WORKING PAPERS AND STUDIES

2003 EDITION

COPYRIGHT

Luxembourg: Office for Official Publications of the European Communities, 2003

ISBN 92-894-6844-0
ISSN 1725-4825
Cat. No. KS-AN-03-051-EN-N

Business survey data: Do they help forecasting the macro economy?

EUROPEAN COMMISSION

eurostat

EURO INDICATORS

Europe Direct is a service to help you find answers to your questions about the European Union

New freephone number:
00 800 6 7 8 9 10 11

A great deal of additional information on the European Union is available on the Internet.
It can be accessed through the Europa server (http://europa.eu.int).

Luxembourg: Office for Official Publications of the European Communities, 2003

ISBN 92-894-6844-0
ISSN 1725-4825

4TH EUROSTAT AND DG ECFIN
COLLOQUIUM ON MODERN TOOLS FOR BUSINESS CYCLE ANALYSIS

"GROWTH AND CYCLE IN THE EURO-ZONE"

20 TO 22 OCTOBER 2003

Luxembourg, European Parliament
Hémicycle, Schuman building

Business survey data: Do they help forecasting the macro economy?

Jesper Hansson, *National Institute of Economic Research, Stockholm, Sweden*
Per Jansson, *Sveriges Riksbank, Stockholm, Sweden*
Mårten Löf, *National Institute of Economic Research, Stockholm, Sweden*

This version: May 28, 2003

Business survey data:

Do they help in forecasting the macro economy?

Jesper Hansson[a], Per Jansson[b, *], Mårten Löf[a]

[a]*National Institute of Economic Research, P.O. Box 3116, SE-103 62 Stockholm, Sweden*

[b]*Sveriges Riksbank, Monetary Policy Department, SE-103 37 Stockholm, Sweden*

Abstract

In this paper we examine whether data from business tendency surveys are useful for forecasting the macro economy in the short run. Our analyses primarily concern the growth rates of real GDP but we also evaluate forecasts of other variables such as unemployment, price and wage inflation, interest rates, and exchange-rate changes. The starting point is a so-called dynamic factor model (DFM), which is used both as a framework for dimension reduction in forecasting and as a procedure for filtering out unimportant idiosyncratic noise in the underlying survey data. In this way, it is possible to model a rather large number of noise-reduced survey variables in a parsimoniously parameterised vector autoregression (VAR). To assess the forecasting performance of the procedure, comparisons are made with VARs that either use the survey variables directly, are based on macro variables only, or use other popular summary indices of economic activity. As concerns forecasts of GDP growth, the procedure turns out to outperform the competing alternatives in most cases. For the other macro variables, the evidence is more mixed, suggesting in particular that there often is little difference between the DFM-based indicators and the popular summary indices of economic activity.

Keywords: Business survey data; Dynamic factor models; Macroeconomic forecasting

---

[*]Corresponding author. Tel.: +46-8-787 01 55; fax: +46-8-21 05 31. *E-mail address:* per.jansson@riksbank.se (P. Jansson).

1. Introduction

The interest in, and demand for, macroeconomic analyses at high frequencies, most notably forecasts, has increased substantially in recent years. One reason for this may be the rapid evolution of global capital and financial markets that has affected the preconditions of economic policy making in important ways. With larger financial markets, capital flows gain in importance, and are more easily and rapidly transmitted to the real parts of the macro economy. The same holds true for expectational effects which, to a significant extent, are affecting the prices set on financial markets. This, in turn, creates a need amongst policy makers to analyse and follow economic developments on a more frequent basis.

Another conceivable reason is that economic policy in recent years has successively become more target-oriented. For example, many countries have introduced targets for their rates of inflation (including Sweden, the country that we study). Similarly, in the case of fiscal policy, targets for budget surpluses and debt or spending levels have been formulated. In order to be able to continuously monitor such objectives, policy makers need to have access to quick and reliable information about current economic conditions and about possible directions of developments in the near future. To have a good understanding of the current stance of the macro economy is also a prerequisite for making good judgements about developments in the longer term (and for being able to give credible explanations of such developments).

Making analyses and forecasts of data observed at relatively high frequencies is not an easy task. Compared with annual data, data that are observed daily, monthly, and quarterly typically display more complicated dynamics, are seasonal, and are – at least as concerns real variables – more frequently revised. One category of data that has the potential of being rather useful in this context is that produced by surveys. Survey data have the advantage of essentially being instantaneously accessible, never being revised, and, furthermore, having little or no measurement errors. The objective of the present paper is to exploit whether such data can successfully be used for purposes of forecasting important variables of the macro economy. Our empirical application is based on the Swedish Business Tendency Survey (BTS).

The Swedish BTS is a large business survey based on questions about economic activity posed to approximately 7 000 different firms in various sectors of the Swedish economy. The sectors currently included are manufacturing, construction, and, since 1991, services. As a percentage of the total number of employed workers, these sectors cover around 50 percent of the Swedish economy. The full survey is undertaken quarterly, but a subset of the survey has also been available monthly since 1996. The questions are both coincident (regarding the development the current quarter) and forward-looking (regarding the development the next quarter).[1] If the analysis is limited to the manufacturing and construction industries, then the survey provides continuous time series for most questions since the mid-1970s. In this case, the number of survey questions used is approximately 3 000 and the coverage in terms of employed workers around 25 percent.

Previous research into the forecasting properties of the Swedish BTS has focused on establishing *direct* relationships between the variable to be forecast (typically, the growth rate of industrial production) and the BTS data. The approaches range from simple single-equation models (see, e.g., Bergström, 1992, 1993a, Lindström, 2000) to Kalman-filter-based updating schemes and sophisticated turning-point analyses (see, e.g., Rahiala and Teräsvirta, 1993, Kääntä and Tallbom, 1993, Öller and Tallbom, 1996, Lindström, 1999, Koskinen and Öller,

[1]The questions of the survey are such that the firms are merely asked to specify whether a particular activity (e.g., production or order flows) has increased, been unchanged, or decreased (or, in the forward-looking case, whether the activity is expected to increase, remain unchanged, or decrease). In some cases, the questions are dichotomous, just requiring a "yes" or a "no". The final quantities used are "net balances" obtained by subtracting the weighted percentages of firms that have specified an increase from the weighted percentages of firms that have specified a decrease (or, just the weighted shares if the questions are dichotomous). For further

2003). A common finding is that only very few BTS variables are useful for macro forecasting, and that the information content in the forward-looking BTS series is particularly weak. One of the main results of the present paper is that the forecasting performance of the BTS data can be considerably improved if the BTS variables are appropriately filtered prior to forecasting, and thus *indirectly*, rather than directly, related to the variable to be forecast.[2]

The benefits of making use of an indirect, rather than direct, link between the BTS data and the data to be predicted proceed from the fact that changes in the BTS data can not always be assumed to contain signals that are relevant for activity at the aggregate level. More specifically, it seems likely that idiosyncratic sector-specific changes in a particular series are largely unrelated to the overall state of economic activity. The filtering technique thus entails getting rid of this series-specific "noise" and only keeping those parts of the data that are common to the series under consideration. In the terminology of Burns and Mitchell (1946), we wish to identify a "reference cycle" which is associated with co-movements in different forms of economic activity.

