QUALITATIVE SURVEY RESPONSES AND PRODUCTION OVER THE BUSINESS CYCLE

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Abstract

An examination of Swedish manufacturing data on real output and qualitative business tendency survey (BTS) responses from 1968 through 1998 reveals that survey-based attitude data typically improve the fit of simple autoprojective models of manufacturing output growth. It also turns out that traditional autoregressive distributed lag (ADL) models based on business survey data can provide more accurate one-quarter-ahead forecasts of output growth than naive alternatives. Another finding is that when BTS variables concerning *ex post* (*ex ante*) output growth are included in the empirical specifications, then no other *ex post* (*ex ante*) business survey variables seems to include any additional information about output growth.

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1. Introduction

Researchers, policy makers, and participants in the financial markets have paid considerable attention to the empirical relevance of various economic leading indicators.[1] The empirical concern of, for example, so-called qualitative Business Tendency Survey (BTS) responses is of large importance since business survey data are very likely to provide significant and early information about the current and future state of the economy. As a consequence, BTS data may have a substantial effect on both financial markets and the policy trends of Central Banks and Treasury Departments. The quarterly business surveys of the National Institute of Economic Research (NIER) in Sweden are an interesting attempt to supply a large dissemination of data and ready availability of high-quality analysis. In these business survey data, the responding manufacturing firms are asked whether they perceive or expect certain variables to increase, decrease, or stay the same over time. For example, these survey data include detailed time-series records on aggregate response percentages of firms whose perceived output in the current quarter has increased, decreased or stayed the same compared to the preceding quarter, and whose expected analogues will increase, decrease or stay the same the next quarter compared to the current quarter. The main reason why survey questionnaires generally require the respondents to provide subjective judgments in terms of directions of change rather than traditional point forecasts is that directions of change are much easier to provide by the respondents than high-precision point forecasts.[2]

These business surveys regularly arrive prior to the corresponding official statistics, and hence they are the first reports in every quarter on how the industrial sector in Sweden performs. It thus follows that these survey data may provide useful leading information about movements in the Swedish industrial sector and aggregate output. A

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[1] Important research contributions include Theil (1952), Carlson and Parkin (1975), Batchelor (1982), Teräsvirta (1986), Hanssens and Vanden Abeele (1987), and Koskinen and Öller (1998).

[2] Using Swedish survey data on inflationary perceptions, Jonung (1986) observed that the share of uncertain respondents increased as they were asked to provide numerical point estimates rather than only directional estimates.

number of surveys are now conducted worldwide on a regular basis. In general, the survey questionnaires are designed to explore individual firms' and/or households' *ex post* perceptions and *ex ante* expectations about an array of economic variables. The most recognized survey-based leading indicator today is the U.S. National Association of Purchasing Managers (NAPM) Index. This indicator has been published monthly since the 1930*s* and is used primarily for predictions of short-term cyclical movements in output.[3]

The empirical relevance of business survey data when analyzing industrial production has been recognized by Teräsvirta (1986), who found substantial evidence in Finnish metal and engineering industries that business survey data include useful information about future industrial production. Moreover, Bergström (1992, 1993b) found support for the claim that Swedish business survey data may improve the fit of simple autoregressive models of the change in manufacturing production. Furthermore, Christoffersson *et al.* (1992) showed that Swedish business tendency survey data are useful when predicting fluctuations in production over the business cycle, and Rahiala and Teräsvirta (1992) found evidence in Finnish and Swedish metal and engineering industries on leading information in business survey data. Support for the relevance of survey data when predicting business cycle turning points was found in Öller and Tallbom (1996), and, using Swedish manufacturing survey data, Koskinen and Öller (1998) showed that a Markov regime-shifting model can yield commendable predictions of business cycle turning points.

The above-referenced body of economic analysis hence confirms the assumption that Swedish (and Finnish) business survey data are closely related to industrial output and that they typically contain useful leading information about movements in the business cycle. In contrast, however, Batchelor (1982) showed that although survey-based growth expectations in Belgium, France, Germany, and Italy produce lower root mean square errors (RMSE) than simple extrapolative predictors, they include no additional

[3] See Bretz (1990) for an overview. For an empirical examination of the effectiveness of a subjective probability approach to quantifying three-category qualitative responses using NAPM data, see Dasgupta

information in more complex autoregressive integrated moving average (ARIMA) forecasting models. Moreover, on the basis of survey response data on short-term production expectations from Belgium, France, Germany, Netherlands, and Italy, Hanssens and Vanden Abeele (1987) found that survey expectations do not Granger-cause objectively measured production levels.[4] Hence, although it may seem intuitively plausible that business tendency survey data provide additional information in standard time series models of output growth, empirical studies provide somewhat different results.

This paper begins with the observation that macroeconomic policy makers typically are (partially) uncertain about the state of the economy and its reaction to policy. As a consequence, there is a substantial need to further investigate to what extent leading business survey variables offer relevant and timely insights into the real economy that can help analyze and predict fluctuations in aggregate output over the business cycle. The present work focuses on the relationship between BTS data and industrial production in Swedish manufacturing. It draws on (and updates) earlier empirical work by, among others, Teräsvirta (1986), Hanssens and Vanden Abeele (1987), and Bergström (1992, 1993b). The principal purpose of the study is to determine, within traditional time-series regression techniques, to what extent Swedish business tendency survey data can be used for quantitative model-based predictions of manufacturing production. In particular, I examine the short-term forecasting value of two different classes of quarterly business survey variables – those regarding perceived outcomes and those regarding expected outcomes.

Altogether, I find substantial empirical evidence that business survey variables may improve simple autoprojective models of manufacturing output growth. This finding is obtained when autoregressive models of output growth are expanded to include various business survey variables. The Schwarz (1978) information criterion values from these

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and Lahiri (1992). Föreningssparbanken provides a similar NAPM measure for Sweden called ICI (Inköpschefsindex). This measure dates back to around 1995.

