WORKING PAPER No. 17
November 1992

ELICITING TURNING POINT WARNINGS FROM BUSINESS SURVEYS

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Svensk resumé på sid 14.

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Abstract: Some guidelines are derived for choosing between business survey answers "higher", "equal" or "lower", or any linear combination of these when forecasting output. The ubiquitous balance is not defined on the scale used and is one of many possible linear combinations. Seasonal variation is found in survey answers and possibly a unit root. Data does not contradict rational output expectations. Corroborating earlier findings, survey data seem to contain early warning information on business cycle turning points.

Keywords: Trichotomous data, Turning point prediction, Exponential smoothing, Rational expectations.

1 Introduction

A host of methods help forecasters to predict the business cycle. Still, it happens that a turning point is discovered only when it has already occurred. Many reasons can be given for why turning points are hard to predict. The most important one is that data arrives with a considerable delay. Given only shaky preliminary figures on output 3-6 months ago it is not easy to predict what is going to happen from now on. Econometric models have to rely on that same data. If there are few and short lags most of the predictive power of a model rests on exogeneous autoprojections that seldom signal turning points in advance. ARIMA models are entirely autoprojective, an extreme case of which is the naive forecast that never predicts a turn.

What would be needed is some variable that registers shocks that will turn the cycle. By closely monitoring the economy one may learn to distinguish potentially pivotal shocks. But how do we know what shock will? This has led to a search for reliable, "early warning" data. People with a forward position in the production machinery can be expected to posess some ability to discern major changes in advance, or at least as they occur. This was the start of the business surveys in the beginning of the 1950's. The still ongoing research on how to use survey data in forecasting shows that creating survey-based anticipatory data did not solve the problem. One reason is that survey data is not recorded in the same metric as time series on production. There are many ways to interpret, use and transform survey answers and there are few clues for how to handle the data, that typically is contaminated by noise.

In this article we will take a closer look at business survey time series. In Section 2 we discuss problems of scale, transformations and choice of survey answers.

Section 3 presents some correlation patterns of how people respond on a trichotomous scale. In Section 4 we look for unit roots in Swedish industrial production. Here the question is raised if there could be unit roots in survey series, too. The problem of seasonal variation in survey data is briefly touched upon, as well as differences in seasonal patterns.

The relationship between survey series and production is analyzed in Section 5. Cross correlations show where one could expect leading information in survey series. We return to the problem of using a linear combination or single survey series. When specifying the models we draw on results by Bergström (1992), Cristoffersson et al. (1992) and Teräsvirta and Rahiala (1992). Exponentially smoothed data is used when modelling the relationship between survey and production data on the business cycle frequency band. The rationale for doing this is based on Öller (1986) and Christoffersson et al. (1992). The model chosen for forecasting accomplishes model fit mainly through the ARMA part, while the turning point warning basically stems from survey information. This is the approach that was found to work well in Finnish data (Öller, 1990).

Section 6 concludes this study.

2 Balances or single answers?

Because business surveys generally allow for three alternative answers, eg. "higher", "equal" or "lower", one gets three different series of percentage points, all of which could be used to forecast output, as could any combination of these. The most commonly used variable is the balance between "higher" and "lower", which, of course, is a linear combination. However, in some empirical studies single answers produce more accurate forecasts, cf. Teräsvirta (1986) and Öller (1990), using Finnish, and Entorf (1991), using German data.

The best way to find out is of course to test. But with three alternative answers, many time lags, several survey questions and branches, empirical testing can become a formidable task, in which any analytical guidelines may be of help in the search.

For simplicity, suppose there are just two alternative answers: "higher" and "lower". Then it is easy to show that it doesn't matter if you choose "higher" or "lower", or indeed the balance. Denote the relative share answering "higher" by p. Then the share "lower" is $1-p$. Let output be y. Then

$$r(y,p) = -r(y,1-p),$$

where r is the coefficient of (linear) correlation. This is because r is invariant to linear transformations in the variables between which it measures the correlation (cf. eg. Cramér, 1945, p. 279). Writing the balance

$$p - (1-p) = 2p - 1,$$

we see that this, too, is a linear transformation of the share "higher".

Adding one more alternative changes the situation entirely. Instead of one degree of freedom we now have two, so that the correlation between the three alternatives, or between a linear combination of these, and the variable y may be very different.

Again we can form a balance between answers "higher" and "lower". Denote, higher by p, as before, and let "equal" be q. Then the balance is

$$p - (1 - p - q) = 2p + q - 1. \tag{2.1}$$

Formula (2.1) shows that the balance can be seen as a linear combination of answers "higher" and "equal", assigning the weights 2 to "higher" and 1 to "equal", respectively.