As it happens, the proposed filtering procedure also has the property of implying a dimension-reduction framework for the BTS variables. From the forecasting literature it is well known that forecasting approaches using many explanatory variables, and thus many estimated parameters, generate forecasts that quickly become inefficient and unstable. Parsimony is thus considered to be a desirable feature of a forecasting model. Our proposed procedure addresses this issue by summarising the observable information of the large BTS data set by a single common-factor index.

---

details, see www.konj.se (the homepage of the National Institute of Economic Research, which publishes the survey).

[2]One previous analysis that supports the premise that the forecasting performance of the Swedish BTS may be enhanced by filtering techniques is that undertaken by Christoffersson, Roberts, and Eriksson (1992). Although these authors do not explicitly favour the kind of filtering procedure that we propose, they show, using methods in the frequency domain, that the BTS series both are noisy at high frequencies and highly collinear. This makes it difficult to directly include them as explanatory variables in a conventional forecasting equation.

To undertake the filtering of the BTS data we employ a standard so-called dynamic factor model (DFM). Such models have previously been used for similar purposes, but have hardly been applied to survey data. Useful general references include Stock and Watson (1989, 1991, 1999, 2002), Camba-Mendez, Kapetanios, Smith, and Weale (1999), Fukuda and Onodera (2001), Forni, Hallin, Lippi, and Reichlin (2000, 2003). The European Commission (2000), Goldrian, Lindbauer, and Nerb (2001), and Bruno and Malgarini (2002) are examples of studies that make use of survey data.[3] The DFM, and further issues related to the BTS data, are discussed in Section 2.

The forecasting performance of the BTS data filtered by the DFM is investigated using almost-real-time out-of-sample experiments. Here, the idea is that the forecaster takes the estimated common-factor index as given and computes the forecasts as if there is no knowledge about the generating mechanisms of the index. Thus, the forecaster fits a standard dynamic forecasting model, a vector autoregression (VAR). Each VAR consists of the estimated common-factor index and a particular macro variable for which we wish to derive forecasts. Alternatively, the DFM – which also permits dynamic (multi-step) forecasting of the common-factor index – can be integrated fully in the forecasting system, but this requires solving a numerical maximum-likelihood (ML) algorithm in each recursion. To avoid this, the VAR seems to be a plausible alternative for purposes of assessing the forecasting performance of the estimated common-factor index in a realistic manner. Furthermore, our experiments are almost in real time since the forecasts are recursive and based on the one-sided (time t conditional) estimates of the common-factor index.

To assess the relative accuracy of the DFM-based VAR forecasts, we make forecast comparisons using three alternative approaches to forecasting the macro variables. These are VARs that use unfiltered BTS variables (i.e., that include the survey variables directly without

[3]The models developed in Stock and Watson (1999), Camba-Mendez, Kapetanios, Smith, and Weale (1999), and Forni, Hallin, Lippi, and Reichlin (2000, 2003) make use of some survey variables but are mainly based on

employing the DFM filter); VARs that use information on macro variables only; and VARs that use other popular summary indices of economic activity. The DFM-based forecasts of the growth rate of real GDP are discussed in Section 3.1. Alternative forecasts of GDP growth are evaluated in Section 3.2. Finally, forecasts of other macro variables are analysed in Section 3.3.

By making comparisons with VARs based on the unfiltered survey data we are able, in terms of forecast precision, to assess the gain made from first applying the DFM to the BTS data (relative to not doing so). That is, we can quantify the effects in forecasting from parsimoniously modelling the noise-reduced BTS series rather than the original series themselves. The comparisons with macro VARs instead enable us to judge how well we do relative to the "standard forecasting model". They also make it possible to evaluate the comparative loss in forecast accuracy experienced when the forecasting horizon is prolonged. A priori, it may be expected that the BTS data work best for forecasting at short horizons (one or two quarters ahead), while the information in macro data is most useful for forecasting at business-cycle frequencies (a couple of years ahead). Finally, the comparisons with VARs based on other summary indices of activity allow us to shed some light on the performance of our procedure when holding the gains of dimension reduction constant. Like the DFM procedure, such summary indices have the advantage of enabling the use of very parsimonious forecasting models, without having to give up too much of the relevant forecasting information.

macro variables.

2. The dynamic factor model

In this section we discuss and estimate the dynamic factor model used to filter the business survey data. The output of this analysis is an estimate of a common-factor index which summarises the co-movements in a broad range of different economic activities such as production, order flows, time of deliveries, employment, and stocks of raw materials and goods. The index is constructed in such a way that it acknowledges that activities occur in different sectors of the economy and that there may be lead-lag relationships between them. Because, as mentioned previously, the questions of the survey regard both activities in the current and next quarter, the whole analysis is undertaken for two different versions of the index: one coincident (current quarter) and one forward-looking (next quarter).

2.1. Specification

Let the *n* dimensional vector that collects the relevant BTS series be denoted by X_t. It is assumed that the variables in X_t are (stochastically) stationary so that they can be normalised to have mean zero and unit variance. The assumption of stationarity is not restrictive: all BTS series are distinctively cyclical without trends (whether stochastic or deterministic). Standard unit-root tests confirm that all series are stationary $I(0)$.

In the model, X_t is driven by two stochastic components: the unobserved scalar index C_t, which is common to all the variables in X_t, and the equally unobserved *n* dimensional component I_t, which represents the idiosyncratic movements in the series. A slightly generalised version of the model allows C_t to be *k* dimensional with $n > k > 1$. The variables in X_t are in this case thus driven by at least two common indices. When experimenting with different values of *k*, however, we find that it suffices to use $k = 1$. The model, in its general form, is:

$$X_t = \gamma(L)C_t + I_t, \tag{1}$$

$$\phi(L)C_t = \eta_t, \tag{2}$$

where L is the lag operator such that $L^j y_t = y_{t-j}$ for any vector or scalar variable y while $\gamma(L)$ and $\phi(L)$ are vector and scalar lag polynomials, respectively. The elements in I_t and η_t are the system's disturbances such that idiosyncratic shocks are purely temporary while common shocks may display some persistence. The assumption of a purely temporary process for the idiosyncratic component can be relaxed in favour of more general autoregressive specifications but was found to fit the data well in this particular application.

As it stands, model (1)–(2) is a standard DFM. As is well known, it is econometrically unidentified unless restrictions on its feasible set of parameter values are imposed. The following restrictions can be shown to be sufficient for identification: the disturbances in I_t and η_t are mutually and serially uncorrelated; the scalar C_t enters at least one of the variables in (1) only contemporaneously; and, the standard deviation of η_t is normalised to unity (or, equivalently, one of the contemporaneous parameters in $\gamma(L)$ is normalised to unity).