[4] Hanssens and Vanden Abeele found, however, that survey production expectations appear to Granger-cause *survey-reported* production levels. This result suggests that the value of survey expectations might be contingent on the way production is measured.

augmented specifications are typically lower than the information criterion value from the simple autoregressive models. There is, in particular, a strong relationship between perceived *ex post* output in the current quarter compared to the previous quarter and actual manufacturing output growth between these quarters. It also turns out that when perceived *ex post* output is present in the autoprojective model, then no other *ex post* survey variables appear to include any additional information. Hence, according to this result, perceived manufacturing output in the current quarter compared to the previous quarter includes all relevant information in the *ex post* data. Similarly, when trying to forecast short-term fluctuations in output growth using only the *ex ante* survey variables, the expected output in the next quarter compared to the present quarter includes all the relevant information. These findings suggest that business survey data on perceived and expected manufacturing output include leading information on real output growth and that the other survey variables include no extra information. These results are consistent with the findings in Bergström (1992, 1993b). It also turns out that when perceived output is present in the empirical specification, expected output is superfluous. This finding is not surprising since *ex post* perceived output in quarter t should, per construction, be more closely related to actual output in quarter t than the *ex ante* forecasts (which are made in quarter $t-1$). I finally analyze the short-term predictive accuracy of various single equation time-series models based on survey variables. The results suggest that empirical models based on BTS variables typically outperform – in terms of mean absolute errors (MAE) and root mean square errors (RMSE) – simple autoprojective models.

The rest of the paper proceeds as follows: Section 2 briefly documents the business survey data that are used in this study. Section 3 outlines the empirical framework and presents the results, and concluding remarks finally close the paper in section 4.

2. Data Description

The current data set represents a subsample of the Business Tendency Survey (BTS) database, which is provided by the National Institute of Economic Research (NIER). The survey data used in the present analysis contain quarterly aggregate information from 1968:1 through 1998:3 on the direction of manufacturing firms' perceived and anticipated changes of a number of variables between two subsequent quarters. The survey questionnaires require the responding firms to provide (seasonally adjusted) subjective judgments in terms of three categories about changes in output, production capacity, prices, new orders, purchases of raw materials, the time of deliveries, and the number of employees between two subsequent quarters. These categories are defined as 'increase', 'decrease', or 'stay the same'.[5] The data include published time-series records of the so-called *net balance* statistic of the aggregate response percentages under each of the three response categories. This balance is defined as the linear transformation I-D, where I denotes the aggregate response percentages of firms indicating an increase, and D, analogously, denotes the aggregate response percentages of firms indicating a decrease.[6] The firms' answers are aggregated into relative shares by weighting them by the volume of value-added output.

These business survey data are important for prediction purposes because information on officially registered National Accounts production levels is not available to the public at the time for the survey. The reason for this is that, although the information on which the officially registered data are based is gathered at approximately the same time as the survey data, the officially registered data are – due to time-consuming data processing – published with a time lag of around three months. Business survey data are typically released to the public in final form the first or second week after the end

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[5] The bounds of the 'stay the same' interval are not explicitly formulated in the questionnaires. Hence, it is plausible that changes in the variables of interest, either positive or negative, which are proportionally small will not be regarded by the responding firms as increases or decreases but as cases of 'stay the same'. The set of survey questions is detailed in the appendix.

[6] Other linear transformations of these survey answers can, of course, also be constructed. For a discussion of the relationship between various transformations, see Hanssens and Vanden Abeele (1987) and Öller (1992).

of each quarter. As a consequence, at the end of quarter t only survey results from quarter t (that is, perceptions concerning quarter t and expectations concerning quarter $t+1$) and officially registered output statistics for quarter *t-1* are available to the public.

The present sample covers the complete population of manufacturing firms with 50 employees or more, and a stratified sampling procedure has been used for the remaining smaller firms with less than 50 employees and more than 10 employees. In 1998, each quarterly survey included 2.500 manufacturing firms.[7]

(Table 1 about here)

Table 1 reports some descriptive statistics of the net balance of perceived and expected output, production capacity, prices (domestic and export), received orders (domestic and export), the value of acquired raw materials, time for deliveries, the number of employees, and 'confidence'.[8] The last column in Table 1 reports the probability of observing a test statistic at least as large as the obtained Jarque-Bera normality test value, assuming that the null hypothesis of normality is true. This column reveals that the assumption of normality cannot, in general, be rejected.[9] Since the BTS data are expressed in terms of changes, a positive mean value indicates that the level-

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[7] The number of manufacturing firms in the business survey data has varied over time. The principal reasons for this are that the population of total firms changes over time as the business cycle evolves, and that the stratified sampling procedure has changed. For the moment, the data include around 10 percent of all firms with 10-20 employees, 20 percent of all firms with 20-50 employees, and 100 percent of all firms with more than 50 employees.

[8] The 'confidence' variable is calculated as present order-books evaluation minus present inventory evaluation plus expected production. For more details, se Appendix A.

[9] Exceptions are, however, the expected export prices (B304) and the expected number of employees (B308) in the next quarter as compared with the current quarter. These variables are not normally distributed over the relevant sample period. Take also notice that at the time of the Swedish EU membership, the BTS questions were harmonized among all EU member countries. As a consequence, some additional questions were included in the survey data and some were excluded. From 1978 through 1995, therefore, B308 refers to the expected time of deliveries the next quarter as compared to the present quarter. From 1996 onwards, B308 refers to the expected number of employees the next quarter as compared to the current quarter.

counterpart to the survey data typically increases over time. Hence, all variables except the perceived time of deliveries this quarter as compared with the preceding quarter (B108), the expected number of employees the next quarter as compared with the current quarter (B308), and the weighted confidence indicator (BC) appear to increase over the time period. Moreover, the table also reveals that the *ex post* variables (B101-B108) on average have a slightly smaller mean value than the corresponding *ex ante* variables (B301-B308), and that the standard deviation of the *ex post* variables typically is larger than the standard deviation of the corresponding *ex ante* variables. This finding suggests that the firms are, in general, somewhat over-optimistic *ex ante*, and that their expectations are relatively cautious in the sense of being more invariable over time than perceived outcomes. Furthermore, it is apparent from inspection of Figure 1 that annual changes in manufacturing production (as measured by officially registered National Accounts data) correlates significantly with the net balance of the perceived production volume in the current quarter as compared with the preceding quarter. The correlation coefficient is almost 0.8. Since all BTS data series are highly correlated (their cross correlation coefficients generally lie between 0.2 and 0.9), the four-quarter logarithmic change in officially measured production also correlates significantly with the other survey variables. The lowest correlations are, not surprisingly, between the survey price variables (i.e., B103, B104, B303, B304) and manufacturing output growth. Table 2 shows the correlation coefficients between the current value of output growth and the business survey variables of different lags.