Interpretation (2.1) is not unique. By calling answers "lower" r and "equal" q, as before, the balance can be written:

$$(1 - r - q) - r = 1 - q - 2r\,, \tag{2.1'}$$

showing that the balance can also be seen as a linear combination of answers "lower" and "equal" that assigns weight -2 to the former and weight -1 to the latter.

Formulas (2.1) and (2.1') shed some light on the question of balances vs. single variables. One may think that balances do not contain information on answers "equal". For just two degrees of freedom this is not true. The weight of "equal" is half the weight of the two opposites "higher" and "lower". Furthermore, the weights of "equal" have the same signs as those of *both* extremes. Presently, we shall look into the implications of this. Other linear combinations could be more suitable[1)]. Finally, a single answer may correlate more with output and/or may give earlier warnings, in which case only this variable should be given non-zero weight.

As compared to the dichotomous setup, trichotomous answers are surprisingly difficult to interpret. This is because answers "higher", "equal", and "lower" define just a hierarchy, ie. they are observations on an *ordinal* scale, where eg. differences (balances) are not defined. As a simple example, consider the following answers from periods t_1 and t_2:

	lower	equal	higher
t_1	12 %	50 %	38%
t_2	17 %	40 %	43 %

Now, has the situation improved in period t_2, as compared to t_1? According to the balance, no change has occurred since 38-12=43-17=26. Answers "higher" show an improvement, while answers "lower" tell the opposite. This can be compared to a series on output, usually an index number. Here we are on an *interval* scale where sums and differences are defined. Let t_0='100' and assume the following production numbers in three periods:

	t_0	t_1	t_2
OUTPUT:	100	101	105

Has production grown faster between t_1 and t_2 than between t_0 and t_1? The answer is yes, because 105-101=4>101-100, and there is no ambiguity! If the survey would have concerned this particular case, answers "higher" would have been the right choice.

When would one expect one answer to contain almost all the information of all three alternatives? This would happen if there is one more linear constraint that is almost satisfied. One such case is if one of the alternatives is almost constant and nearly all variation takes place between the remaining two. Another is when changes between the three alternatives occur in almost the same proportions. In the former case there would be strong correlation between the varying alternatives and low between these and the almost constant one. Modeling output, one would first try either of the two strongly varying alternatives, it doesn't matter which one. In the latter case there would be strong correlation between all three alternatives and any one of them would tell the same story. In all less clear cases it is impossible to tell in advance which variable or pair (but not triple!) of variables will be the best starting point.

Let's now turn back to the balance. We saw in (2.1) and (2.1') that the balance resulted in three sets of weights on the three alternatives:

	Higher	Equal	Lower
Set 1	2	1	0
Set 2	0	-1	-2
Set 3	1	0	-1

As long as nothing more is assumed about the alternatives than that they are mutually exclusive classes that can be ordered, this is what happens. We have to assume that the middle alternative is "neutral" (origin) and that both extremes are at one unit's distance from that origin in order to get just one scale, Set 3 above. This, of course, is the balance. It will work if this is the way people interpret the three alternatives. In that case an overall characterization of the distribution of anwers is the weighted average:

$$BAL_t = H_t x_1 + E_t x_2 + L_t x_3, \tag{2.2}$$

where

$$x_i = 2 - i, \quad i=1,2,3, \tag{2.3}$$

are the scale arguments of Set 3 above and H="higher", E="equal", L="lower" and BAL=balance.

When the two extremes are not perceived as symmetric around a neutral origin scale (2.3) is not appropriate for computing the mean of the distribution. Using the same symbols as in (2.1) and (2.1'), consider the linear combinations:

$$s_1 = ap + b(1-p-q)=(a-b)p -bq + b \tag{2.4}$$

$$s_2 = a(1-q-r) + br = (b-a)r -aq +a \tag{2.4'}$$

where a and b are constants, a>0 and b<0. Substituting a=1 and b=-1 brings us back to the balance expressed in (2.1) and (2.1'). In (2.4) the difference between the weight on "higher" and on "equal" is a, while the difference between "lower" and "equal" in (2.4') is b. Choosing a and b properly we can make answers "equal" come closer to "higher" or to "lower", depending on how people understand these alternatives. We see from (2.4) and (2.4') that the larger is b as compared to a, the more answers "equal" are pulled in the direction of "higher" (and away from "lower"). As an example, consider a=1 and b=-2. Then

$$s_1 = 3p + 2q -2 \text{ and } s_2 = -3r - q + 1,$$

assigning the weight difference 1 between "higher" and "equal" versus 2 between "lower" and "equal".

The coefficients of correlation can give a hint of how people look upon the alternatives. When there is high negative correlation between "equal" and "lower", equal is close to being *complementary* to "lower" and one would let $|b|-a$ be large. Principal component analysis could also be used, cf. Entorf (1991).

