a stratified sample of firms with more than five employees, covering 100 % of all major firms. Hence, the sampling error is negligible.

The main problem with *BTS* is the scale of measurement. The questions are designed in such a way as to be easy to answer, even with very little information about the present and future activity of the company. This is a compromise between getting a fast reply and being precise. Respondents are asked just to tick one of three (sometimes two) alternatives, such as "higher" (*H*), "same" (*S*) or "lower" (*L*) production. These trichotomous answers are then pooled across firms, resulting in weighted average percentages, the weights being the number of employees in each firm. One then gets three time series, each one possibly containing information on the course of the economy.

The earliest attempt, presented in Theil (1952), to solve the information problem was to postulate a probability distribution on an interval scale[5]. The area under a density function is filled in proportion to the percentages of answers in each of the three categories, starting with *L* from the left, continuing with *S* symmetrically around zero, and *H* filling it up to the right. The transformed variable is the mean of the distribution, measured on an interval scale. There is very little evidence that a sophisticated transformation is a better predictor than simple combinations of answers, or perhaps just the answer that is most correlated with the *STS* analogue (cf. Öller, 1990). The most common transformation is the balance H - L. Is this a good predictor for its analogue among *STS*?

BTS is measured on an *ordinal* scale, where strictly speaking the subtraction H - L does not exist! One only knows that $L<S<H$ but not the unit of measurement. This is no mathematical subtlety that can be ignored in practice: it reflects the genuine ambiguity in interpeting trichotomous ordinal data. The balances 38 % - 12 % and 43 % - 17 % are numerically equal, even if in fact the latter may be much more pessimistic, i.e. if negative answers carry more weight than positive ones.

The balance assumes that the answers L, S and H are frequencies on the real axis, located at the points -1, 0 and 1, respectively. Then the answers can be regarded as a discrete probability distribution. Its mean $-1 \cdot L + 0 \cdot S + 1 \cdot H$ (cf. Theil's approach) is the balance that one assumes to be (usually semi-log-linearly) related to its *STS* analogue. We see that this transformation assumes that the distance between H and S is the same as that between S and L, cf. the example above. If this is not the case, the balance is not the "mean" of the answers.

Entorf (1993) presents evidence of large asymmetries in German *BTS* data. The balance is shown to be a poor predictor. However, this is not the case with Swedish *BTS* data. Experimenting with different definitions, we found that the balance produced the best forecasts.

A problem that sometimes turns up in *BTS* data is *seasonality*. When respondents are asked to make comparisons with the previous period, they are told to eliminate any seasonality. This can be difficult for those who have never heard about seasonal adjustment. In Lönnqvist (1959), seasonality is found in production answers in the Swedish *BTS*. König and Nerlove (1985) and Entorf (1993) report seasonality in German *BTS* data. Table 1 displays seasonal averages of the differenced manufacturing series and the seasonal averages of corresponding *BTS* series for two time horizons. We use an F test for the hypothesis that all averages are equal. As expected, the null hypothesis is rejected for the first series. It is accepted for all contemporaneous *BTS* series, but not for the forward-looking ones. We have not been able to find any definite explanation to this, but we will venture a plausible reason. For the horizon t, there already exists a crude estimate of the production in the company and the respondents remove seasonality by comparing it to last year's figure. Christoffersson et al. (1993) presents evidence suggesting that respondents adjust for seasonality by making annual comparisons.

[Table 1]

However, when the survey asks for production at $t+1$, the respondent has to come up with a genuine forecast, free of seasonal variation. Our guess is that the answer often is simply the *plan*, generally overoptimistic, for the increase in production during the whole year, as compared to the year before, and adjusted for what has possibly already accrued that year. In Fildes and Hastings (1994) it is reported that one of the most important reasons to bad forecasts is that managers substitute *plans* for forecasts. Looking at the seasonal averages of the *BTS*($t+1$) in Table 1, answers "higher" fall and "lower" rise uniformly during the year. Hearty optimism thus turns more and more realistic. Note that the seasonal pattern of the *BTS* series has no similarity with that of the corresponding *STS*. Still, the seasonal component is small in the Swedish *BTS*, and will prove to be ignorable.

3. Constructing indicators

If *STS* is accurate but late, a conventional model, relating *STS* to timely *BTS* seems appropriate. The model forecast then combines univariate dynamic properties of *STS* and *BTS*, transforming the relevant information in *BTS* to the scale of *STS*. A symbolic picture of this is trying to hit an immobile target.

However, data may be contaminated by so much noise that the resulting indicator becomes shaky enough to produce false turning point signals. It may even be impossible to pin-point turning points in the *STS*. Then the question is: can a reliable indicator be constructed by *smoothing* the data, where necessary, relying on possible low frequency coherence between *STS* and *BTS*? In this case, too, one minimizes the distance between outcome and the forecast, based on *BTS* as above. The variation in *STS* that also appears in *BTS* is regarded as better verified information on production intensity than the *STS* "outcome". We still use mean "error" criteria to choose the best indicator, but this is now a measure of verified information on the unobserved production intensity.

The problem with smoothing when forecasting is that one is forced to use one-sided filters that may generate a time shift. The choice then is between an early, but inaccurate signal, and an accurate but late signal. In Section 3.4 a rule will be presented that switches smoothing on and off. The resulting forecasts are called *hybrid indicators*.

The vehicle for extracting relevant information from BTS is the *Kalman Filter (KF)*. We applied the well tested procedure and *KF* algorithm that in Rahiala and Teräsvirta (1993) was applied on Swedish and Finnish metal and engineering industries (*ISIC 38*). Since *BTS* contains both coincident and forward-looking information, two indicators, one *coincident* and one *forward-looking* were constructed for the *STS*.

As benchmarks for forecasting accuracy, we used forecasts generated by the univariate part of the *KF*. The criterion for forecasting information in *BTS* is the Granger-Newbold (1986) test. Naive forecasts are not considered because we are mainly interested in turning points.