(Figure 1 about here)

(Table 2 about here)

Although Figure 1 demonstrates that output growth measured as the four-quarter logarithmic change in the volume of seasonally unadjusted manufacturing production correlates significantly with the BTS data on perceived output changes, the rate of output growth could also be measured as the first difference of the logarithm of seasonally adjusted manufacturing production. This measure is intuitively appealing because it is consistent with the construction of the survey data, which explicitly asks the responding firms to compare consecutive quarters while adjusting the answers for seasonal effects. However, some variation due to seasonality may nevertheless still be present in the survey data.[10] Therefore, in the empirical section I follow Teräsvirta (1986) and use the first difference of the logarithm of (seasonally unadjusted) output in combination with quarterly time dummy variables.

(Figure 2 about here)

A closer look at Figure 2 reveals that the responding firms' *ex ante* anticipations about the level of production the next quarter compared to the current quarter repeatedly overstated the *ex post* outcomes during the period 1997:3-1998:3. This finding may correspond to a successive deterioration of world-wide export markets and demand due to the Asian crisis that was not completely anticipated by the responding firms.

One possible limitation of the available survey data is that the answers are trichotomous (that is, they are represented by three single categories). While it is most certainly the case that such directional data are easier to provide by the firms than traditional point forecasts, they are nevertheless non-standard in the sense that they use categorical scales rather than interval scales. For example, it is certainly not obvious that these survey data have any cardinal significance at the aggregate manufacturing level, although they have ordinal significance at the firm level. Moreover, since BTS data are measured by aggregate response percentages, they are limited to the interval between minus one and one. As a consequence, these variables might be less suitable as dependent variables in regressions.[11]

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[10] Christoffersson *et al.* (1992) found that although some of the *ex ante* answers appear to contain seasonal patterns, *ex post* variables are in general characterized by rather small seasonal components.

[11] Models characterized by limited dependent variables have been used frequently in the empirical literature when studying, for example, household expenditures on durable goods and wages of married women. The standard way of dealing with this kind of limited dependent variables is to use non-linear transformations based on the assumption of a continuous latent variable.

A final potential limitation is that we have reams of noisy survey data drawn from complex non-experimental settings that are imperfectly understood. If this is the case, then spurious inferences might cause severe specification difficulties in the empirical analysis. For example, since the perception of the boundaries of the 'stay the same' interval may, at least to some extent, differ between the responding firms, the BTS data may contain some measurement errors and inconsistencies at the level of individual firms. Although these measurement errors are likely to be partially cancelled out at the aggregate manufacturing level (this problem is hence likely to be less pronounced in the present data), this problem may sometimes call for special estimation techniques. The present analysis disregards from this potential difficulty.

3. Econometric Analysis and Results

This section describes the methodology for analyzing the relationship between the business tendency data and manufacturing output. Selecting an appropriate empirical model is, of course, rather difficult since the specific model selection process cannot be completely guided by theory or previous empirical work. The empirical models in this section are dynamic, and lag structures with no *à priori* lag specification must as a consequence be specified. Guided by earlier empirical work, the empirical route is to use Teräsvirta's (1986) three-step procedure in order to select an appropriate empirical model. In the first step of this procedure, the growth rate of manufacturing output, measured as the first difference of the logarithm of the seasonally unadjusted volume of manufacturing production, is expressed as a simple autoprojective function of a constant, past output changes and quarterly time dummy variables. Here, the first five lags of output growth are used on the right-hand side of the equation (that is, the maximum lag length is five), and the optimal specification is derived using the Schwarz (1978) information criterion.[12]

[12] The Schwarz information criterion is defined as $-2l/T+(k/T)log(T)$, where k is the number of estimated parameters, T is the number of observations, and l is the value of the log likelihood function. This information criterion asymptotically selects the 'true' model if it exists among the alternative models.

The second step is to formulate a so-called single survey variable (SSV) model for each business survey variable. This model expresses the growth rate of manufacturing output as a function of a constant, past output changes, time dummy variables, and present and time-delayed measures of the survey variable of current interest. The largest SSV formulation always includes the first five lags of the dependent variable as explanatory variables, and the relevant survey variable is always represented by lags 0 to 4.[13] The optimal specification is derived with respect to the Schwarz information criterion. If the autoprojective model is characterized by a smaller Schwarz criterion value than the SSV specification, then the survey variable of current interest is omitted from further empirical consideration.[14] This procedure is then performed separately for each of the *ex post* and *ex ante* survey variables.

In the third step of this procedure, I combine the remaining survey variables and lags (that is, the survey variables and the lag structure that, according to the second step of this procedure, provided additional information in the output growth regressions) into a large model of output growth. Hence, this model expresses the growth of manufacturing output as a function of a constant, past output changes (lags 1 to 5), seasonal time dummy variables, and the relevant business survey variables and their lags that were found in the second step. The Schwarz information criterion is used as a model selection device.

In the following, officially registered data on manufacturing output are available from 1968:1 through 1998:3, and the business tendency survey data on perceived outcomes in the current quarter compared to the preceding quarter are available from 1964:1 through 1998:4. The range of the expected analogues is typically 1964:1-1999:1.[15] Hence, the regressions in this section cover the period 1968:1 to 1998:3. According to

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[13] This lag structure is roughly the same as the one used by Teräsvirta (1986).