In this section we have discussed the question of how the attitudes in a survey can be accurately characterized. The results may save modeling time but of course the data may still prefer some other solution. Estimating parameters a and b in (2.4) one may find out what kind of linear combination, if any, is the best predictor.

The "bad scaling problem" has been known from the start of surveys. In Theil (1952) it is discussed at length. Here the percentages of the three alternatives are interpreted as probabilities for production, given on an interval scale. Both a rectangular and a normal distribution are presented. The latter reappeared in the lirature many years later in Carlson-Parkin (1975). The area under the density function is filled in proportion to the number of answers in each of the three categories. The interval of answers "equal" is symmetric around the origin and the distribution moves on the horizontal axis as the proportions vary. In analogy with (2.2) the single value chosen to represent the trichotomous answers is the mean of this distribution[2)].

Logarithmic odds of the type $log[p/(1-p)]$ have also been suggested, cf. Öller (1990). It is hard to find evidence in the literature of gains in forecasting accuracy due to any of these transformations.

3 Characteristics of some business survey data

The survey series to be studied here concern total industrial production in Sweden, and are published quarterly by The Swedish National Institute of Economic Research[3)]. Entrepreneurs are asked about their production in the current quarter t, the next quarter, t+1, and in the next half year. The last question is asked twice about the same half year. This seems to lead to inconsistent timing. The problem is not so serious after all because, as we shall see, the question seems generally to be understood as to mean a slightly longer perspective than t+1. We shall regard this question as pertaining to t+2. All questions can be answered by "higher", "equal" or "lower". As in (2.2) symbols H, E and L will be used. A number after the letter signifies the lead. For example, $H2$ means "higher" at t+2. In the next section we will try to find a model forecasting Swedish total industrial production using this survey data.

For comparative purposes we will also look at two analogous questions on output in Finland and on a business climate variable (a combination of perspectives zero and two) for Germany, here assigned to period t+1. The comparative numbers are shown in Exhibit 1. For balances to work we require answers "equal" to be, weakly and symmetrically correlated with the extremes. There are just two cases of weak correlation: between "equal" and "higher" in Sweden for horizons t and t+1. But in both cases there are considerable negative correlations between "equal" and "lower". For "lower", both "higher" and "equal" are complementary alternatives, but the only altarnative to "higher" is "lower". Hence variations in "lower" are ambigous, they can mean both more/less "higher" and "equal", whereas more/less "higher" always means less/more "lower".

For the Swedish data the variable "higher" seems to be the most consistent survey answer. There is symmetry and weak correlation in the Finnish data for horizon $t+1$. The same applies to a smaller extent to the Swedish survey for $t+2$. In these cases balances could be worth trying. In other cases, and especially for German data, balances would probably not be a good choice. "Equal" is strongly complementary to "lower" and weakly supplementary to "higher" in the German data. Entorf (1991) gets the best models when he combines different lags of "lower" and "equal", balances being clearly inferior.

4 Unit roots and seasonality

Exhibit 2 shows the logarithm of industrial production in Sweden 1970-1988. There are both non-stationarity and deterministic features in this typical macroeconomic output series. In Exhibit 3 we have removed a regular seasonal pattern by taking a seasonal difference. Now, for long periods the series stays above and below its mean. This could signal that it is still non-stationary. In Exhibit 4 we can see that the answers "higher" to the question on next half year, *H2* looks slightly similar to seasonally differenced output. This series could be nonstationary for the same reason. We shall now look further into the question of nonstationarity.

Stationarity can be tested. The first tests were presented in Fuller (1976) and Dickey and Fuller (1979) for frequency zero. In Hylleberg, Engle, Granger and Yoo (1991) a test is proposed that helps to decide whether to take a *quarterly* difference $1-B^4$, where $B^4x_t=x_{t-4}$. This operator has unit roots on frequencies 0, $\pi/2$ and π, i.e. on infinite, one year and half year waves. Two test values are obtained for the annual frequency. The test will here be called the "HEGY test". Detailed instructions for how to use this test can be found in HEGY (1991). Suffice it here to say that a significant test value indicates the *absence* of a unit root (stationarity) on that frequency. For a recent study on unit roots in *monthly* data, cf. Franses (1991).

Exhibit *5a* shows HEGY test values for the logarithm of Swedish industrial production 1970-1988. The rows are obtained by including in the regression a constant, a constant and seasonal dummies, a constant and a trend, and a constant, a trend and seasonal dummies. There are no significant test values on the 5 % level. However, when including a seasonal dummy in the regression, the annual and biannual unit roots almost disappear. In Exhibit *5b* the seasonal difference and this plus an ordinary difference are tested for unit roots on frequency zero using the Dickey-Fuller test. The augmented test indicates no unit root. When taking a double difference both tests signal stationarity. Given this short series on industrial production, statistical tests provide no definite answer as to what to choose: seasonal differences, double differences or an ordinary difference and seasonal dummies, when modeling the series.