There are many reasons for using seasonal differences of the *STS*. For every variable we experimented with ordinary differences and seasonal dummies, but the best forecasts were obtained with seasonal differences. Unit root tests of rather short time series did not contradict our choice of differencing. Furthermore, recall the results of Christoffersson et. al. (1993) in paragraph 2.2.

Many statistical techniques could be used in the present case (eg. ARMAX). For continuous real-life forecasting we found *KF* to be both convenient and elegant. A formal description of the *KF* used here follows next.

3.1 The Kalman filter

Denote by x_t the logarithm of a quarterly *STS* at time *t*, and write $\Delta_4 x_t = x_t - x_{t-4}$. An autoregressive (*AR*) model for $\Delta_4 x_t$ is estimated through *T*-1:

$$\Delta_4 x_t = \begin{pmatrix} \phi_1 & \phi_2 & \cdots & \cdots & \phi_p & \mu \end{pmatrix} \begin{pmatrix} \Delta_4 x_{t-1} \\ \Delta_4 x_{t-2} \\ \vdots \\ \vdots \\ \Delta_4 x_{t-p} \\ 1 \end{pmatrix} + e_{1,t}, \quad t = 5+p, 6+p, \ldots, T\text{-}1.$$

Consider the exponential smoothing algorithm:

$$\Delta_4 \tilde{x}_t = \lambda \Delta_4 x_t + (1-\lambda)\Delta_4 \tilde{x}_{t-1}, \quad \Delta_4 \tilde{x}_5 = \frac{(\Delta_4 x_5 + \Delta_4 x_6)}{2}; \quad \Delta_4 \tilde{x}_t = 0, \ t \leq 4,$$

where $\sim$ denotes "smoothed" and λ, $0 < \lambda < 1$, is a constant. The *AR* model and the smoothing algorithm can be expressed in a stacked vector autoregressive, *VAR*(1) form:

$$\begin{pmatrix} \Delta_4 \tilde{x}_t \\ \Delta_4 x_t \\ \Delta_4 x_{t-1} \\ \vdots \\ \vdots \\ \Delta_4 x_{t-p+1} \\ 1 \end{pmatrix} = \begin{pmatrix} (1-\lambda) & \lambda\phi_1 & \lambda\phi_2 & \cdots & \cdots & \lambda\phi_p & \lambda\mu \\ 0 & \phi_1 & \phi_2 & \cdots & \cdots & \phi_p & \mu \\ \vdots & 1 & 0 & \cdots & & \cdots & 0 \\ & 0 & 1 & 0 & \cdots & & \vdots \\ & \vdots & & \ddots & & & \vdots \\ \vdots & & & & 1 & 0 & 0 \\ 0 & \cdots & & & \cdots & 0 & 1 \end{pmatrix} \begin{pmatrix} \Delta_4 \tilde{x}_{t-1} \\ \Delta_4 x_{t-1} \\ \Delta_4 x_{t-2} \\ \vdots \\ \vdots \\ \Delta_4 x_{t-p} \\ 1 \end{pmatrix} + \begin{pmatrix} \lambda e_{1,t} \\ e_{1,t} \\ 0 \\ \vdots \\ \\ \vdots \\ 0 \end{pmatrix},$$

and in matrix notation:

(1) $$\mathbf{\Delta_4 x_t} = \mathbf{A \Delta_4 x_{t-1}} + \mathbf{e_{1,t}}, \text{ for } t = 5+p, 6+p, \ldots, T\text{-}1,$$

where $\mathbf{\Delta_4 x_t}$ is the state vector[6]. In $\mathbf{\Delta_4 x_t}$ smoothed (first element) and unsmoothed (second element) values are generated in parallel. Note that the estimation occurs in unsmoothed data. The second row of the matrix **A** constitutes the *AR*(p) equation, whereas the first row is the smoothing algorithm. Smoothing is performed within the *KF* for convenience only and could as well be done outside the filter. The rest of the matrix updates $\mathbf{\Delta_4 x_t}$ one period. $e_{1,t}$ is an error term, assumed to be i.i.d. $(0,\sigma_1^2)$. Expression (1) is the *transition equation* of the *KF*.

A *BTS* series, y_t, for $t=5+p,\ 6+p,\ldots,\ T\text{-}1$ is estimated as a stochastic linear function of *STS*. Assuming $m<p$, the scalar valued regression can be written:

$$y_t = \begin{pmatrix} 0 & \beta_1 & \beta_2 & \cdots & \beta_m & 0 & \cdots & 0 & \gamma \end{pmatrix} \begin{pmatrix} \Delta_4\bar{x}_t \\ \Delta_4 x_t \\ \Delta_4 x_{t-1} \\ \vdots \\ \vdots \\ \Delta_4 x_{t-p+1} \\ 1 \end{pmatrix} + e_{2,t}\,,$$

and in matrix notation:

(2) $$y_t = \mathbf{b}\Delta_4\mathbf{x}_t + e_{2,t}\ ,\ \text{for } t = 5+p,\ 6+p,\ \ldots,\ T\text{-}1,$$

where $e_{2,t}$ is i.i.d. $(0,\sigma_2^2)$. This is *the measurement equation*.

3.2 Coincident forecasts

By using transition equation (1), we forecast *STS* for *T* and smooth it in the same filtering operation:[7]

$$\Delta_4\mathbf{x}_{T|T-1} = \mathbf{A}\Delta_4\mathbf{x}_{T-1},$$

where the unknown $e_{1,T|T-1}$ is set to its expected value of zero. Analogously, the measurement equation (2) is used to forecast a *BTS* for the same period, based on the *AR* prediction $\Delta_4\mathbf{x}_{T|T-1}$:

$$\hat{y}_{T|T-1} = \mathbf{b}\Delta_4\mathbf{x}_{T|T-1}.$$

But at time *T*, the actual value of the *BTS* is known. Any discrepancy between the forecast of *BTS*, $\hat{y}_{T|T-1}$, and the outcome of the *BTS*, y_T , would imply that the last observation deviates from the estimated historical pattern, described by the measurement equation. Then the *STS*, $\mathbf{\Delta_4 x_T}$, should also deviate from its estimated pattern, since both estimates are essentially based on the same history (of $\mathbf{\Delta_4 x_t}$, $t=5+p,6+p,\ldots,T\text{-}1$). For this reason, if the two *BTS* values differ, an adjustment of the *VAR* forecast of $\mathbf{\Delta_4 x_{T|T-1}}$ is called for. The correction is achieved by the *updating equation*[8]:

$$(3) \qquad \mathbf{\Delta_4 x^*_{T|T}} = \mathbf{\Delta_4 x_{T|T-1}} + \mathbf{k_T}\,[y_T - \hat{y}_{T|T-1}],$$

where $\mathbf{k_T}$ is the gain vector and depends on the forecasting variances of the transition equation and the measurement equation:

$$\mathbf{k_T} = \mathbf{V(\Delta_4 x_{T|T-1})b'}V^{-1}(y_{T|T-1}),$$

where $\mathrm{V}(\mathbf{\Delta_4 x_{T|T-1}})$ is the one step ahead forecasting variance-covariance matrix of $\mathbf{\Delta_4 x_{T|T-1}}$, and $\mathrm{V}(y_{T|T-1})$ is the one step ahead forecasting variance of y.[9] This gain can be said to be determined by the historical correlation between *BTS* and *STS*. If the series display a low degree of correlation or if the forecast error 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* can be accurately estimated from historical values of $\mathbf{\Delta_4 x}$. Hence, the value of $\mathbf{\Delta_4 x_T}$ should be equally correctly forecasted by the univariate model (3), and hence no adjustment of that forecast would be needed. The vector, $\mathbf{\Delta_4 x^*_{T|T}}$, is referred to as *the KF coincident forecast*.

3.3 Forward-looking forecast

In order to make a *real time* forecast of *STS* for $T+1$ using the *BTS*, the *KF* coincident forecast is substituted into the transition equation (1). The missing value of the *BTS* series for the coming period $T+1$ can be substituted by forward-looking information in the survey, concerning expectations, $y_{T+1|T}$, and there may also be such information in other *BTS* variables concerning *T*, here summarized in the vector $\mathbf{y}_{T|T}$, eg. as in Table 4. A forward-looking linear regression equation, cf. Rahiala and Teräsvirta (1993), lying outside the *KF* produces an *estimated* "outcome"of the *BTS* series, $\check{y}_{T+1|T}$ according to:

$$(4) \qquad \check{y}_{T+1|T} = h\,[\, y_{T+1|T}\,,\, \mathbf{y}_{T|T} \,],$$

where dummies can be included in the linear function h(·), if necessary. This estimated outcome substitutes, in (3), for the actual outcome for the period in (3). We proceed as in the coincident case, and get forward-looking forecasts of $\Delta_4 x_{T+1}$.

3.4 Swiching off smoothing in sharp turning points

Exponential smoothing induces a time shift that varies with the frequency. With a smoothing constant of 0.3, the breaking point between positive and negative time shifts, is cycles of approximately four years, cf. Öller (1986). Signals are delayed in sharp turns because these can be viewed as arches of oscillations of higher frequency. This is evident in Figure 1, (eg. 1980), where unsmoothed and smoothed manufacturing are compared.

Between turning points one wants to minimize the risk of false turning point signals. In, and right after turning points, the signal is strong, and here it mustn't be late. This leads to the conclusion that the ideal indicator should switch between a normal time regime where smoothing is on, and a critical regime, where smoothing is turned off. The crucial point here is to find a mechanism that correctly performs the switching. This is tantamount to finding an early turning point warning, and could be regarded as an unsurmountable obstacle, were it not that *BTS* has been found to contain such information, cf. Batchelor (1982) for Belgium, France, Germany and Italy, and Öller (1990) for Finland.

The way to find turning point information in *BTS* must essentially be an *ad hoc* problem. Before we describe a rule that works with Swedish data, a turning point has to be defined:

Definition. *A turning point is considered to have occurred if the seasonal logarithmic difference $\Delta_4 x_t$ changes sign, and keeps it for at least four quarters.*

A false signal then is the opposite: a false turning point signal is registered whenever $\Delta_4 x_t$ changes sign, but then changes it back again before four quarters have elapsed. Note that turning points are defined in seasonal *not* ordinary differences.

It will be convenient to group the modeling results in the next section using this definition, into three categories:

(i) The *STS* and the indicator that uses *BTS* are such that no false turning point signals occur,

(ii) False turning point signals occur, but can be eliminated by smoothing, and

(iii) The *STS* has most of its variance on relatively high frequencies.

In case (i), no smoothing is needed, neither in the hopeless case (iii), where there is no low frequency component to be recovered from the data. Hence, when looking for a switching mechanism, we can concentrate on case (ii). The rule that worked in Swedish data is the following:

Let the indicator be in the normal (smoothing) regime between two turning points. If in the next quarter the *smoothed* (coincident and forward-looking) forecasts do not change signs, while the *unsmoothed* forecasts *both change* signs, this is a signal that a turning point has occurred in the current quarter and that smoothing should be turned off, cf. Table 7, eg.observation 1978:4. When, subsequently, *both smoothed forecasts change signs*, switch back to the normal regime, *if* the smoothed coincident change is larger than the unsmoothed ditto, cf. Table 7, eg. 1980:2, *or* the two unsmoothed forecasts get different signs, cf. Table 7, eg. 1978:2. This is our *hybrid indicator*.

4. Results

Only the best forecasting models will be reported here and we will focus on aggregated Swedish manufacturing, cf. SNA (1970:1-1993:3), and only briefly report on models for other *STS* in paragraph 4.4. Time series of seasonally differenced quarterly data starting at 1970:1 are used[10]. As shown in Section

2, *balances* of the *BTS* data, cf. SBTS (1970:1-1993:4), could be employed. The models are estimated through observation 1987:4. The coincident forecasts are generated for the period 1988:1 - 1993:4, while the forward-looking model is used to forecast the period 1988:2 - 1994:1. The long out of sample period is due to the fact that the manufacturing series is not yet final for the period 1991 - 1994, when writing this report. We wanted only final figures in the estimation, and also some comparisons between forecasts and final figures (1989-1990), cf. Section 2.