[14] According to Teräsvirta (1986), this minimum Schwarz criterion procedure is asymptotically equivalent to an *F*-test (of the joint hypothesis that the survey-variable coefficients in the SSV models are insignificantly different from zero) only if the autoprojective model is nested into the SSV model.

[15] The only exception is the expected number of employees in the next quarter as compared with the current quarter, which covers only the time interval 1978:2-1999:1. This variable, however, refers to

the model selection process described above, the optimal autoprojective model becomes:

$$\Delta y_t = \underset{(0.026)}{0.046} - \underset{(0.072)}{0.242}\Delta y_{t-1} + \underset{(0.072)}{0.615}\Delta y_{t-4} + \underset{(0.044)}{0.001}d_{1,t} - \underset{(0.021)}{0.032}d_{2,t} - \underset{(0.044)}{0.135}d_{3,t} + \varepsilon_t,$$
$$R^2 = 0.97,\quad s = 0.037,\quad LM(4) = 6.55\ (0.16),\quad Schwarz = -3.575. \tag{1}$$

The OLS residuals are represented by ε_t and the estimated standard errors of the parameters are presented in parentheses. R^2 shows the adjusted *R*-square. Three time dummy variables are used in the equation to adjust the intercept for the deterministic part of the seasonal variation: the binary variable $d_{j,t}$ takes the value of 1.0 in the *j*th quarter of each year and 0.0 in all other quarters. *s* denotes the estimated standard deviation of the residuals. *LM(4)* reports the Breusch-Godfrey Lagrange Multiplier (LM) test statistic for serial correlation in the residuals, where the highest order of serial correlation to be tested is 4. The null hypothesis of this test is that there is no serial correlation. In order to derive this statistic, the OLS residuals from equation (1) are first regressed on the right-hand side variables of (1) and the first four lags of the residuals. The LM test statistic, which under the null hypothesis has a χ^2 distribution, is then calculated as the adjusted *R*-square from this regression times the number of observations. The probability of observing a test statistic at least as large as the obtained *LM(4)* value, assuming that the null hypothesis is true, is presented in the parenthesis. The Schwarz information criterion value in the equation is approximately –3.575. The next step of the estimation procedure is to derive separate SSV models for each of the survey variables. Here, five lags of output growth are considered as explanatory variables, and a maximum of four lags is considered for the survey variable of current interest.[16] For each SSV model, the optimal specification is

expected time of deliveries 1978-1995 and expected number of employees from 1996 onwards (se also footnote 9).

[16] When business survey variables are added to the right-hand side of equation (1), they are in general statistically significant at conventional levels, and the Scwartz information criterion value is typically lower than the corresponding value from the autoprojective model. This finding suggests that the survey variables are likely to improve the simple autoprojective model. However, since the model specifications of these SSV models typically suffer severely from serial correlation in the residuals, I follow Teräsvirta

identified using the Schwarz information criterion. Table 3 presents some test statistics of the autoprojective and the obtained SSV models. The table has six columns. The first gives the type of model that is estimated. The second column contains the significant lags of the model. In the first row of the second column, lags refer to delayed observations of output growth in the autoprojective model, and in the remaining rows lags refer to the particular survey variable in each of the SSV models. Column three to five provide the estimates of the standard deviation of the residuals *s*, the Schwarz value for the optimal SSV model, and the value of the Breusch-Godfrey LM test statistic of residual autocorrelation, respectively. The probability of observing a test statistic at least as large as the obtained LM value, assuming that the null hypothesis of no autocorrelation is true, is presented in the parentheses of column five. The final column reports the values of the root mean squared error (RMSE) when the model tries to predict the three quarterly values of manufacturing output growth in 1998, given knowledge of the entire path of the right-hand-side BTS variables until 1998:3. For each quarter from 1998:1 through 1998:3, the previously forecasted values of output growth are used in constructing a forecast of the subsequent value of output growth (that is, the forecast is dynamic).[17]

(Table 3 about here)

The principal message of Table 3 is that the survey variables in general appear to improve the simple autoprojective model. Perceived output in the present quarter as compared with the preceding quarter (B101) shows the lowest Schwarz criterion value, and expected output in the next quarter as compared with the current quarter (B301) shows the second lowest Schwarz value. These results are consistent with the findings in Bergström (1992, 1993b). The table moreover reveals that variable B308 does not improve the simple autoprojective model. In addition, the last column of Table 3

(1986) and Bergström (1992, 1993b) by respecifying the lag structure of output growth in all SSV models.

[17] Here, the empirical models are estimated on all available data (i.e., through 1998:3), implying that RMSE refers to within-sample forecasts. When the forecasting ability of the final specifications are investigated in more detail (see below), out-of-sample forecasts will be performed and the forecasting technique will be dynamic as well as static.

shows that the predictive ability of the *ex post* survey variables typically is larger than the *ex ante* variables.[18] A more careful analysis of the forecasting power of the BTS variables would, of course, require out-of-sample forecasts and an estimation of the deviation between the predicted values and true outcomes over several different time periods. This is accomplished below, when the final empirical specifications are analyzed in detail.

Combining the *ex post* variables in Table 3 into a single model of output growth and selecting an appropriate specification using the Schwarz information criterion yields the following model: [19]

$$\begin{aligned}
\Delta y_t &= \underset{(0.019)}{0.041} - \underset{(0.065)}{0.878}\,\Delta y_{t-1} - \underset{(0.073)}{0.695}\,\Delta y_{t-2} - \underset{(0.059)}{0.682}\,\Delta y_{t-3} + \underset{(0.029)}{0.119}\,B101_t + \underset{(0.032)}{0.147}\,B101_{t-1} - \\
&- \underset{(0.033)}{0.004}\,d_{1,t} - \underset{(0.028)}{0.025}\,d_{2,t} - \underset{(0.030)}{0.123}\,d_{3,t} + \varepsilon_t, \\
R^2 &= 0.99, \quad s = 0.027, \quad LM(4) = 9.39\ (0.05), \quad Schwarz = -4.096.
\end{aligned} \tag{2}$$

Model (2) is, in fact, identical to the SSV model for survey variable B101. Hence, according to this result, variable B101 appears to contain all relevant information in the *ex post* survey data, when trying to explain manufacturing output growth.