In business surveys, entrepreneurs are asked to eliminate seasonal variation from their answers. Yet, it is well known that answers often display high autocorrelation on the seasonal lag. According to Exhibit 8, there are high autocorrelations on lag 4 for all survey series. We differenced the output and estimated quarterly averages of this series and of *H*1 and *H*2. Then an *F* test was used to find out if the quarterly averages were significantly different from zero. The test indicates significant seasonality for *H*1 but not for *H*2. Hence, if one wants to use *H*1 as a predictor for output one would have to eliminate the seasonality. Exhibit 7 shows the seasonal profiles of output, *H*1 and *H*2 and the test results. The seasonality in output is dominated by the (in Europe) well known trough in quarter 3 and the rush at the end of the year. The profile of *H*1 is completely different. It seems as if entrepreneurs were influenced by optimistic targets set around New Year, after which the predictions have continously to be revised downward. The statistically insignificant seasonality of *H*2 looks more like that of output.

In the previous section we saw that *H*2 can be suspected of containing a unit root. Fischer (1989) points out that if an output series has a unit root, then predictive survey anwers, as proxies for expectations, should have the same unit root, and the two series should be cointegrated (rational expectations). There are two problems in the present case. First, survey observations are percentages (or shares) that without transformation hardly satisfy the distribution assumptions of the tests. Secondly, there are very few observations on series *H*2 (44). Hence the test results should rather be regarded as suggestive. Since no significant seasonal variation was found in *H*2 there is no reason to use the *HEGY* test - an ordinary Dickey-Fuller will do. Exhibit 6 indicates that the series may indeed contain a unit root on frequency zero, but that an ordinary difference, or at the most a second difference will stationarize the series. A cointegration test of seasonally differenced output and *H*2 indicated that if indeed both series have a unit root on frequency zero they could be cointegrated (because the residuals in the testing regression have no unit root). Hence our data does not contradict rational expectations.

5 Modeling the relationship between anticipatory survey data and output

In this section we will try to exploit the predictive power in the survey data at hand. There is evidence of such power. Here we limit our scope just to Swedish survey data. Bergström (1992) finds predictive power in balances H-L and $H1$-$L1$, for total manufacturing. He also finds that these series contain all the predictive information there is in the survey, except that he doesn't analyze two periods ahead questions. Teräsvirta and Rahiala (1992) report a significant improvement in accuracy as compared to autoprojective forecasts.They analyze the Swedish metal industry. Christoffersson et al. (1992) show that on the business cycle frequency band, seasonally differenced output and the survey series concerning output are very much alike, and that the latter leads. They also suggest that respondents think in terms of seasonal differences when asked to eliminate seasonality from output.

Toward the background of analytical results in Section 2 and the correlation patterns reported in Section 3, we would not start from balances but rather from single variables or some linear combination of two, other than the balance. Among single variables we saw that answers $H2$ may be a good starting point.

Exhibit 8 shows auto and cross correlations. The first column contains estimated autocorrelation functions (*ACF*) for the seasonally differenced log. output (*D4LY*), followed by the survey answers concerning production at t+1 and t+2. As could be expected from the study of seasonal profiles, $H2$ has the smallest autocorrelation on the seasonal lag 4. The *ACF* looks very much like that of *D4LY*. The *ACF*'s of answers "equal" behave strangely. Looking at estimated cross correlation functions (*CCF*) in the second column, one would like to see low values up to and including lag zero, followed by high values for survey answers leading production. According to *CCF*, neither $E1$, nor $E2$ have any predictive power. All H and L answers seem to lead production, but all except $H2$ have high cross correlation on lag zero, which could reflect the autocorrelation in both output and survey series (the first column). Again $H2$ emerges as a promising regressor.

Since we want to concentrate our attention on the business cycle, both output and survey data were smoothed exponentially

$$z_t = \lambda Z_t + (1 - \lambda) z_{t-1}\,,\quad 0 < \lambda < 1\,,$$

where z signifies a smoothed, Z an unsmoothed value and λ is a smoothing constant given the value 0.3, cf. Öller (1986).

In this study, the most important criterion for a forecasting model is that it accurately, and as early as possible signals business cycle turning points, also outside the sample. Close fit has only second priority. Even a naive forecast can provide a good fit but according to its definition it cannot signal turning points in advance.

For testing the models outside the sample we have saved observations

1989 1Q - 1991 3Q. Turning points are defined as min/max values of *D4LY*, exponentially smoothed. Other model selection criteria were Root Mean Squared Error (*RMSE*), both in the sample and *ex ante*, Akaike's *AIC* and the Bayes criterion *BIC*. No significant autocorrelations were accepted in the residuals. The best univariate model and the best model containing survey data, together with diagnostic characteristics of the models are given in Exhibit 9.