To estimate the model, it is cast in so-called state-space form. One can then apply the Kalman filter together with an ML routine to obtain estimates of the unknown parameters and the unobserved components, i.e., the common-factor index C_t and the idiosyncratic noise processes in I_t (for details see Harvey, 1989, Hamilton, 1994). The analysis permits calculation of both one-sided and two-sided estimates of C_t (and I_t). The former are conditional on the information available at time *t* (written $C_{t|t}$) while the latter are conditional on the information available at end of sample (written $C_{t|T}$, with *T* being the last observation of the sample). The two-sided estimates $C_{t|T}$ may thus be regarded as being the "best" possible guesses of C_t, given a particular sample $t = 1,..., T$.

In the forecasting exercises presented below we make use of the one-sided estimates of C_t only. The reason is that we wish to simulate a recursive out-of-sample forecasting experiment without having to update the estimated DFM in each recursion. Given that the BTS data are not revised over time, the one-sided estimates will be approximately real time provided the DFM is empirically stable. Ideally, the experiments should be made using the two-sided estimates generated by a recursively updated DFM but, since the model has to be solved numerically, this approach is in practice unfeasible.[4]

Having discussed the technical aspects of the DFM, we now turn our attention to the BTS variables included in the vector X_t. Although model (1)–(2) is quite flexible, it is parametric and thus has limitations as concerns the number of variables that it can handle. All in all, the quarterly Swedish BTS at present includes 39 variables related to the manufacturing sector, and 19 variables related to the construction sector. Of these, roughly 25 percent are available as forward-looking (8 for manufacturing and 4 for construction). When deciding which of the variables to use in the DFM the following circumstances have been important. First, some of the variables have rather short time series and are therefore not well suited for econometric analyses of the kind undertaken here. Second, a couple of variables give information about similar activities and are therefore redundant. Third, nominal variables, which only provide

[4]Although it may not be possible to update the DFM itself recursively, the two-sided estimates of the common-factor index are easily updated recursively given the full-sample estimate of the DFM. The empirical results

indirect information on the amount of real activity, are excluded altogether. Using these criteria we end up with a feasible set consisting of 12 coincident variables and 7 forward-looking variables. The details are shown in Table 1.

[Insert Table 1 here]

As discussed previously, the questions of the BTS are typically trichotomous; i.e., firms merely have to indicate whether a particular activity has increased, remained unchanged, or decreased (or, in the forward-looking case, whether the activity is expected to increase, remain unchanged, or decrease). However, for publication purposes, only the differences between the two extreme alternatives are used (the so-called net balances). Since such transformations are not sufficient in a statistical sense, it may be the case that analyses based on the full trichotomous scale yield better results than do those that just use the net balances. In this paper we nevertheless choose to stick to variables transformed in form of net balances. This choice is based partly on previous research that suggests that the transformation is not very restrictive (Bergström, 1993b), and partly on the fact that the net balances are the officially published quantities.

2.2. Results

The estimates of the coincident and forward-looking indices obtained by using model (1)–(2) and emanating from the variables listed in Table 1 appear in Fig. 1. As emphasised above, the indices are constructed directly from the one-sided estimates of the common factors using

---

when using these estimates instead of the one-sided ones were approximately the same. The paper uses the one-sided estimates because they are somewhat easier to compute and more common.

either only coincident BTS data or only forward-looking BTS data.[5] Because the DFM is a pure time-series filter, its parameters have no particular interpretation. For this reason, and for expository convenience, we do not explicitly present the estimated model parameters here (although these are of course available upon request). Error-term diagnostics (again not shown for purposes of saving space) suggest that the two estimated DFMs by and large have acceptable statistical properties.

[Insert Fig. 1 here]

The time paths of the two estimated indices very much confirm the commonly held view about the development of economic activity in Sweden during the 1980s and 1990s. In the early 1980s, the economy moved towards a recession following the cost shocks associated with the oil-price hikes of 1979−1981. Around those years, the estimated indices reached their local minima during the last quarter of 1981. Two large currency devaluations were undertaken during the third quarter of 1981 and the fourth quarter of 1982. These led to a dramatic improvement of the Swedish economy's competitiveness, and formed the basis for the persistent boom during the remaining years of the 1980s. Gradually, however, the competitive advantages from the devalued exchange rate were eroded by wage increases that substantially exceeded those in other countries. On top of that, markets of asset prices ran into severe problems in the late 1980s due to excessive increases in, among other things, real estate and share prices. All this eventually led to the very sharp downturn of 1990−1992, vividly depicted by the two estimated indices. Presumably, the downturn was also partly related to the interest-rate shock necessary to defend the fixed exchange-rate system that

[5]We also experimented with models that were based on differences between the coincident and forward-looking variables but such models did not turn out to perform well. The final models include variables BTVI101, BTVI105, BTVI301, BTVI305, BTVI306, BTVI308, BBOA101, BBOA102, BBOA106, BBOA201, BBOA202, and BBOA204 (cf. Table 1).

prevailed at that time. In November 1992, Sveriges Riksbank (the Swedish central bank) abandoned the fixed exchange rate in favour of a floating exchange rate. The currency depreciated sharply in response to that switch, and activity again increased. After having reached a peak in 1994–1995, the economy experienced a short-lived slowdown mainly due to slackening economic activity in foreign countries (in particular, in central Europe). During the course of 1996 Sveriges Riksbank lowered its policy rate by approximately 5 percentage points, from around 9 percent to roughly 4 percent. In 1997 and most of 1998 the policy rate stayed within the interval 4–4.5 percent, to be further lowered during the end of 1998 and during 1999. Together with a recovery in the international economy, this monetary policy stance had positive effects on activity in 1997–2000. The mild downturn around the fourth quarter of 1998 and the first quarter of 1999 mainly resulted from shocks on international financial markets, including the suspension of debt payments in Russia. During 2000 a more serious slowdown occurred. This decrease in activity was related to a weakening of the international business cycle, including a correction of the over-optimism that had been established within the perceived “New Economy”.

To sum up, the coincident and forward-looking indices estimated from the BTS data appear to accord rather well with common interpretations of cyclical developments in the Swedish economy over the last two decades. The next issue to be dealt with is to investigate whether this information can also successfully be used for the purpose of out-of-sample forecasting.

3. Forecasts

In this section we undertake an almost-real-time out-of-sample forecasting experiment that aims at shedding light on how useful the two estimated common-factor indices are for forecasting the macro economy in the short run. The forecasting model throughout is a standard VAR. The macro variables to be forecast are GDP growth, employment growth, unemployment, short- and long-term interest rates, exchange-rate growth, wage inflation, and price inflation (both underlying and headline).[6] Evaluations of forecast accuracy are undertaken for four different forecast horizons: one quarter, two quarters, four quarters, and eight quarters.