The accuracy of the forecasts is measured in *RMSE* (Root Mean Square Error)[11] and *MAE* (Mean Absolute Error). Large errors affect *RMSE* more than *MAE*. Because of their popularity, calendar year forecasts are also presented. The annual figures in the lower part of Tables 5, 6 and 8 measure the errors in level, based on one step ahead quarterly forecasts. Turning point behavior is shown in Figures 2-5 and in Table 7.

The forecasts are one step ahead, in the sense that each forecast's origin is the best figure available today (1994:2). This, of course, is favorable to the models, once again reminding us of the problems encountered in practice when one has to work with shaky preliminary data as the forecast origin.

4.1 Equations

The transition equation (1) together with some test statistics are given in Table 2. Tables 3 and 4 show the measurement equation (2) and the equation estimating a BTS "outcome" one period ahead (4), respectively.

Significant autocorrelation is present in the measurement equation (2), Table 3, and in the equation (4) for *BTS* one period ahead, Table 4. The autocorrelation disappears when introducing *MA* and *AR* terms, but since the forecasts do not improve, the extra terms were dropped.

[Tables 2, 3 and 4]

In Section 2 (Table 1), we found seasonality in *BTS* answers concerning $t+1$. By modelling seasonality we were not able to improve forecasting accuracy, so, after all, the problem was not serious in our data.

4.2 Smoothed and unsmoothed forecasts

The *BTS* data significantly improve the coincident as well as the forward-looking forecasts, when comparing smoothed figures, see Table 5.

We have argued that the annual figures of the manufacturing series are the most reliable ones. Therefore, it is worthwhile to sum the quarterly forecasts for calendar years and compare the results to the annual unsmoothed *STS*. Table 5 indicates that *BTS* helps from the year 1990 on.

[Table 5]

Because of an unusually long boom period during the larger part of the 80's, there is only one distinct turning point outside the sample. Hence, also turning point behavior *within* the sample had been considered. This is shown in Figure 2 for coincident forecasts. The model well forecasts smoothed outcome. As seen from Figure 1, this also means that we are late in turning points, eg. 1978 and 1980.

[Figure 2]

The *unsmoothed* coincident, Figure 3, and forward-looking (not shown) forecasts generated by the *KF* model better capture fast occurring turns. However, they also signal false turning points, due to high frequency fluctuations, eg. 1982 and 1986. This occurs although the mainly *AR*-based forecasts can also be viewed as low-pass filtered values of the *STS*. The *BTS* significantly improves on the quarterly forecasts, as indicated in Table 6. The *AR* forecasts seem to be somewhat better when summing the forecasts for calendar years. One exception is the trough in 1991, where the *BTS* adjusts the *AR* forecasts in the right direction.

[Figure 3]

[Table 6]

4.3 The hybrid indicator

Table 7 shows the switching mechanism introduced in paragraph 3.4. The forecasts are compared with the outcome corresponding to the regime (smoothed/unsmoothed) the model is operating in. The *BTS'* improvement on *AR* forecasts is overwhelmingly significant as seen from Table 8. Now, also calendar year forecasts are very close to outcome.

[Table 7 and 8]

The forecasting accuracy of the switching models is also shown in Figures 4 and 5, where the switching regimes are illustrated graphically (Table 7). Because of the construction of the switch and the fact that forward-looking forecasts are real time forecasts, the regimes in Figure 5 will trail those in the coincident case, Figure 4, by one quarter.

[Figures 4 and 5]

The period 1992 - 1993 provides a challenge to the hybrid indicator. The *STS*, except for a spurious increase in 1992:3, signals a turning point in 1993:3, whereas the hybrid forecasts indicate a turn in 1992:4. The *STS* is *not* yet final, so it is impossible to tell which is right.

4.4 Other *STS*

Does our hybrid indicator work equally well for other series covered by the *BTS*? We have modeled the *STS*: *hours worked, employment* and *exports of manufactured goods*, all belonging to *ISIC 3* and *manufacturing* for *ISIC 31* and *33 - 38*. The series are assigned to three groups of *STS* defined in Section 3.4. The classification is presented in Table 9.

[Table 9]

Dating of the turning points in the unsmoothed *exports* series is impossible due to occasional strong high frequency fluctuations. However, it does not belong to category (iii) of *STS* containing no information. Meaningful forecasting information can be recovered from this series if we apply the smoothing switch proposed in Section 3.4, but in a slightly different manner: the smoothing is off as long as the unsmoothed forecasts for T and $T+1$ have the same signs, and switched on when they differ.

No business cycle information could be extracted from the *STS* of group (iii). In all cases the *BTS* contributes to more accuracy in both smoothed and unsmoothed forecasts, but, coherence appears only on high frequencies.

5. Conclusions

It has been shown how inaccurate and late statistics can be combined with early, but badly measured survey data to produce new series that are early and at least as reliable for monitoring as any one of their two components. The trick is to rely mainly on the low frequency component of the *STS* data, and when needed, add simple exponential smoothing to the Kalman filter used for forecasting. The time shift due to one-sided filtering when the *STS* series turns sharply, is counteracted by switching off the smoothing as soon as both the unsmoothed coincident and the forward-looking indicators signal a turning point. This proved to be an unmistakable alarm in the present data. We call the resulting forecast a *hybrid indicator*. Once you have found such a switch, you can answer the most important question that an economic forecaster faces, i.e. if the economy is in a turning point. In periods between sharp turns, the new smoothed indicator provides a sensible picture of what is going on in the economy.