Model *M2* including *H2* has a noise part that is almost the same as the ARIMA model *M1*, but *H2* adds a significant contribution to the explanation of output. We tried both with and without differencing and the former case forecasted slightly better. Also we tried first to specify a model and then smooth the forecast. Again the models *M1* and *M2* were more accurate. Furthermore, other lags of *H2* were tested, as well as answers to questions on domestic and foreign orders, but none of them could beat *M2*.

Looking now at model accuracy we see that the gain in fit from including *H2* is only marginal. The crucial advantage of basing forecasts on *H2* is that one gets slightly earlier turning point warnings. The *ARIMA* model is mostly correct in forecasting turning points, which is surprising but is probably due to the longer than one quarter lags on both sides of the model. Still, it never gives an early warning and once is too late by half a year. In the critical period outside the sample, *M2* better catches the dramatic fall in production. Notice that in two cases *M2* issues a turning point warning one quarter ahead. This shows that *H2* has a slightly longer horizon than $t+1$, cf. Section 3.

Finally, *M3* is specified as *M2* but the balance *H2-L2* has taken the place of *H2*. As can be seen from the ordinary diagnostics, this model is no improvement on *M2*. Still, the turning point characteristics are not bad. There is no late warning but there is one with a two quarters lead.

We also tried *h2* and *l2* as free variables. The coefficients of this regression were not significantly different from 1 and -1, respectively. This reflects the fact that there is fairly good symmetry for *H2*, and *L2* around *E2*, as compared to these questions concerning horizons t and $t+1$, cf. Sections 2 and 3. This is probably why balances work in *M3*.

6 Conclusions

We have seen that business survey data have special features that may be worth studying, before squeezing them into regression models. Also, when using balances one must remember subtraction is not defined on the ordinal scale, used by business surveys. If correlation or principal component analysis reveal assymmetries one should first try single answers or free linear combinations of answers, not balances.

It would be interesting to see a proper sociological analysis of the way people behave when answering surveys. We found indications of differences between Sweden, Finland and Germany. It could be added here that Finns seem to be much more pessimistic than Swedes, something that both Ilmakunnas (1990) and Rahiala and Teräsvirta (1992) also report. Incidentally, negative answers have been reported to work well in Finnish forecasting models, cf. eg. Öller (1990), whereas we got good forecasts using "higher" from more optimistic Swedish survey data.

Corroborating earlier results on survey data (ibid., see also Batchelor (1982)), the main contribution of such data in forecasting models is to improve the accuracy when forecasting turning points.

Acknowledgement

Support by the Economic Council of Sweden and by the Finnish Society of Sciences and Letters is kindly acknowledged.

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1) Entorf (1991) concludes that a linear combination of answers including "equal" results in a better model than those based on balances. The reason must be that his weights produce a better fit than the 2:1 weights of balances. Also, he uses different time lags in his combinations.

2) For an early study of how to quantify trichotomous business survey answers, cf. Lönnqvist (1959), Ch. IV. Probably unaware of Theil's results, Lönnqvist introduces a bivariate normal distribution for business survey data. The distribution of attitudes is depicted in one dimension, the inaccuracy of survey answers in estimating production in another dimension. Furthermore, conditions are presented for when there is a one-to-one relationship between survey and production data.

3) *Statistics Sweden* and *Business Tendency Survey* published by The National Bureau of Economic Research, Sweden. Data on single survey answers available starting from 1978. German data: Ifo Institut für Wirtschaftsforschung, Postfach 860460, D-8000 Munich, Germnany. Finnish data: Confederation of Finnish Industries, Etelä Ranta 10, SF-00130 Helsinki, Finland.

Att framlocka vändpunktsvarsel ur barometerdata

Det finns gott om metoder, som kan hjälpa den som skall göra konjunkturprognoser. Ändå händer det att en kritisk vändpunkt inträffar utan att man fått varsel om den i förväg. Detta beror till stor del på att det tar sin tid att ens få fram preliminära och ofta rätt osäkra statistiska uppgifter. Det var mot den bakgrunden man på 1950-talet började utveckla industribarometrar. Tanken var att företagarna var i den bästa positionen att spana sig till förändringar i konjunkturbilden.

Men problemet var ingalunda därmed löst. Barometerdata är inte så lätta att tolka som man kanske tror. Främst beror detta på att man mäter svaren på en sk. ordinal skala. Vanligen publiceras enbart nettotal, dvs. skillnaden mellan optimistiska och pessimistiska svar. Men med den tredelade skala "större", "lika", "mindre" man har är nettotal faktiskt inte matematiskt definierade. Man frågar sig då om det skulle finnas andra kombinationer eller kanske rentav bara något av svaren som skulle ha högre prognosvärde. Problemet är bara det att man ofta tvingas experimentera med ett mycket stort antal varianter av barometervariabler. Då kan man fråga sig om det inte kunde finnas någon analytisk genveg för att hitta en bra prediktor till till industriproduktionen.