For natural reasons, the forecasts that are of greatest interest are those of the economy's total output performance, i.e. of the growth rate of GDP. In what follows we thus put special emphasis on these forecasts and describe the results for the other macro aggregates somewhat more summarily. Also, due to the high-frequency nature of the survey data, the forecasts at the longer horizons (i.e., at the four- and eight-quarter horizons) should not be expected to perform very well. Most of our discussions will therefore relate to the forecasts at the relevant one- and two-quarter horizons.

For variables expressed in growth rates, two different transformations are considered: log first differences and log four-quarter differences; i.e., if y is the original series in levels, then we consider forecasts of either $\log(y_t) - \log(y_{t-1})$ or $\log(y_t) - \log(y_{t-4})$ (at which y possibly is seasonally adjusted in the case of first differences). Unemployment and the two

[6]Details of the data are given in the Data Appendix. To make the analysis genuinely in real time while still evaluating forecasting performance in the most appropriate way, it appears that one would like to make use both of preliminary and final data releases. Formally, if y is the variable to be forecast and z the variables contained in the conditioning set, then one would like to estimate the forecasting function g based on preliminary data releases, $y(p) = g(z(p)) + e(p)$, but evaluate the forecast error with respect to final releases, $y(f) - g(z(p))$ (provided the absolute value of $y - y(f)$ is smaller than the absolute value of $y - y(p)$, where y is the true outcome). In this paper, the macro variables are nevertheless constructed using final (most recent) data releases. Investigating the importance of preliminary data releases (that are of lower quality than final releases) is left to future work.

interest rates however are always in levels. All in all, this means that we evaluate forecasts of 15 variables: 6 variables in consecutive quarterly growth rates, 6 variables in four-quarter growth rates, and 3 variables in levels.

Concerning the arrival of information, we make the following assumptions. In the case of real variables and wage inflation, there is an information lag of one quarter such that when we observe the BTS variables in quarter t, the variables to be forecast are only known up to and including quarter $t-1$. The nominal variables (except wage inflation), on the other hand, have no information lag and are thus observed simultaneously with the BTS data in each quarter. These information lags correspond approximately to the publication lags that prevail today for these particular variables.[7]

The VARs that are estimated are as follows:

$$Y_t = \alpha(L)Z_t + \beta(L)Y_t + \varepsilon_t, \tag{3}$$

$$Z_t = \tilde{\alpha}(L)Z_t + \tilde{\beta}(L)Y_t + \tilde{\varepsilon}_t, \tag{4}$$

where constants are omitted for expository convenience. The scalar variable Y is the variable to be forecast and Z is a $q-1$ dimensional vector of predictors, such that the full VAR is q-variate, $q \geq 2$. When the BTS variables and the popular summary indices are used, the polynomial $\alpha(L)$ includes contemporaneous effects; i.e., Z enters equation (3) both contemporaneously and lagged. The macro VARs are, on the other hand, restricted such that Z only enters (3) lagged. The remaining polynomials $\beta(L)$, $\tilde{\alpha}(L)$, and $\tilde{\beta}(L)$ are always restricted to exclude contemporaneous effects. The lag length is determined by minimising the system-based Bayesian information criterion (BIC).

[7]The information lag associated with wage inflation derives from the fact that this variable is generated from wage sums and hours worked; i.e., variables that are part of the national accounts.

The VARs that are based on the estimated common factors and the popular summary indices are always bivariate ($q = 2$). Thus, in these models, Z is a scalar containing a single leading indicator of Y. In the case of macro VARs and VARs based on unfiltered BTS variables, we impose the restriction that the variable dimension is at most of fifth order ($q \leq 5$). Given the feasible sets of explanatory macro variables (see the discussion above) and BTS variables (see Table 1), this implies that we estimate a total of 2 916 macro VARs and 13 365 VARs based on unfiltered BTS variables. Thus, in the case of macro VARs and VARs based on unfiltered BTS variables, we are able to analyse empirical distributions of forecasts and forecast errors. Here, different distributions obtain for each of the 9 variables that are forecast (GDP growth; employment growth; unemployment; the short-term interest rate; the long-term interest rate; exchange-rate growth; wage inflation; underlying CPI inflation; headline CPI inflation) and type of forecasting model (consecutive quarterly macro VAR; four-quarter macro VAR; consecutive quarterly VARs based on unfiltered coincident BTS variables; four-quarter VARs based on unfiltered coincident BTS variables; consecutive quarterly VARs based on unfiltered forward-looking BTS variables; four-quarter VARs based on unfiltered forward-looking BTS variables).

The forecasts are computed as follows. The full sample period has 2001:3 as its last quarterly observation. To undertake the out-of-sample experiments we exclude quarters 1995:3–2001:3 (25 observations). Since we wish to derive the forecasts recursively the procedure entails repeated re-estimation of equations (3) and (4) by successively adding observations from the excluded quarters. In each recursion, we generate forecasts of the macro variables at the one-quarter, two-quarter, four-quarter, and eight-quarter horizons. With 25 quarters excluded from the full sample, this generates (for each variable to be forecast and type of forecasting model) 25, 24, 22, and 18 recursive forecasts (and corresponding forecast errors) at the one-quarter, two-quarter, four-quarter, and eight-quarter horizons, respectively.

The exact procedure in the case Z in equations (3)–(4) is the estimated coincident or forward-looking common factor is outlined in Table 2.

[Insert Table 2 here]

The analysis of forecast accuracy is mainly based on the out-of-sample (root) mean-squared (forecast) error (RMSE) associated with a particular forecasting procedure. Under the hypothesis of unbiasedness, the RMSE is simply the standard deviation of the out-of-sample forecast errors. When analysing performance in relative terms, we compute ratios of RMSEs. Under certain circumstances, it is possible to undertake a test of the hypothesis that the relative RMSE equals unity (see Clark and McCracken, 2001, and Stock and Watson, 2001). If this hypothesis is rejected, then we can conclude that there is a statistically significant difference between the performances of the two forecasting models under consideration. But such tests require that the forecasting models that are being compared are nested, i.e., are related by a parametric simplification. This does not apply to the models compared in the present analysis, and the distributions of the relative RMSEs are therefore unknown. However, critical values tabulated in previous research may still serve as rules of thumb. For example, the 5 percent critical values reported by Stock and Watson (2001) indicate that relative RMSEs greater than 1.02–1.04 and smaller than 0.96–0.98 are statistically significant. By this measure, most relative RMSEs reported in this paper are statistically significant.