While working closely with data, both *STS* and *BTS*, one becomes critical of the accuracy of what forecasters usually take as given: the "outcome" of what one is forecasting. The data we have handled mostly prove to be jumpy estimates that often have little to do with quarter to quarter true production intensity. This is a new challenge to the *IIF* and the journals that jointly try to improve the accuracy of forecasts, not just the complexity of forecasting methods. If the criterion for judging if a method works is by comparing forecast and outcome, we may just be comparing two estimates. Continuing to put the main efforts into finding better forecasting methods, can be likened to inventing new and more tasty recipes, while using low quality, or even putrid ingredients. We have suggested a simple way of handling this situation, while waiting for better data.

The hybrid indicators are used in real forecasting at the National Institute of Economic Research, Sweden. This may to some extent be due to the relative simplicity of our approach.

Remarks

The *KF* programming is done in GAUSS386i® VM version 3.01. The graphs are drawn in AREMOS/32® and then imported into WORDPERFECT® version 6.0 where the tables are constructed. Some of the analysis was done in SURVO®. All data used are available either on paper or diskette by the authors.

Acknowledgement

We are grateful to Professor Emeritus Erik Ruist whose suggestions have led to significant improvements. We also thank participators in seminars organized by the Economic Council of Sweden and collegues at the *NIER* for helpful comments. Economic support from the Economic Council of Sweden is gratefully acknowledged.

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Notes

1. In fact, bad data jeopardize the whole econometric approach. This problem was early recognized in the literature as "errors in variables", and in techniques for outliers, cf. Chen and Liu (1993).

2. Swedish *BTS* data have also been analysed by Lönnqvist (1959), Virin (1968) and Bergström (1992, 1993 a,b).

3. *International Standard of Industrial Classification of All Economic Activities*, third revision, 1968.

4. The main data suppliers are the branch organisations.

5. Lönnqvist (1959) suggests a two-dimensional normal distribution, where the second dimension is the reliability of the survey answers.

6. *KF* can be used for smoothing by running it backward in time, cf. Harvey (1989, p. 149). When forecasting, this is not possible, and the smoothing must be forward recursive. However, an obvoius alternative method would be band spectrum regression, cf. Engle (1974), however it is not clear how switching could be accomplished for high frequency but strong signals.

7. $\mathbf{x}_{T+k|T}$ denotes a forecast for T+k, k=1,2,3,... based on information up to time T.

8. $\mathbf{x}^*_{T+k|T-1}$ denotes *KF* adjusted forecast for T+k, k=0,1,2,... based on information up to time T-1.

9. These can be updated as follows:

$$\mathbf{V}(\Delta_4\mathbf{x})_{T+1|T} = \mathbf{V}[\mathbf{e}_{1,T}]$$

$$\mathrm{V}(\mathrm{y})_{T+1|T} = \mathbf{bV}[\mathbf{e}_{1,T}]\mathbf{b}' + \mathrm{V}[\mathrm{e}_{2,T+1}]$$

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

$$\mathbf{V}(\Delta_4\mathbf{x})_{T+1|T+1} = \mathbf{V}(\Delta_4\mathbf{x})_{T+1|T} - \mathbf{k}_{T+1}\,\mathrm{V}(\mathrm{y})_{T+1|T}\,\mathbf{k}'_{T+1}$$

10. Since manufacturing was affected by the labor market conflict in the second quarter of 1980, a dummy variable for this event has been introduced. 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. There are no scale invariance problems involved because all *STS* are measured in seasonal log. differences, which is close to percentage annual change, the most common measure used in macroeconomic forecasts.

Tables

Table 1: F tests of seasonality

	1Q	*2Q*	*3Q*	*4Q*	*F*	*df1*	*df2*
Δx_t♠	-.081	.072	-.257	.279	951**	3	51
"Higher", t	-.016	.010	-.003	.007	0.46	3	52
"Lower", t	.025	-.026	.000	.002	0.95	3	52
Balance, t	-0.39	.038	-.001	.007	0.73	3	52
"Higher", t+1♠♠	.027	.004	-.003	-.028	3.36*	3	52
"Lower", t+1	-.037	-.002	-.015	.054	3.58*	3	52
Balance, t+1	.065	.006	.018	-.082	3.75*	3	52

Legend: ** = Significant on level 0.01

* = Significant on level 0.05

♠ $\Delta x_t = x_t - x_{t-1}$

♠♠ The question is asked in quarter *t* concerning quarter *t*+1.

The figures for the *BTS* variables are quarterly deviations from the overall means for the variables proper. The null hypothesis is that the mean is the same for all quarters.

Table 2: The AR transition equation for manufacturing

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	.51	.24	-.55	.70		-0.09
t-value	4.68	4.70	2.20	-5.72	1.98		-3.37
	s	*LB(8-4)*	*ML(2)*	*sk*	*ek*	*JB*	R^2
value	.025	4.16	3.97	-.55	-.15	3.11	.78
p-value		.38	.14			.21	

Legend: The symbols in the lower part are:

s is the standard deviation 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 (no *ek* if the value is close to zero) and

JB is the test of normality by Jarque and Bera.

We also give the probability of the null hypothesis being true.

Table 3: *The measurement equation for manufacturing*

lags	$\Delta_4 x_{t-1}$					
coeff	2.45					
t-value	10.89					
	s	*LB(8)*	*ML(2)*	*sk*	*ek*	*JB*
value	.09	16.84	.55	-.05	-.29	.23
p-value		.03	.76			.89

Table 4: *The equation for forecasting a value of the BTS series: balances of 'production volume', for T+1 at time T,* $\tilde{y}_{T+1|T}$

variables	y_T^*	y_T	Balances of 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*
value	.05	14.67	4.34	-.10	-.04	.12
p-value		.07	.11			.94

Legend: y_T^* denotes the *BTS* variable: balances of "volume of production", *next quarter.*
y_T denotes the *BTS* variable: balances of "volume of production", *current quarter.*