Det man då kan utnyttja är att antalet frihetsgrader med två svarsalternativ är bara en och med tre alternativ har man bara två frihetsgrader. Det betyder att man med två svar kan studera vilketdera man vill eller vilken linjär kombination som helst - alla innehåller samma information. Med tre svarsalternativ behöver man aldrig kombinera mer än två svar. Här kan man pröva fria linjära kombinationer för att se om koefficienterna faktiskt kunde vara 1 för "större" och -1 för "mindre", vilket gäller för nettotal. Finns det mycket stark korrelation mellan två svarsalternativ kan det räcka med att pröva ett av svaren.

Frågan om hur man skall transformera barometerdata så att bästa möjliga prediktor erhålles för en produktionsserie är lika gammal som barometerenkäterna själva. Theil (1952) innehåller en transformation baserad på ett antagande om normalfördelade svar. En sådan lösning dök pånytt upp i Carlson och Parkin (1974). Antagligen även han omedveten om Theils lösning föreslog Lönnqvist (1959) en bivariat normalfördelning, som dessutom beaktade osäkerheten i företagarnas skattningar av sin egen produktion. I detta pionjärarbete anges även villkor för att samstämmighet skall gälla mellan barometerdata och produktionsstatistik.

Barometersvar skall ges i säsongfri form. Trots det kan säsongvariation påvisas i många barometerserier. Dessutom verkar denna variation ha en annan profil än den som finns i industriproduktionen. Ett undantag är den fråga i enkäten, som berör följande halvår. Här kan inte säsongvariation påvisas. Trots att svaren i detta fall är inkonsistenta såtillvida, att respondenterna två gånger uppmanas ange sin uppfattning om samma framförliggande halvår, visar sig denna variabel vara intressant ur prognossynpunkt. Antagligen uppfattas den som en allmän fråga om konjunkturen på litet längre sikt.

Den totala industriproduktionen och frågan om produktionen nästa halvår testas för enhetsrötter. Serierna är i kortaste laget så man vågar bara säga att data inte motsäger att produktionsserien kan kräva både en vanlig och en säsongdifferens för att bli stationär. Barometerserien kan ha en enhetsrot på frekvensen noll (slumpgång) och denna kan den ha gemensam med produktionsserien. De blir då kointegrerade och då vore villkoret för rationella produktionsförväntningar uppfyllt, såsom det formulerats av Fischer (1989).

Här framhävs betydelsen av att modellen varslar om vändpunkter. Precisionen mätt i roten av kvadratfelet är såtillvida mindre intressant, att hög precision kan uppnås även med en naiv prognos (ingen förändring), vilken definitionsmässigt aldrig kan varsla om det blir ett omslag i konjunkturen följande kvartal. Det har dessutom påpekats av bl. a. Christoffersson et al. (1992) att det är på konjunkturfrekvensen man skall vänta sig att barometersvaren har prediktivt värde. Detta framgår tydligt även av denna studie. Filtrering sker med hjälp av exponentiell utjämning och det visar sig då att även en autoprojektiv modell har en viss förmåga att tidfästa vändpunkter rätt pga. att lagpolynomen då får höga gradtal. Svar "högre" nästa halvår förbättrar dock både precisionen och försteget något. Just för denna fråga visar det sig att svarsalternativen "högre" och "lägre" uppfattas som symmetriska runt "samma" så att nettotalet blir en representativ linjär kombination, åtminstone på konjunturfrekvensbandet.

Till slut efterlyses en sociologisk studie av barometersvar i olika länder.

Exhibit 1. Pairwise Correlation between Answers, Sweden, Finland and Germany

	SWEDEN			FINLAND			GERMANY		
Horizon: t	**Lower**	**Equal**	**Higher**	**Lower**	**Equal**	**Higher**	**Lower**	**Equal**	**Higher**
Lower	1.0			1.0					
Equal	-.51	1.0		-.12	1.0				
Higher	-.83	-.07	1.0	-.77	-.54	1.0			
Horizon: t+1									
Lower	1.0			1.0			1.0		
Equal	-.68	1.0		-.37	1.0		-.83	1.0	
Higher	-.77	.06	1.0	-.73	-.36	1.0	-.77	.34	1.0
Horizon: t+2									
Lower	1.0								
Equal	-.43	1.0							
Higher	-.75	-.28	1.0						

Exhibit 2. Total Industrial Production in Sweden 1970-1988, log.