Now, consider the same model selection process as above using only the *ex ante* survey variables in Table 3.[20] The result is

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[18] The only exceptions are variables B107 and B108. However, since variable B108 concerns perceived time of deliveries and variable B308 the expected time of deliveries (1978-1995) and the number of employees (1996-1998), the RMSE of these two variables should not be compared (see also footnotes 9 and 15).

[19] Note that a total of 2^x different empirical specifications are considered when the number of right-hand-side variables (excluding the intercept and the time-dummy variables) in the original empirical specification is *x*. Here, *x* equals 19 (5 lags of output growth plus 14 *ex post* variables), implying that the Schwarz information value from $2^{19} = 524.288$ empirical models are compared.

[20] The total number of empirical specifications when deriving the *ex ante* model is $2^{15} = 32.768$. The number of right-hand-side variables is thus 15 (5 lags of output growth plus 10 *ex ante* variables).

$$\Delta y_t = \underset{(0.020)}{0.055} - \underset{(0.065)}{0.771}\Delta y_{t-1} - \underset{(0.074)}{0.620}\Delta y_{t-2} - \underset{(0.064)}{0.693}\Delta y_{t-3} + \underset{(0.024)}{0.276}B301_t - \underset{(0.035)}{0.017}d_{1,t} -$$
$$- \underset{(0.027)}{0.083}d_{2,t} - \underset{(0.032)}{0.142}d_{3,t} + \varepsilon_t,$$
$$R^2 = 0.98, \quad s = 0.029, \quad LM(4) = 7.59\ (0.11), \quad Schwarz = -3.965. \tag{3}$$

Also in this case, the final model is identical to its SSV model counterpart. Hence, the results obtained thus far suggest that the business tendency survey data on perceived and expected production include all relevant information in the BTS data.[21] Note that model (2) is practically operative at the end of quarter *t*, since all the right-hand side variables are available at the end of this quarter. Model (3) is also operative at the end of quarter *t*, even though the use of early *ex ante* data would perhaps suggest that this model would in fact be operative one quarter earlier. The reason why the *ex ante* model is operative at the end of quarter *t* (and not earlier) is that national account data on Δy_{t-1} is not available until the end of quarter *t*.[22]

The third empirical specification is then derived by combining all *ex post* and *ex ante* business survey variables, presented in Table 3, into a single model. Remember that the table specifies the relevant lag structure of all survey variables and that variable B308 is excluded because its SSV model is characterized by a larger Schwarz information criterion than the simple autoprojective model. Minimizing the Schwarz information criterion and searching over all possible combinations of the right-hand-side variables yield the same equation as equation (2).[23] Hence, this result indicates that when the *ex post* data are present in the empirical specification, the *ex ante* data are redundant.

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[21] The same conclusion was reached by Bergström (1992, 1993b), who analyzed quarterly aggregate Swedish manufacturing data over the time period 1968-1990.

[22] Remember that the *ex ante* variable *B301* is available already at the end of quarter *t-1*, and that Δy_{t-3} is available at the end of quarter *t-2*. The variable Δy_{t-2} is available at the end of quarter *t-1*.

[23] In order to restrict the total number of possible empirical specifications, I use only a subset of the relevant business survey variables in Table 3 when deriving this model. While contemporary as well as lagged perceived/expected output growth are included on the right-hand side in the regressions, the other survey variables, i.e., B102-B108 and B302-B307, are included only in unlagged form.

In order to compare the equations (1)-(3) with a model not derived from the Schwarz information criterion, I have derived an additional empirical specification of output growth. This specification is derived by consecutive exclusion of insignificant (5 percent level) right-hand-side variables, using the complete set of BTS variables shown in Table 3 (that is, variable B308 is also included). This procedure results in a model that includes more independent variables than equation (2) and (3):

$$\Delta y_t = -\underset{(0.042)}{0.964}\Delta y_{t-1} - \underset{(0.085)}{0.734}\Delta y_{t-2} - \underset{(0.074)}{0.727}\Delta y_{t-3} + \underset{(0.037)}{0.112}B101_t + \underset{(0.040)}{0.120}B101_{t-1} +$$
$$+\underset{(0.072)}{0.204}B302_{t-2} - \underset{(0.028)}{0.070}B308_{t-3} + \underset{(0.022)}{0.037}d_{1,t} - \underset{(0.025)}{0.009}d_{2,t} - \underset{(0.021)}{0.068}d_{3,t} + \varepsilon_t,$$
$$R^2 = 0.98,\ \ s = 0.028,\ \ LM(4) = 0.91\ (0.92),\ \ Schwarz = -3.911. \tag{4}$$

Apart from perceived output in the present quarter compared to the preceding quarter (B101), equation (4) also contains the expected production capacity lagged two quarters (B302) as well as variable B308 lagged 3 quarters (B308). The inclusion of B308 is surprising because B308 refers to the expected time of deliveries (1978-1995) and the expected number of employees (1996-1998).

(Table 4 about here)

While the above empirical evidence is suggestive, an alternative statistical assessment of the importance of various business survey data can be given by investigating the forecasting ability of the models (1)-(4). In Tables 4 and 5, the predictive ability of the survey variables is analyzed in detail. Here, the predictive power of the variables is measured in terms of the root mean square error (RMSE) and the mean absolute error (MAE). The calculated RMSE and MAE include four quarters in 1996 and 1997, respectively, and three quarters in 1998. All the forecasts are out-of-sample in the sense that both RMSE and MAE are calculated on data not used for estimation. The models are estimated on data until 1995:4 when RMSE and MAE are calculated for 1996. Analogously, when calculating RMSE and MAE for 1997 (1998), the models are estimated on data until 1996:4 (1997:4). The models are estimated on data until 1994:4 when analyzing the forecasting power over the whole period 1995:1-1998:3. Note that it is implicitly assumed here that the forecaster knows the entire path of the right-hand side business survey variables over the time period used for prediction. Although this assumption is, of course, unrealistic in most real applications, this way of analyzing the usefulness of certain variables can provide some important insights. In Table 4 the calculations are based on one-quarter-ahead forecasts of the dependent variable, that is, these forecasts are *static*. In Table 5 previously forecasted values of the dependent variable are used when forming a forecast over the subsequent period, that is, these forecasts are *dynamic*.