Table 5: Forecasting accuracy of smoothed forecasts

	Coincident forecasts 1988:1 - 1992:4		Forward-looking forecasts 1988:2 - 1992:4	
	AR	*KF*	*AR*	*KF*
RMSE	0.0100	0.0072	0.0123	0.0104
MAE	0.0081	0.0062	0.0104	0.0087
G-N (p-val.)	0.0138		0.0596	
	Calendar year errors (compared to unsmoothed outcome)			
1988	0.0035	0.0037	0.0082	0.0114
1989	0.0047	0.0074	0.0088	0.0119
1990	0.0100	0.0063	0.0094	0.0077
1991	0.0501	0.0432	0.0509	0.0441
1992	0.0211	0.0168	0.0146	0.0131
1993	0.0044	0.0084	0.0089	0.0075

Table 6: Forecasting accuracy of unsmoothed forecasts

	Coincident forecasts 1988:1 - 1992:4		Forward-looking forecasts 1988:2 - 1992:4	
	AR	*KF*	*AR*	*KF*
RMSE	0.0383	0.0273	0.0400	0.0298
MAE	0.0312	0.0237	0.0327	0.0265
G-N (p-val.)	0.0066		0.0040	
	Calendar year errors			
1988	0.0108	0.0213	0.0165	0.0277
1989	0.0027	0.0118	0.0079	0.0188
1990	0.0099	-0.0126	-0.0018	-0.0068
1991	0.0364	0.0132	0.0370	0.0145
1992	-0.0036	-0.0169	-0.0124	-0.0162
1993	-0.0086	0.0074	-0.0004	-0.0029

Table 7: Recoveries and recessions in manufacturing, and coincident and forward-looking forecasts smoothed and unsmoothed

t	O_t	S_t	S_{t+1}	U_t	U_{t+1}	R	*t*	O_t	S_t	S_{t+1}	U_t	U_{t+1}	R
77:1	-	-	-	-	-	2	85:3	+	+	+	+	-	1
:2	-	-	-	-	-	2	:4	-	+	+	+	+	1
:3	-	-	-	-	-	2	86:1	+	+	+	+	+	1
:4	-	-	-	-	-	2	:2	-	+	+	+	+	1
78:1	-	-	-	-	-	2	:3	+	+	+	-	+	1
:2	-	-	-	-	+	1	:4	+	+	+	+	+	1
:3	-	-	-	-	+	1	87:1	-	+	+	+	+	1
:4	+	-	-	+	+	2	:2	+	+	+	+	+	1
79:1	+	-	+	+	+	2	:3	+	+	+	+	+	1
:2	+	+	+	+	+	2	:4	+	+	+	+	+	1
:3	+	+	+	+	+	2	88:1	+	+	+	+	+	1
:4	+	+	+	+	+	2	:2	+	+	+	+	+	1
80:1	+	+	+	+	+	2	:3	+	+	+	+	+	1
:2	-	⊕	+	+	+	1	:4	+	+	+	+	+	1
:3	-	+	+	-	-	2	89:1	+	+	+	+	+	1
:4	-	-	-	-	-	2	:2	+	+	+	+	+	1
81:1	-	-	-	-	-	2	:3	+	+	+	+	+	1
:2	+	-	-	-	-	2	:4	-	+	+	+	-	1
:3	-	-	-	-	-	2	90:1	-	+	+	-	-	2
:4	-	-	-	-	+	1	:2	+	+	-	-	-	2
82:1	-	-	-	+	-	1	:3	+	-	-	-	-	2
:2	+	-	-	-	-	1	:4	-	-	-	-	-	2
:3	-	-	-	-	-	1	91:1	-	-	-	-	-	2
:4	-	-	-	+	+	2	:2	-	-	-	-	-	2
83:1	+	-	+	+	+	2	:3	-	-	-	-	-	2
:2	+	+	+	+	+	2	:4	-	-	-	-	-	2
:3	+	+	+	+	+	2	92:1	-	-	-	-	-	2
:4	+	+	+	+	+	2	:2	-	⊖	-	-	-	1
84:1	+	+	+	+	+	2	:3	+	-	-	-	+	1
:2	+	+	+	+	+	2	:4	-	-	-	+	+	2
:3	+	+	+	+	+	2	93:1	-	-	-	+	+	2
:4	+	+	+	+	+	2	:2	-	-	-	+	+	2
85:1	+	⊕	+	+	+	1	:3	+	-	-	+	+	2
:2	+	+	+	+	+	1	:4	+	+	+	+	+	2

Legend: O = *STS* (unsmoothed) outcome,
S_t = *smoothed* coincident forecasts,
S_{t+1} = *smoothed* forward-looking forecasts,
U_t = *unsmoothed* coincident forecasts,
U_{t+1} = *unsmoothed* forward-looking forecasts,
R = regime in which the hybrid indicator is operating; R=1: smoothing, R=2: no smoothing,
+ / - = recovery / recession.
⊕ / ⊖ = switch in regimes because the absolute value of the smoothed coincident forecast in recovery/recession is greater than that of the unsmoothed ditto.

Table 8: Forecasting accuracy of the hybrid indicator for manufacturing

	Coincident forecast	Forward-looking forecast
RMSE	0.0185	0.0187
MAE	0.0137	0.0150
G-N (p-value)	0.0003	0.0001
	Calendar year errors	
1988	-0.0039	0.0031
1989	0.0071	0.0182
1990	-0.0113	-0.0113
1991	0.0076	0.0128
1992	0.0099	0.0008
1993	-0.0052	-0.0144

Table 9: Classification of STS according to smoothness group

	Group (i)	Group (ii)	Group (iii)
ISIC 3:			
Employment	X		
Hours worked	X		
Exports		X (u)	
Manufacturing:			
ISIC 3		X (u)	
ISIC 31			X
ISIC 33			X
ISIC 34		X (s)	
ISIC 35	X		
ISIC 36			X
ISIC 37			X
ISIC 38		X (u)	

Legend: With the *STS* smoothed in type (ii) the *BTS* can be smoothed (s) or unsmoothed (u).