In our benchmark estimations, we fit all VARs without paying any attention to the models' in-sample performance. To gain some insights into how the analysis is affected if the VARs are required to fulfil criteria of in-sample performance, we repeat all forecasting experiments conditional on the forecasting equations satisfying certain tests of error-term adequacy. We compute three standard tests of model misspecification: the Breusch-Godfrey

LM test against autocorrelation; Engle's LM test against ARCH effects; and, Chow's parameter stability test. For the in-sample conditioning filter not to be too restrictive, we choose to consider a particular model as having acceptable in-sample properties if it passes at least two of the three error-term tests (at the conventional 5 percent test error margin). The reason for conditioning the forecasting models on their in-sample performance is that forecasters in practice presumably would pay some attention to such aspects when deriving their models. On the other hand, there is evidence that suggests that the link between in-sample and out-of-sample performance is (at best) weak (see, e.g., Stock and Watson, 2003). Therefore, using in-sample criteria that are too restrictive may entail eliminating models that do not perform very well in sample but nevertheless work well for purposes of out-of-sample forecasting. This constitutes the main reason for disregarding in-sample performance in the benchmark estimations, and only using an informal procedure when investigating robustness of results with respect to such considerations.

3.1. GDP-growth forecasts using the estimated common factors

Details of the misspecification tests, and the results that obtain when applying them to models fitted to GDP growth, are shown in Table 3. As can be seen, the two-out-of-three requirement means that all VAR models that use the estimated common factors and GDP growth (whether measured as consecutive quarterly or four-quarter growth) qualify for the conditional out-of-sample forecasting comparisons. We note that, to the extent that the models do not pass the misspecification tests, it is the parameter stability requirement that seems to be the most difficult criterion to fulfil.[8] This is interesting because the models have been explicitly designed to be (very) parsimoniously parameterised. Thus, although parsimonious, the models still display tendencies of instability. Judging from previous evidence, whether this is a problem or not when it comes to out-of-sample forecasting is unclear. The results in this paper (as is shown below) support the previous finding that in-sample performance is largely unrelated to out-of-sample forecasting accuracy.

[Insert Table 3 here]

Table 4 summarises the properties of the recursive GDP-growth forecasts using various measures of forecast accuracy. Looking first at the reported RMSEs we conclude that forecasts, even at very narrow horizons, are surrounded by a considerable amount of uncertainty. A 95 percent confidence interval for normally distributed forecast errors at the one- and two-quarter horizons has a width of around 2.2–2.4 percentage points when GDP growth is measured at a consecutive quarterly rate. For four-quarter growth, the width is around 3–4 percentage points.

The size of the typical forecast error (as measured by the mean absolute error, MAE) at the one- and two-quarter horizons is in the range 0.4–0.5 percentage points for consecutive quarterly growth, and 0.6–0.8 percentage points for four-quarter growth, reflecting the high uncertainty associated with the forecasts. Not surprisingly, all forecasts become successively less accurate as one prolongs the forecasting horizon.

[Insert Table 4 here]

From a more detailed study of the time paths of the forecast errors it becomes evident that particularly large errors occur when the growth rate is at, or close to, a "turning point" (in the

[8] This is a general finding that holds true for all forecasting models investigated in this paper.

sense that positive growth switches to negative growth and vice versa). To discern the extent to which the measures of forecast accuracy are influenced by large prediction errors that occur relatively infrequently, Table 4 also gives median-based measures of forecast accuracy (called RMedSEs and MedAEs). Comparing the root of the median-squared errors with the usual RMSEs, it can indeed be seen that large errors in the tails of the forecast-error distributions (which translate to the distributions of squared errors being skewed to the right) contribute to significantly worsening the forecasting performance of the procedures. In the case of median-based uncertainty measures, the widths of the aforementioned confidence intervals decrease by around 1 percentage point for both the consecutive quarterly and four-quarter growth forecasts. Similarly, a comparison of the median absolute errors with the usual MAEs shows that the typical forecast error is generally smaller when judged by the median-based MAE, often by an amount around 0.1–0.2 percentage points. This "turning-point problem" is typical for linear forecasting models, which are highly influenced by the (average) persistence of the variables in the conditioning set. A non-linear alternative provides a potential solution to the problem, but applying such a framework would go beyond the scope of this paper. Investigating the effects of making the DFM framework more flexible by allowing for non-linearities is thus left to future work.

The final measure of forecast accuracy reported in Table 4 is Theil's U. This measure normalises the usual RMSE by measuring it in relation to the standard deviation of the actual data. In this way, it is possible to make comparisons between different series that are forecast, no matter what their scales are. Because four-quarter GDP growth is a series that displays much greater volatility than consecutive quarterly GDP growth, the RMSEs of the forecast errors for these two series cannot be compared without taking this feature into account. As shown by the figures in the last column of Table 4, if the comparisons of forecast accuracy are performed taking the scale difference between the two series into account, then forecasts of four-quarter growth (at the horizons of interest) are approximately twice as accurate as forecasts of consecutive quarterly growth. This suggests, as expected, that it is generally easier to forecast four-quarter rather than consecutive quarterly growth.[9]

3.2. Alternative GDP-growth forecasts

The DFM-based forecasts of GDP growth are compared with various alternative GDP-growth forecasts in Tables 5–10. The comparisons with unfiltered BTS variables appear in Tables 5 and 6, with macro data in Tables 7 and 8, and with other popular summary indices of activity in Tables 9 and 10. These tables have the same basic format: the entries are relative RMSEs computed for various forecast horizons at which the RMSEs of the DFM-based VARs appear in the denominator so that numbers greater (smaller) than unity mean that the DFM-based VARs outperform (are outperformed by) the alternative forecasts.

Tables 5–8 have further similarities: in these tables, we compare the RMSEs of the DFM-based VARs with RMSEs of alternative forecasts generated by making use of empirical distributions. These distributions are obtained from the forecasts of all possible q-variate VARs given certain feasible conditioning sets (see the discussion above) and the restriction that $q \leq 5$ (including GDP growth). The first two rows in the upper and lower panels of Tables 5–8 construct the relative RMSEs by making use of the medians and means of the RMSE distributions of the alternative forecasts. The interpretation of these numbers is thus that they give a yardstick for assessing the performance of the DFM-based VARs relative to a typical alternative forecast that would obtain when using the BTS data unfiltered (i.e., without

[9] Another interesting feature of Theil's U is that it implicitly provides a benchmark against the random-walk forecasting model. In the case of a random walk, Theil's U always takes on the value of unity. Thus, if a model produces a Theil's U strictly less than unity, then it outperforms the random-walk alternative. From the last column in Table 4 it is seen that the DFM-based VAR forecasts always outperform the random-walk forecasts.

employing the DFM filter) or making use of macro variables only. The remaining rows in the upper and lower panels of these tables ("Best *x*-quarter") substitute the central-tendency moments for the optimised RMSEs at the *x*-quarter horizon, $x = 1, 2, 4, 8$, and report the relative RMSEs that obtain when residually using the same model to derive the forecasts at the other horizons. These numbers thus allow us to undertake a comparison with the best possible forecast at a certain horizon that can be derived using the BTS variables unfiltered or the macro variables (and also to see how well the model used to compute this forecast performs, in relative terms, at other horizons).