(Table 5 about here)

The principal conclusion from Table 4 is that the forecasting performance generally improves when the business survey variables are included on the right-hand side of the econometric specifications. According to the predictive accuracy, as measured by the RMSE and the MAE, model (2) and (4) always perform better than the simple autoprojective model (1). Model (3), in contrast, performs worse than the autoprojective model in 1998 according to both RMSE and MAE, and also, according to MAE, in 1997 and over the period 1995-1998. The same conclusions can roughly be drawn from the dynamic forecasts presented in Table 5. This table shows that when previously forecasted values of output growth are used when calculating the forecasts, model (3) always (with one exception) performs worse than the simple autoprojective model. Note, however, that since it is implicitly assumed here that the forecaster knows the entire path of the business survey variables over the time period used for prediction, dynamic forecasts are perhaps neither intuitively meaningful nor practically relevant. The reason is that *predicted* values of the left-hand side variable are used on the right-hand side when calculating a forecast, while *true outcomes* are used for the business tendency survey variables. Forecasted values of the survey variables cannot be used here since no econometric models for these variables are available. It is also interesting to notice that model (4) performs better, in terms of predictive accuracy, than the other models.

While each of the empirical models above has provided some important insights, none has been entirely successful in explaining exactly how the *ex ante* survey variables should best be used in practice. In particular, although model (3) shows that survey-based *ex ante* data may sometimes improve simple autoprojective models of manufacturing output growth, this model is not operational earlier than its *ex post* counterpart. The reason is that the right-hand side term Δy_{t-1} is not available at the same time as the relevant *ex ante* variable $B301_t$. Δy_{t-1} is available at the end of quarter *t* while $B301_t$ is available already at the end of quarter *t-1*. Therefore, in order to take full advantage of the early arrival of the *ex ante* data, an empirical specification should be derived without the Δy_{t-1} term on the right-hand side. However, such empirical specifications typically suffer severely from autocorrelated residuals.

The results presented in this section suggest that business survey variables may contain significant information that can be used for prediction purposes. Now, it certainly is a legitimate question to ask whether this information can be extrapolated to movements in economic activity, as measured by changes in real GDP. Since manufacturing output growth is highly correlated with GDP growth (the correlation coefficient is around 0.7), the answer is yes. These survey variables are rather likely to provide relevant short-term information also about movements in real GDP.

4. Concluding Remarks

To summarize, this paper has presented some empirical results as regards the relevance of various qualitative business tendency survey variables for predicting the volume of manufacturing output growth in Sweden. These business survey variables are provided by the National Institute of Economic Research (NIER) in Sweden, and they constitute a very interesting attempt to supply to the market important and early economic information of a kind that is not otherwise readily available. Researchers, policy makers, and participants in the financial markets have paid considerable attention to this type of information since they are generally more or less uncertain about the current state of the economy and its reaction to various policy changes. Survey data have therefore been analyzed in detail in a number of studies. A common empirical finding on Swedish and Finnish data is that business survey variables contains useful leading information about future industrial production. This information can hence help predict movements in the industrial sector and aggregate output.

The main achievement of this paper is twofold. First, it offers a brief overview of the business tendency survey data provided by NIER. The survey data reveal that Swedish manufacturing firms occasionally are over-optimistic *ex ante* and that their expectations are more stable over time than perceived outcomes. For example, the responding firms *ex ante* expectations about output growth repeatedly overstated the *ex post* outcomes during the period 1997:3-1998:3. One possible explanation for this miscalculation may be that the Asian crisis resulted in a gradual deterioration of world-wide export markets and demand that was not entirely anticipated by the responding firms. Second, this paper updates earlier analysis by Bergström (1992, 1993b). The study identifies some empirical specifications that statistically outperform (in terms of Schwarz (1978) information criterion as well as forecasting accuracy) simple autoprojective models of manufacturing output growth. The essence of the empirical approach relies on Teräsvirta's (1986) three-step procedure. It turns out that there is a rather strong relationship between perceived *ex post* output in the current quarter compared to the previous quarter and actual manufacturing output growth between these quarters. Perceived *ex post* output appears, in fact, to include all the relevant information in the *ex post* data about officially registered output. A similar result was found among the *ex ante* survey variables: when expected output in the next quarter compared to the present quarter is present in the empirical specification, no other *ex ante* variables seem to include any useful information. Finally, when analyzed the short-term predictive accuracy of single equation time-series models based on survey data, I found that BTS-augmented models typically produce lower (absolute and mean) squared errors than autoprojective models.

Appendix A: Questions in the Business Tendency Survey

The National Institute of Economic Research (NIER) asks the Swedish manufacturing firms a wide range of questions. When the current quarter is compared with the preceding quarter, the questions are termed *ex post* questions, and when the next quarter is compared with the current quarter the questions are termed *ex ante* questions. The *ex post* questions are presented below.

B101: Volume of production in the current quarter as compared with the preceding quarter.
B102: Production capacity in the current quarter as compared with the preceding quarter.
B103: Domestic prices in the current quarter as compared with the preceding quarter.
B104: Export prices in the current quarter as compared with the preceding quarter.
B105: Orders received from the domestic market in the current quarter as compared with the preceding quarter.
B106: Orders received from the export market in the current quarter as compared with the preceding quarter.
B107: Purchases of raw materials in the current quarter as compared with the preceding quarter.
B108: Time of deliveries in the current quarter as compared with the preceding quarter.

Note that B103 and B104 address changes in price levels and not changes in the rate of inflation. The *ex ante* variables concern the same variables, but refer to the expected outcomes in the next quarter as compared with the current quarter. Note, however, that the variable B308 differ from B108 since it concerns the expected number of employees the next quarter as compared with the current quarter 1996-1998. From 1978 to 1995, however, this variable concerns the expected time of deliveries the next quarter as compared with the present quarter.