Figures

Figure 1:

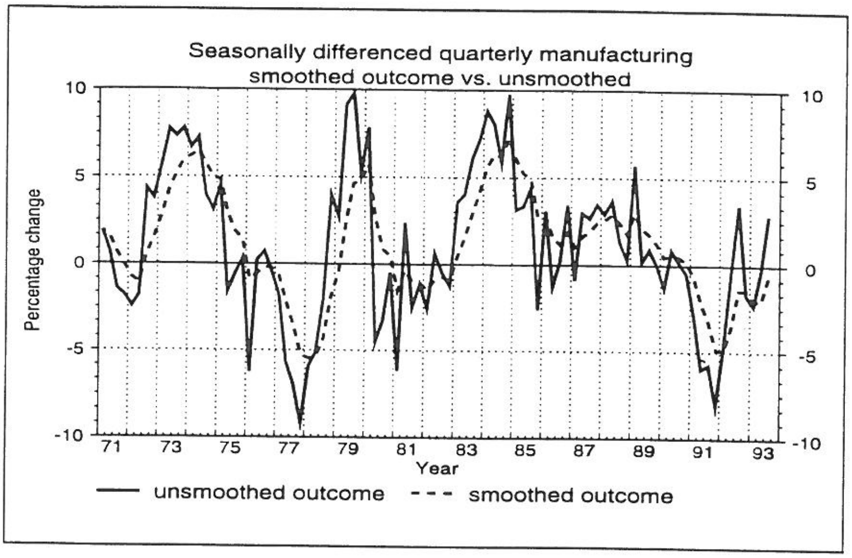


Figure 2:

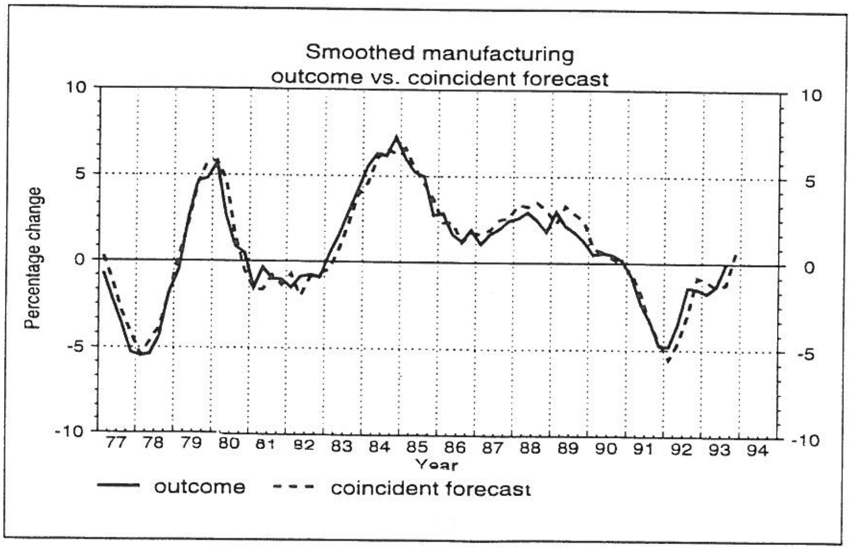


Figure 3:

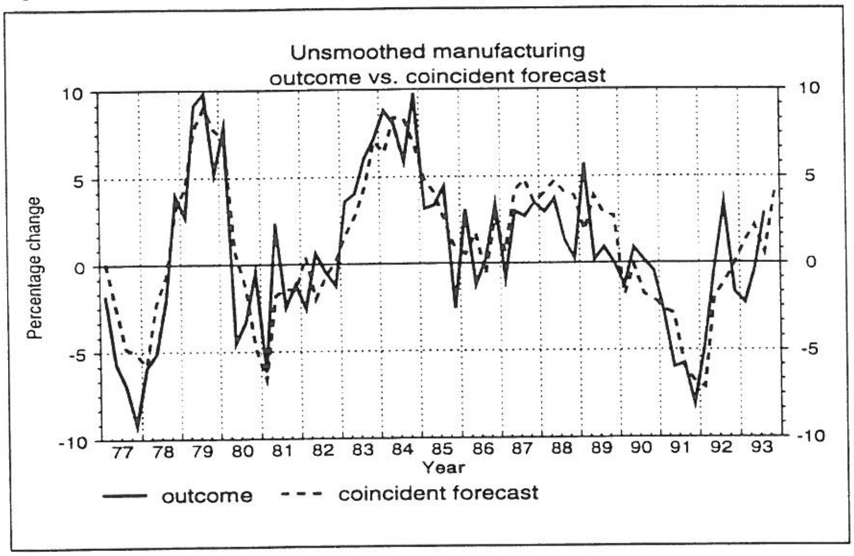


Figure 4:

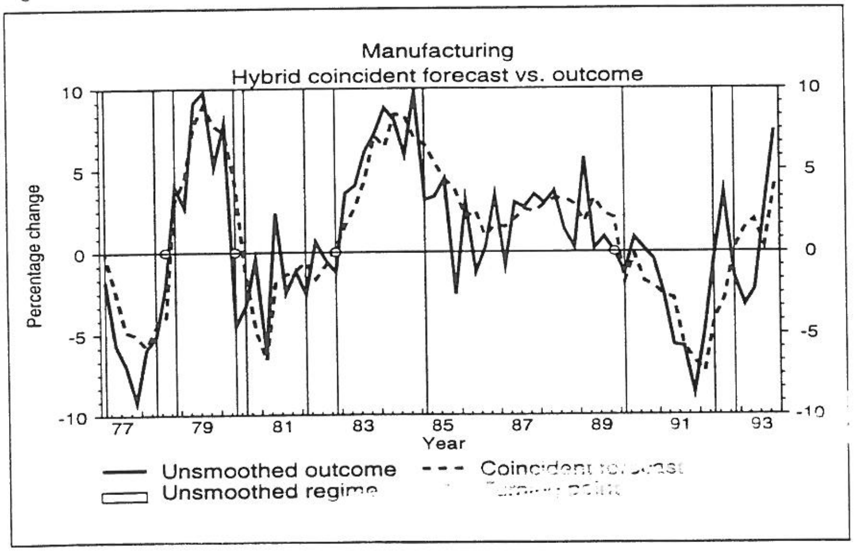
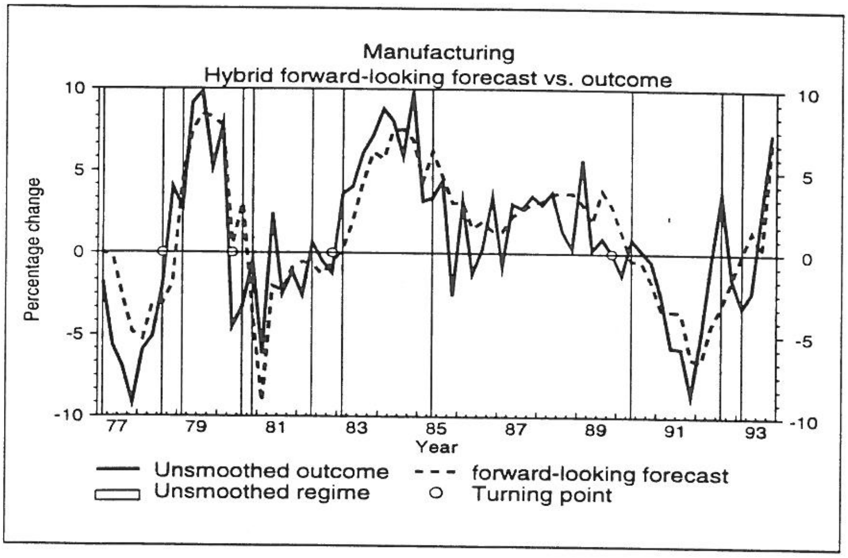