Turning first to the results in Tables 5 and 6, it is seen that the DFM filter generally improves the forecasting performance of the VARs. This holds true especially in the case of the forward-looking variables. For these variables, the DFM-based VARs outperform the rival models at the one- and two-quarter horizons in all cases, even if the models based on the unfiltered variables are optimised (with respect to the particular forecast horizons). Moreover, the results do not depend on whether GDP growth is measured at a consecutive quarterly or four-quarter rate.

[Insert Tables 5 and 6 here]

From the results in brackets, we see that the picture is unaltered when conditioning the forecasting models on their in-sample performance (see the discussion above). The difference between the numbers without and within brackets is marginal even though as much as 20–30 percent of the models are discarded in some cases (coincident data in Table 5). The finding in previous studies that in-sample performance is largely unrelated to out-of-sample performance is thus confirmed here.[10]

[10]This is a general finding for the models analysed in this paper, cf. Section 3.3.

Next, turning to the comparison with macro data (Tables 7 and 8), we find that the DFM approach again outperforms the rival models at all one- and two-quarter horizons. As before, the results are enhanced for the forward-looking data. As expected, the gains from using macro variables increase with the length of the forecast horizon: at the eight-quarter horizon the DFM forecasts never give lower RMSEs than the forecasts based on macro variables. But, the DFM-based models, in several cases, do surprisingly well even at the four-quarter horizon (see Table 8).

[Insert Tables 7 and 8 here]

The results that compare the DFM-based GDP-growth forecasts with the forecasts of GDP growth based on popular summary indices of activity are in Tables 9 and 10. They are qualitatively similar to those in the previous tables: the DFM forecasts dominate at short horizons and the improvement is somewhat larger for forward-looking variables. One particularly interesting feature of the comparisons with the popular summary indices is that the DFM – except in the case of coincident data at the four-quarter horizon – outperforms the so-called activity index of Statistics Sweden by a relatively large margin (see the last row in each panel in Tables 9 and 10). This is interesting because the activity index is explicitly designed to be a short-run indicator of the growth rate of GDP and in practice used by many of the professional forecasters. Since both indicators are now being analysed and published continuously (see www.scb.se and www.konj.se), future work may make a further contribution by comparing the performance of these indicators in genuine real time.

[Insert Tables 9 and 10 here]

3.3. Forecasts of other macro variables

Having established that the estimated common factors work rather well for purposes of forecasting the growth rate of GDP, it seems plausible that they would also be useful for forecasting other key variables that depict the development of the macro economy. The results compiled in Tables 11–14 shed light on this issue.

Generally, the picture that emerges from inspecting these tables is far less clear-cut than that obtained for the growth rates of GDP. While the DFM-based forecasts on average still outperform the forecasts based on macro variables and unfiltered BTS variables, the popular summary indices now often show a performance that comes quite close to that of the common factors. In particular, this holds true for the analyses undertaken with consecutive quarterly data (see Tables 11 and 13).

It is of interest to note that details of measurement now seem to matter in a significant way. This was not the case for forecasts of the growth rate of GDP. For example, in the case of consecutive quarterly data and inflation forecasts, the DFM typically outperforms the popular summary indices of economic activity (see the first two columns in Tables 11 and 13). However, when the data are in four-quarter rates, the opposite finding obtains (see the same columns in Tables 12 and 14). Similarly, while the DFM is generally outperformed by the popular summary indices in the case of consecutive quarterly data and employment-growth and unemployment forecasts (see columns 5–8 in Tables 11 and 13), it is the other way around when these forecasts are obtained using data measured in four-quarter rates (see the same columns in Tables 12 and 14). Results for forecasts of wage inflation depend moreover on the measurement of the common factor. Here, there is a tendency that the DFM works better for BTS data that are coincident rather than forward-looking (cf. the last two columns of Tables 11–14).[11]

[Insert Tables 11–14 here]

4. Summary and concluding remarks

In this paper we examine whether data from business-tendency surveys are useful for forecasting the macro economy in the short run. Our analyses primarily concern the growth rates of real GDP but we also evaluate forecasts of other variables such as unemployment, price and wage inflation, interest rates, and exchange-rate changes.

The starting point is a so-called dynamic factor model (DFM), which is used to summarise the information content of the survey data. The benefits of the DFM proceed from the fact that changes in the survey data can not always be assumed to contain signals that are relevant for activity at the aggregate level. More specifically, it seems likely that idiosyncratic sector-specific changes in a particular series are largely unrelated to the overall state of economic activity. The filtering technique thus entails getting rid of this series-specific "noise" and only keeping those parts of the data that are common to the series under consideration. The proposed filtering procedure has the additional property of implying a dimension-reduction framework for the survey variables. From the forecasting literature it is well known that forecasting approaches using many explanatory variables, and thus many estimated parameters, generate forecasts that quickly become inefficient and unstable. The procedure

[11]The measurement of the common factor is found to be important for the GDP-growth forecasts as well, see Section 3.2. But for these forecasts, the results are found to improve (rather than deteriorate) when the BTS data are forward-looking instead of coincident.

addresses this issue by summarising the observable information of the large survey data set by a single common-factor index.

Because the questions of the survey regard activities in the current as well as in the next quarter, we are able to use the DFM to estimate both a coincident and forward-looking index. These indices are then used in a VAR analysis together with the macro variables that we wish to forecast.

To assess the relative accuracy of the DFM-based VAR forecasts, we make forecast comparisons using three alternative approaches to forecasting the macro variables. These are VARs that use unfiltered BTS variables (i.e., that include the survey variables directly without employing the DFM filter); VARs that use information on macro variables only; and VARs that use other popular summary indices of economic activity. By making comparisons with VARs based on the unfiltered survey data we are able, in terms of forecast precision, to assess the gain made from first applying the DFM to the BTS data (relative to not doing so). That is, we can quantify the effects in forecasting from parsimoniously modelling the noise-reduced BTS series rather than the original series themselves. The comparisons with macro VARs instead enable us to judge how well we do relative to the "standard forecasting model". Finally, the comparisons with VARs based on other summary indices of activity allow us to shed some light on the performance of our procedure when holding the gains of dimension reduction constant. Like the DFM procedure, such summary indices have the advantage of enabling the use of very parsimonious forecasting models, without having to give up too much of the relevant forecasting information.

The evaluations are undertaken by subjecting both the DFM-based VARs and the rival models to a recursive out-of-sample forecasting competition. Most of our analyses concern forecasts at the one- and two-quarter horizons but, in some cases, we also investigate performance at slightly longer horizons (one year and two years in the future).

In our benchmark comparisons, we fit all VARs without paying any attention to the models' in-sample performance. However, to gain some insights into how the analysis is affected if the VARs are required to fulfil criteria of in-sample performance, we repeat all forecasting experiments conditional on the forecasting equations satisfying certain standard tests of error-term adequacy. The difference between the benchmark comparisons and the comparisons that condition on in-sample performance turns out to be small despite the fact that many models are rejected when subjected to the in-sample criteria. This confirms the finding in previous studies that in-sample performance is largely unrelated to out-of-sample performance.