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Table 1. Summary statistics of the BTS data during the period 1968:1-1998:3.

Variable	*Mean*	*Median*	*Std. dev.*	*Min*	*Max*	*Obs.*	*Prob.*
B101	8.286	10.000	15.451	-27.000	42.000	140	0.196
B102	6.971	7.000	6.704	-11.000	23.000	140	0.850
B103	15.564	15.500	16.021	-14.000	70.000	140	0.303
B104	15.643	14.000	20.977	-26.000	78.000	140	0.198
B105	0.371	2.000	15.797	-41.000	39.000	140	0.147
B106	8.250	9.000	20.443	-50.000	57.000	140	0.753
B107	5.436	4.000	17.645	-31.000	53.000	140	0.446
B108	-5.779	-6.000	13.470	-36.000	24.000	140	0.235
B301	10.823	12.000	13.669	-27.000	39.000	141	0.298
B302	8.200	8.000	7.413	-17.000	28.000	140	0.245
B303	17.745	16.000	14.757	-11.000	69.000	141	0.030
B304	18.348	17.000	18.633	-22.000	81.000	141	0.015
B305	3.355	4.000	11.360	-31.000	31.000	141	0.078
B306	12.865	14.000	13.492	-26.000	41.000	141	0.185
B307	4.730	5.000	11.799	-23.000	39.000	141	0.857
B308	-11.667	-85000	16.828	-54.000	17.000	84	0.026
BC	-11.164	-12.000	16.897	-44.000	23.000	140	0.100

Note: The variables B101-B108 indicate *perceived* (*ex post*) data on production volume, production capacity, prices (domestic), prices (export), orders received (domestic market), orders received (export market), purchase of raw materials, and time of deliveries in the current quarter as compared with the preceding quarter. Variables B301-B307 indicate the *expected* (*ex ante*) analogues the next quarter as compared with the current quarter. Variable B308 concerns the expected time of deliveries (1978-1995) and the number of employees in the next quarter as compared with the current quarter (1996-1998). Variable BC is a *confidence indicator* measured as a weighted average of the responding firms' subjective judgements about the present volume of orders, inventories, and production. The total number of observations in B302 and B308 is 140 and 84 (rather than 141), which is due to missing observations in the beginning of the sample period.

Table 2. Cross correlations between the current value of the fourth-quarter logarithmic change in manufacturing production and the BTS series of different lags during the period 1968:1-1998:3.

Var.	*t-4*	*t-3*	*t-2*	*t-1*	*t*	*t+1*	*t+2*	*t+3*	*t+4*
B101	0.340	0.614	0.728	<u>0.813</u>	0.787	0.614	0.448	0.295	0.122
B102	0.208	0.393	0.547	0.661	<u>0.747</u>	0.701	0.638	0.537	0.376
B103	-0.103	0.017	0.177	0.277	0.314	<u>0.330</u>	0.263	0.161	0.048
B104	0.011	0.154	0.302	0.351	<u>0.364</u>	0.274	0.211	0.023	-0.135
B105	0.411	0.589	0.710	<u>0.771</u>	0.714	0.522	0.318	0.142	-0.073
B106	0.564	0.650	<u>0.697</u>	0.646	0.530	0.311	0.095	-0.119	-0.311
B107	0.279	0.483	0.659	0.754	<u>0.758</u>	0.616	0.463	0.284	0.063
B108	0.387	0.527	0.646	<u>0.716</u>	0.661	0.535	0.347	0.158	-0.047
B301	0.259	0.444	0.582	0.721	<u>0.769</u>	0.702	0.554	0.455	0.295
B302	0.014	0.170	0.354	0.513	0.663	<u>0.712</u>	0.654	0.641	0.501
B303	-0.188	-0.094	0.029	0.089	0.166	0.188	<u>0.191</u>	0.102	0.025
B304	-0.166	-0.039	0.111	0.186	<u>0.258</u>	0.202	0.161	0.017	-0.133
B305	0.319	0.466	0.587	0.670	<u>0.680</u>	0.579	0.393	0.234	0.080
B306	0.466	0.532	<u>0.562</u>	0.551	0.441	0.260	0.072	-0.063	-0.210
B307	0.164	0.350	0.565	0.712	<u>0.762</u>	0.700	0.548	0.412	0.211
B308	-0.032	0.133	0.305	0.486	0.622	<u>0.665</u>	0.605	0.555	0.449
BC	0.366	0.537	0.672	0.743	<u>0.787</u>	0.738	0.606	0.427	0.236

Note: The highest value in each row is underlined.

Table 3. Testing Single Survey Variable (SSV) models with Schwartz information criterion against a simple autoprojective model of the growth rate of manufacturing output.

Survey variable	*Lags*	*s*	*Schwarz*	*LM(4)*	*RMSE*
Autoprojective	1,4	0.037	-3.575	6.55 (0.16)	0.0390
B101	0,1	0.027	-4.096	9.39 (0.05)	0.0359
B102	0,4	0.032	-3.727	8.91 (0.06)	0.0467
B103	0,2	0.034	-3.634	9.37 (0.05)	0.0265
B104	0,3	0.034	-3.639	11,30 (0.02)	0.0309
B105	0	0.030	-3.890	9.63 (0.05)	0.0231
B106	0	0.032	-3.753	11.67 (0.02)	0.0375
B107	0	0.030	-3.863	13,38 (0.01)	0.0352
B108	0	0.033	-3.708	11.37 (0.02)	0.0378
B301	0	0.096	-3.965	7.59 (0.11)	0.0464
B302	0,2	0.034	-3.668	6.03 (0.20)	0.0451
B303	4	0.036	-3.584	8.20 (0.08)	0.0468
B304	0,2	0.034	-3.611	5.60 (0.23)	0.0350
B305	0	0.032	-3.752	8.04 (0.09)	0.0365
B306	0	0.034	-3.660	6.10 (0.19)	0.0412
B307	0,3	0.030	-3.800	10.03 (0.04)	0.0272
B308	0,3	0.033	-3.528	2.44 (0.66)	0.0325
BC	1,3	0.030	-3.828	9.41 (0.05)	0.0330

Note: When the Schwartz information criterion value of the autoprojective model (i.e., -3.575) is smaller than the corresponding value of the SSV model, then this particular survey variable is excluded from further consideration. The second column presents the significant lags of the right-hand-side variables. In the first row lags refer to delayed output growth in the autoprojective model, and in the remaining rows lags refer to the lag structure of the survey variable of current interest. The three lowest Schwarz values are underlined.