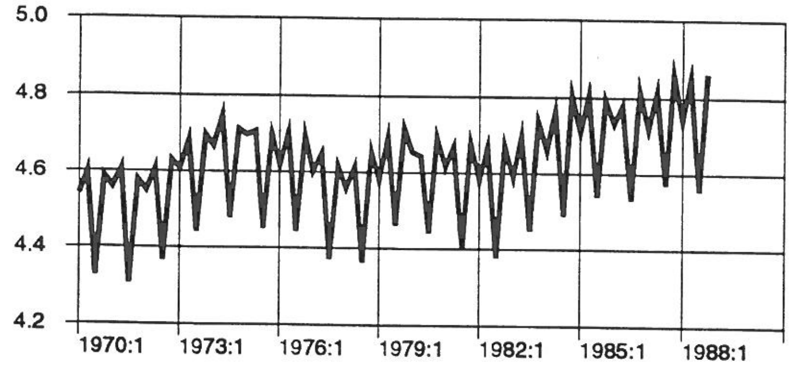


Exhibit 3. Seasonally Differenced Production 1978-1988, log.

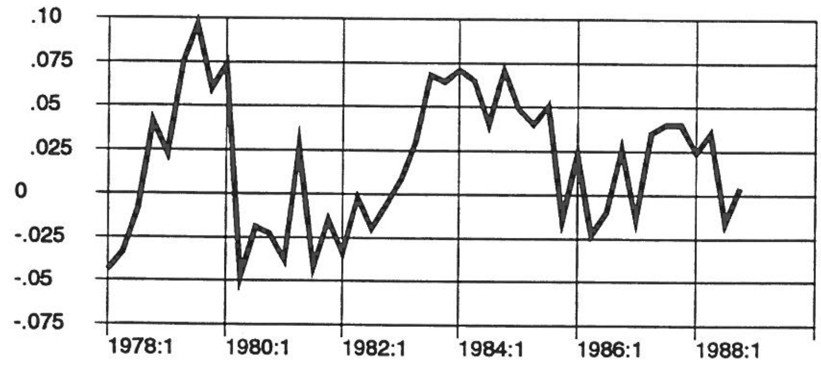


Exhibit 4. Answers "Higher" Next Half Year (*H2*)

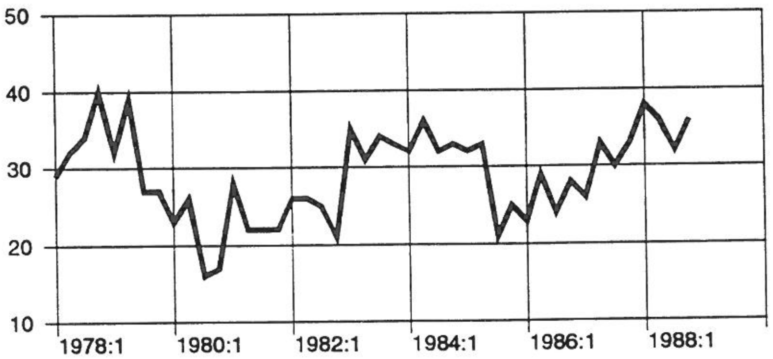


Exhibit 5. Testing for Unit Roots in Total Industrial Production (log.)

(a) HEGY Test of the Level

Auxiliary Regressors	*Roots* 0/year	2/year	1/year	l/year
None	-1.0	-0.1	-0.6	0.1
Constant	-0.8	-0.1	-0.6	0.2
Constant & Seas.	-1.3	-2.5	-3.3	-1.6
Constant & Trend	-1.6	-0.1	-0.6	0.2
Const., Tr. & Seas.	-2.1	-2.6	-3.4	-1.5

(b) Dickey-Fuller Test of the Seasonal Difference D4 and of the Double Difference DD4

	D4	*DD4*	*5% Conf.*
Ordinary Test	-3.3	**-12,3**	-3.4
Augmented "	**-3.0**	**-4.6**	-2,8