As concerns forecasts of GDP growth, the DFM procedure outperforms the competing alternatives in most cases. Its performance is particularly striking in the case of forward-looking survey data, where it consistently outperforms the rival alternatives. As expected, the performance of the macro VARs improves as the forecast horizon is prolonged. These VARs almost never outperform the DFM-based VARs at the one- and two-quarter horizons, but generate growth forecasts that are reliably more accurate at the eight-quarter horizon.

For the other macro variables, the evidence is more mixed. While the DFM-based forecasts generally still outperform the forecasts based on macro variables and unfiltered survey variables, the popular summary indices now often show a performance that comes quite close to that of the common factors.

A general finding of interest when it comes to forecasts of other macro variables is that details of measurement seem to be of greater importance than in the case of GDP-growth forecasts. For example, forecasts that are accurate for variables measured in consecutive quarterly growth are not necessarily accurate when the same variables are measured at a four-quarter rate (and vice versa).

The findings in this paper relate to the recent research that reports good forecasting performance results for dynamic factor models (Forni, Hallin, Lippi, and Reichlin, 2000, 2003, and Stock and Watson, 1999, 2002). However, in a recent paper, Stock and Watson (2003) find evidence that simple mean combination forecasts (derived from simple indicator regressions augmented with AR terms) outperform DFM-based forecasts in many cases. The simple mean forecasts are found to work well, although the underlying individual forecasts display substantial instability. Our analyses do not comprise an evaluation of a mean combination forecast alternative. The reason for this is that we became aware of the finding of Stock and Watson (2003) after having completed our research. Another limitation of our analyses is that they do not allow for forecasting models that are non-linear. To allow for non-linearities would be interesting, especially since we find that many models suffer from problems of parameter instability and large forecast errors at, or around, turning points. We intend to address these issues in future work.

Acknowledgements

We thank Jimmy Miller and seminar participants at the National Institute of Economic Research (NIER), Sveriges Riksbank, and the Ministry of Finance for helpful comments. Most of the research undertaken in this paper was accomplished while Per Jansson was Deputy Director of the Department of Forecasting at the NIER. The views expressed in this paper are those of the authors and do not necessarily reflect those of Sveriges Riksbank or the NIER.

Data Appendix

The sources of data are as follows. GDP growth, price inflation (underlying UND1X and headline CPI), wage inflation, unemployment, and employment growth are from Statistics Sweden and the NIER. The short-term interest rate is from IMF Financial Statistics. The long-term interest rate is from OECD Main Economic Indicators and Sveriges Riksbank. The exchange-rate growth is from Sveriges Riksbank and the NIER. The survey data (Swedish Business Tendency Survey, BTS) are from the NIER (see Table 1). The popular summary indices are from Statistics Sweden and the NIER (see Tables 9 and 10).

CPI inflation, underlying (UND1X) inflation, unemployment, short- and long-term interest rates, and the exchange-rate growth are in quarterly averages. The wage variable is obtained by dividing the wage sum by the number of hours worked. Unemployment is open (official) unemployment in the age group 16–64. The short-term interest rate is a three-month rate while the long-term interest rate is a ten-year rate. The employment variable is based on the number of hours worked. The exchange-rate variable is the effective rate and computed using the IMF's TCW (Total Competitiveness Weights).

For variables expressed in growth rates, two different transformations are considered: log first differences and log four-quarter differences. Except for exchange-rate growth, all first-differenced variables are seasonally adjusted. Among the level variables (unemployment and the two interest rates) only unemployment is seasonally adjusted. In addition, all BTS variables are seasonally adjusted. The method of seasonal adjustment is TRAMO/SEATS (with automatic BIC-based model selection).

References

Bergström, R. (1992). The relationship between manufacturing production and different business survey series in Sweden. Working Paper no. 12, National Institute of Economic Research, Stockholm.

Bergström, R. (1993a). Quantitative production series compared with qualitative business survey series for five sectors of the Swedish manufacturing industry. Working Paper no. 30b, National Institute of Economic Research, Stockholm.

Bergström, R. (1993b). The full trichotomous scale compared with net balances in quantitative business survey data. Working Paper no. 30a, National Institute of Economic Research, Stockholm.

Bruno, G. & Malgarini, M. (2002). An indicator of economic sentiment for the Italian economy. Working Paper no. 28/02, Institute for Studies and Economic Analyses, Rome.

Burns, A. & Mitchell, W. (1946). *Measuring Business Cycles*. NBER, New York.

Camba-Mendez, G., Kapetanios, G., Smith, R., & Weale, M. (1999). An automatic leading indicator of economic activity: Forecasting GDP growth for European countries. NIESR Discussion Papers no. 149, London.

Christoffersson, A., Roberts, R., & Eriksson, U. (1992). The relationship between manufacturing and various BTS (business tendency survey) series in Sweden illuminated by frequency and complex demodulate methods. Working Paper no. 15, National Institute of Economic Research, Stockholm.

Clark, T. & McCracken, M. (2001). Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics*, 105, 85–100.

Doornik, J. & Hendry, D. (1997). *Modelling Dynamic Systems Using PcFiml 9.0 for Windows*. International Thomson Business Press, London.

European Commission (2000). Business climate indicator for the Euro area. (europa.eu.int/comm/economy_finance/indicators/businessclimate_en.htm).

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2000). The generalized factor model: Identification and estimation. *Review of Economics and Statistics*, 82, 540–554.

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2003). Do financial variables help forecasting inflation and real activity in the Euro area? *Journal of Monetary Economics*, forthcoming (www.dynfactors.org).

Fukuda, S. & Onodera, T. (2001). A new composite index of coincident economic indicators in Japan: How can we improve forecast performances? *International Journal of Forecasting*, 17, 483–498.

Goldrian, G., Lindbauer, J., & Nerb, G. (2001). Evaluation and development of confidence indicators based on harmonised business and consumer surveys. EC Economic Paper no. 151, Bruxelles.

Hamilton, J. (1994). *Time Series Analysis*. Princeton University Press, Princeton, New Jersey.

Harvey, A. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press, Cambridge.

Kääntä, P. & Tallbom, C. (1993). Using business survey data for forecasting Swedish quantitative business cycle variables: A Kalman filter approach. Working Paper no. 35, National Institute of Economic Research, Stockholm.

Koskinen, L. & Öller, L-E. (2003). A classifying procedure for signalling turning points. *Journal of Forecasting*, forthcoming.

Lindström, T. (1999). Forecasting business cycle turning points using dispersion measures from survey data: Evidence from Swedish manufacturing. Manuscript. Sveriges Riksbank, Stockholm.

Lindström, T. (2000). Qualitative survey responses and production over the business cycle. Manuscript. Sveriges Riksbank, Stockholm.