Table 4. Testing the forecasting capacity of model (1)-(4). Static forecasts.

Model	*RMSE*				*MAE*			
	1996	1997	1998	95-98	1996	1997	1998	95-98
(1)	0.046	0.045	0.042	0.045	0.036	0.029	0.036	0.034
(2)	0.032	0.031	0.034	0.038	0.027	0.025	0.029	0.029
(3)	0.036	0.034	0.053	0.042	0.031	0.033	0.042	0.035
(4)	0.026	0.024	0.033	0.038	0.025	0.022	0.023	0.032

Note: The Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) measure the predictive power of the business survey variables. The computed RMSE and MAE include four quarters in 1996 and 1997, and three quarters in 1998. The forecasts are out-of-sample in the sense that both RMSE and MAE are calculated on data not used for estimation. The models are estimated on data until 1995:4 when RMSE and MAE are calculated for 1996. Analogously, when calculating RMSE and MAE for 1997 (1998), the models are estimated on data until 1996:4 (1997:4). The models are estimated on data until 1994:4 when analyzing the forecasting power over the period 1995:1-1998:3. It is implicitly assumed here that the forecaster knows the entire path of the right-hand-side business survey variables over the time period used for prediction. The calculations are based on one-quarter-ahead forecasts, i.e., a *static* forecasting technique is used.

Table 5. Testing the forecasting capacity of model (1)-(4). Dynamic forecasts.

Model	*RMSE*				*MAE*			
	1996	1997	1998	95-98	1996	1997	1998	95-98
(1)	0.045	0.050	0.042	0.062	0.040	0.037	0.039	0.049
(2)	0.033	0.045	0.041	0.059	0.032	0.043	0.040	0.049
(3)	0.045	0.056	0.053	0.070	0.044	0.055	0.045	0.062
(4)	0.029	0.044	0.040	0.045	0.023	0.041	0.034	0.040

Note: The predictive power of the business survey variables is measured by the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE). The computed RMSE and MAE include four quarters in 1996 and 1997, and three quarters in 1998. The forecasts are out-of-sample in the sense that both RMSE and MAE are calculated on data not used for estimation. The models are estimated on data until 1995:4 when RMSE and MAE are calculated for 1996. Analogously, when calculating RMSE and MAE for 1997 (1998), the models are estimated on data until 1996:4 (1997:4). The models are estimated on data until 1994:4 when analyzing the forecasting power over the period 1995:1-1998:3. It is implicitly assumed here that the forecaster knows the entire path of the right-hand-side business survey variables over the time period used for prediction. Previously forecasted values of the dependent variable are used when forming a forecast of the subsequent value, i.e., this is a *dynamic* forecasting technique rather than a one-quarter ahead *static* technique.

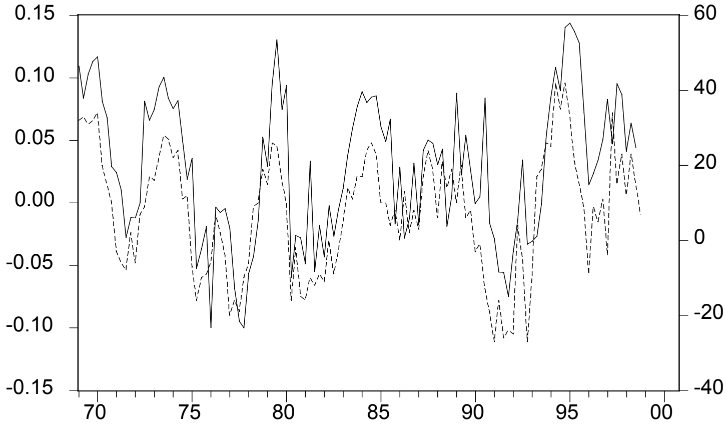

Fig 1. Fourth-quarter logarithmic change in the volume of manufacturing output (solid line, left scale) is compared with the BTS data (net balance) on perceived production the current quarter as compared with the preceding quarter (dashed line, right scale). The correlation coefficient is 0.79.

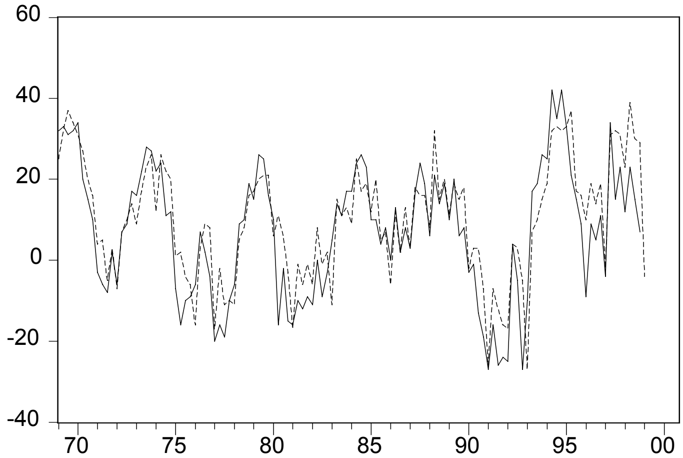

Fig 2. A comparison of the perceived *ex post* production in the current quarter as compared with the preceding quarter (solid line) and the expected *ex ante* production in the next quarter as compared with the current quarter (dashed line). The correlation coefficient is 0.87. Note that the *ex ante* variable in time period *t* equals the predicted value that was made by the firms in period *t-1* (i.e., the time index denotes the relevant period over which expectations are made and *not* the time at which these expectations were made).