Figure 5:


Manufacturing
Hybrid forward-looking forecast vs. outcome
Percentage change
10
5
0
-5
-10
77
79
81
83
85
87
89
91
93
Year
Unsmoothed outcome
forward-looking forecast
Unsmoothed regime
Turning point

Sammanfattning

Ett problem som en prognosmakare ofta ställs inför är otillförlitliga och sena data av statistiska tidsserier (*STS*). Trots detta används dessa data som målvariabler i prognosmakarens modeller. Problemet är markant för kvartalsdata och speciellt preliminära siffror, medan slutreviderade årssiffror måste anses vara de bästa data tillgängliga.

En alternativ typ av data är barometerserier (*BTS*) som är en tendensstatistik över industrin. Fördelarna med *BTS* är att utfallsdata erhålls i direkt anslutning till respektive kvartal samt att barometern innehåller framåtblickande variabler. Nackdelen är att den mäts på en ordinal skala och inte på en intervallskala som *STS*, samt att även den uppvisar kraftiga fluktuationer, om än mindre än *STS*.

Vår studie är en tillämpning av välkänd tidsserieteknik på en verklig problemställning i det löpande arbetet med bevakning och prognosticering av konjunkturen. Metoden är den sedan tidigare beprövade Kalman Filter (*KF*) tekniken. Intresset i detta projekt koncentreras till kvartalsserien av det dagkorrigerade, ej säsongsrensade *förädlingsvärdet* för den totala tillverkningsindustrin (*SNI* 3). Säsongsdifferenser av logaritmerade värden används.

Syftet med denna studie är primärt att skapa en indikator av *produktionsintensiteten* inom svensk tillverkningsindustri. Vi postulerar att intensiteten förändras jämnt över kvartalen och att denna intensitet är en varianskomponent som är gemensam för *STS* och *BTS*.

Den konstruerade indikatorn förlitar sig i huvudsak på de lågfrekventa komponenterna av *STS* som erhålls genom att serien utjämnas exponentiellt inom ramen för *KF*. Eftersom utjämningen görs med ett ensidigt filter kommer det att ge upphov till fördröjda vändpunktssignaler. Detta kan motverkas om utjämningen stängs av vid dessa tillfällen. Problemet är att vid prognostillfället säkert veta att man befinner sig i ett sådant läge. Vi fann en tillförlitlig omkopplare baserad på de prognoser som erhålls vid varje prognostillfälle.

Ett *KF* används som tar fram utjämnade och outjämnade prognoser parallellt, dels för det nyss utgångna, dels för det kommande kvartalet (prognoser i realtid). Vi låter *KF* generera *utjämnade* prognoser tills de *outjämnade* prognoserna för t och $t+1$ *båda* byter förtecken, medan de utjämnade fortfarande har samma tecken som förut. Det är alltså den

gemensamma signalen för de båda outjämnade prognoserna som tas som ett säkert tecken på att årsförändringen av produktionsintensiteten har vänt. Prognoserna fortsätter att vara outjämnade tills endera av två fall inträffar:

(1) bägge utjämnade prognoserna (t och $t+1$) byter förtecken och är lika stora som de outjämnade,

(2) de båda outjämnade prognoserna börjar peka i olika riktningar.

Den resulterande prognosserien kallar vi *hybridindikator*.

Hybridindikatorn klarar de krav en prognosmakare borde ställa på en modell för att kunna bevaka och prognosticera en ekonomisk variabel: förutom att ge tidiga signaler om vändpunkter, bör den inte ge felaktiga signaler och slutligen måste den överensstämma med den mest säkerställda statistiken av variabeln, i detta fall årssiffrorna av förädlingsvärdet.

Vi har även undersökt andra tidsserier på samma aggregeringsnivå, såväl som förädlingsvärdena på en lägre aggregeringsnivå, främst för att se om den framtagna hybriden skull kunna vara tillämplig på andra serier. Resultatredovisningen av de undersökta serierna har begränsats till en katalogisering av serierna i tre grupper. De serier där precisionen i prognoser av vändpunkter och årsfel (och kvartalsfel) är acceptabla utgör två grupper. Den första omfattar de serier som redan är så pass jämna att ingen ytterligare utjämning krävs, grupp (i), och den andra de serier där hybriden fungerar väl, grupp (ii). Trots att *BTS* genomgående bidrar till lägre prognosfel av både utjämnade som outjämnade serier, kan prognoserna trots detta vara av så låg kvalitet att de är ointressanta, dessa serier utgör grupp (iii).

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