Exhibit 6. Testing for Unit Roots in *H2* Using the Dickey-Fuller Test

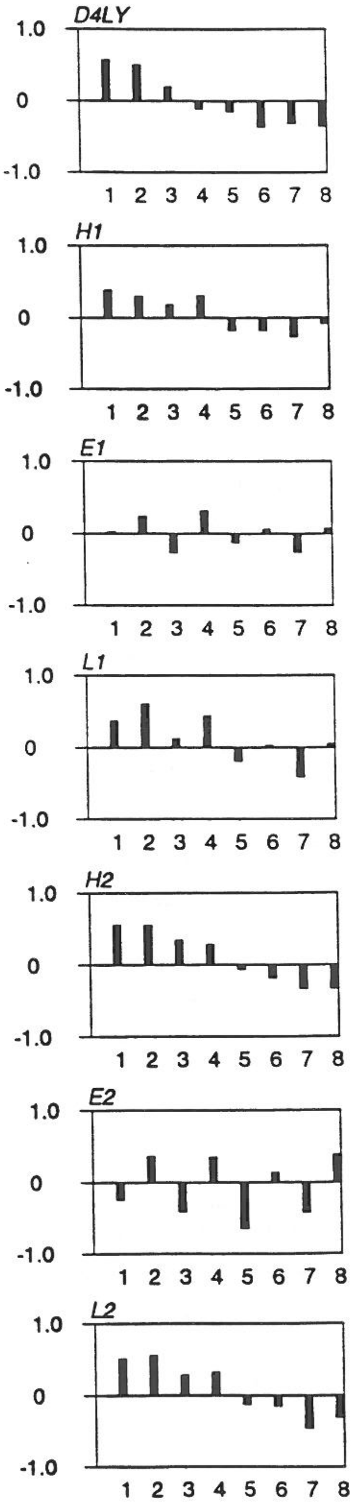
	Level	*D*	*D^2*	*5% Conf.*
Ordinary Test	-0,4	**-11,3**	**-7,5**	-3,4
Augmented "	-0,4	-2,5	**-3,7**	-2,5

Exhibit 7. Seasonal Averages and F Tests

	1 Q	*2 Q*	*3 Q*	*4 Q*	*F*	*P*	*df1*	*df2*
Diff. Ind. Prod.	-.081	.072	-.257	.279	**951**	.001	3	51
"Higher", t+1, *H1*	.027	.004	-.003	-.028	**3.36**	.05	3	52
"Higher", t+2, *H2*	.005	.024	-.020	-.008	1.46	.20	3	52

Exhibit 8. Auto and Cross Correlations of Output and Survey Answers Concerning Output at t+1 and t+2

(a) Auto Correlations



(b) Cross Correlations

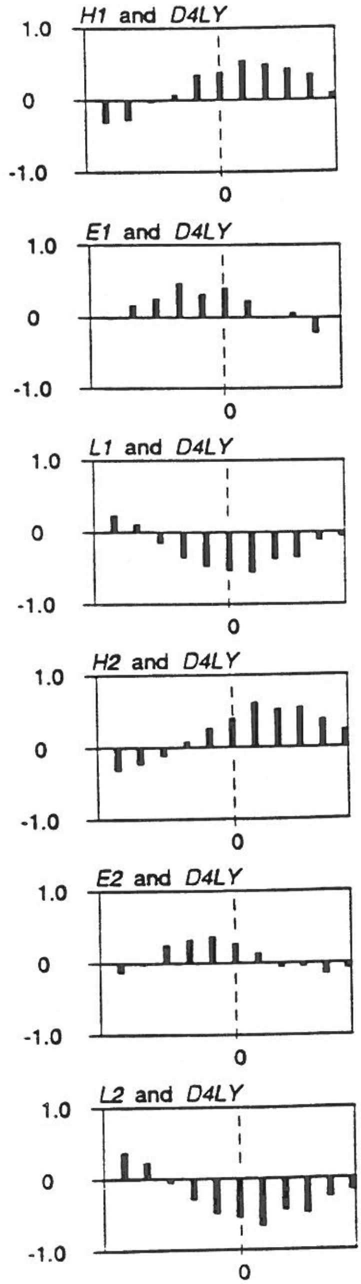


Exhibit 9. One Univariate Model and Two Based on Survey Data

$D = x_t - x_{t-1}$.

$d4ly_t$ = Smoothed values of seaonally differenced log. industrial production in Sweden for t = 1978Q1,..., 1988Q4.

$h2_t$ = Smoothed values of survey answers at t: "higher" in t+2.

bal_t = Smoothed balance $H_t - L_t$.

a_t = White noise error.

Numbers in parentheses are standard errors.

M1, Univariate Model: $\underset{(.114)}{(1 - .450B^2)}D(d4ly)_t = \underset{(.014)}{(1 - .968B^4)}a_t$

M2, Model Incl. Survey Data: $D(d^4ly)_t = \underset{(.000224)}{.000581}D(h2)_{t-1} + \underset{(.119)}{(1-.435B^2)^{-1}}\underset{(.011)}{(1-.963B^4)}a_t$

M3, Model Incl. Balance: $d^4ly_t = \underset{(.00035)}{.00205}bal_{t-1} + \underset{(.075)}{(1-.720B)^{-1}}\underset{(.179)}{(1-.427B^4)}a_t$

			One Step Ahead		At Turning Points		
	AIC	*BIC*	*RMSE*	*RMSE ex ante*	late (Q:s)	time	lead (Q:s)
M1:	-9.89	-9.81	.0068	.0104	1(2)	4	-
M2:	-9.87	-9.74	.0066	.0097	1(1)	2	2(1)
M3:	-9.58	-9.41	.0076	.0121	-	4	1(2)

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