Öller, L-E. & Tallbom, C. (1996). Smooth and timely business cycle indicators for noisy Swedish data. *International Journal of Forecasting*, 12, 389–402.

Rahiala, M. & Teräsvirta, T. (1993). Business survey data in forecasting the output of Swedish and Finnish metal and engineering industries: A Kalman filter approach. *Journal of Forecasting*, 12, 255–271.

Stock, J. & Watson, M. (1989). New indexes of coincident and leading economic indicators. *NBER Macroeconomics Annual*, 4, 351–393.

Stock, J. & Watson, M. (1991). A probability model of the coincident economic indicators. In: Lahiri, K. & Moore, G. (Eds.), *Leading Economic Indicators: New Approaches and Forecasting Records*, Cambridge University Press.

Stock, J. & Watson, M. (1999). Forecasting inflation. *Journal of Monetary Economics*, 44, 293–335.

Stock, J. & Watson, M. (2001). Forecasting output and inflation: The role of asset prices. NBER Working Paper no. 8180 (revised January 2003, www.wws.princeton.edu/~mwatson/).

Stock, J. & Watson, M. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics*, 20, 147–162.

Stock, J. & Watson, M. (2003). Combination forecasts of output growth in a seven-country data set. Manuscript (www.wws.princeton.edu/~mwatson/).

Biographies: Jesper HANSSON is head of the Division of GDP Analysis at the NIER. He received his PhD from Lund University in 2001.

Per JANSSON is an Associate Professor of Economics at Uppsala University since 2000. He is also Deputy Director of the Monetary Policy Department at Sveriges Riksbank. He received his PhD from Uppsala University in 1994.

Mårten LÖF, who also is with the NIER, is a statistician and received his PhD from the Stockholm School of Economics in 2001.

Table 1

The BTS variables[a]

Activity	Coincident	Forward-looking
Manufacturing industries		
Production	BTVI101	BTVI301
Orders received (domestic)	BTVI105	BTVI305
Orders received (exports)	BTVI106	BTVI306
Time of deliveries	BTVI108	
As-of-now judgement of orderbooks	BTVI201	
Number of workers employed	BTVI203	BTVI308
As-of-now judgement of stocks of raw materials	BTVI208	
As-of-now judgement of stocks of finished goods	BTVI210	
Construction industries		
Construction	BBOA101	BBOA201
Stocks of offers accepted	BBOA102	BBOA202
As-of-now judgement of orderbooks	BBOA104	
Number of workers employed	BBOA106	BBOA204

[a] Each entry gives the code used by the National Institute of Economic Research to denote the particular survey question. In the DFM, the variables are normalised to have unit variances and zero means. The sample runs from 1978:1–2001:4 in the case of coincident variables and from 1978:2–2002:1 in the case of forward-looking variables.

Table 2

Set-up for recursive forecasts using the estimated common factors[a]

	Coincident index (C)	Forward-looking index (C)
Variables to be forecast (Y): GDP growth; employment growth; unemployment; wage inflation		
Sample eq. (3)	$1978:4-s$, $s=1995:2,...,2001:2$	$1979:4-m$, $m=1995:2,...,2001:2$
Sample eq. (4)	$1978:4-s$, $s=1995:3,...,2001:3$	$1979:4-m$, $m=1995:3,...,2001:3$
Information set	$C_{78:4},...,C_s,Y_{78:4},...,Y_{s-1}$,	$C_{79:4},...,C_{m+1},Y_{79:4},...,Y_{m-1}$,
	$s=1995:3,...,2001:3$	$m=1995:3,...,2001:3$
Variables to be forecast (Y): price inflation; interest rates; exchange-rate growth		
Sample eq. (3)	$1978:4-h$, $h=1995:2,...,2001:2$	$1979:4-n$, $n=1995:2,...,2001:2$
Sample eq. (4)	$1978:4-h$, $h=1995:2,...,2001:2$	$1979:4-n$, $n=1995:3,...,2001:3$
Information set	$C_{78:4},...,C_h,Y_{78:4},...,Y_h$,	$C_{79:4},...,C_{n+1},Y_{79:4},...,Y_n$,
	$h=1995:2,...,2001:2$	$n=1995:2,...,2001:2$

[a] For each type of recursive model (distinguished by time indices *s*, *h*, *m*, and *n*), the table gives the estimation samples and the information set that are used in each forecasting recursion. For example, if *Y* is GDP growth (top panel of the table) and *C* the forward-looking index (right column of top panel), then the first recursion estimates equation (3) over the sample 1979:4–1995:2 and equation (4) over 1979:4–1995:3. The available information set in this recursion contains GDP growth up to and including 1995:2 and BTS data (in the form of the forward-looking index) up to and including 1995:4. The forward-looking index has fewer observations than the coincident index due to differences in lag structures, procedures for initial values, etc in the DFM.

Table 3

Residual diagnostics for GDP-growth equations in bivariate DFM-based VAR models[a]

Endogenous VAR variables	Autocorr.	Heterosced.	Stability
Coincident index, consecutive quarterly GDP growth	0.06	0.26	0.02
Coincident index, four-quarter GDP growth	0.58	0.52	0.02
Forward-looking index, consecutive quarterly GDP growth	0.10	0.78	0.02
Forward-looking index, four-quarter GDP growth	0.14	0.62	0.04

[a] All numbers are p values. The test against autocorrelation is the Lagrange-multiplier (LM) test of fifth order autocorrelation. The test against heteroscedasticity is the LM test of fourth order ARCH effects (autoregressive conditional heteroscedasticity). The parameter stability test is Chow's breakpoint test of a mid-sample one-off break. All tests are computed as F tests. The orders of the LM tests are the same as they are automatically chosen by the PcGive software package. For further details, see Doornik and Hendry (1997), Chapter 10, Sections 10.8 and 10.9.

Table 4

Forecast-error analysis for bivariate DFM-based VAR models: GDP growth[a]

	RMSE	MAE	RMedSE	MedAE	Theil's U
VAR variables: coincident index, consecutive quarterly GDP growth					
One-quarter	0.52	0.42	0.33	0.33	0.60 (9)
Two-quarter	0.53	0.42	0.32	0.32	0.61 (11)
Four-quarter	0.69	0.56	0.48	0.48	0.76 (16)
Eight-quarter	0.67	0.58	0.60	0.60	0.70 (14)
VAR variables: coincident index, four-quarter GDP growth					
One-quarter	0.98	0.79	0.59	0.59	0.31 (1)
Two-quarter	1.14	0.93	0.71	0.71	0.36 (4)
Four-quarter	1.80	1.58	1.65	1.64	0.57 (6)
Eight-quarter	2.09	1.96	2.05	2.05	0.60 (9)
VAR variables: forward-looking index, consecutive quarterly GDP growth					
One-quarter	0.49	0.35	0.27	0.27	0.57 (6)
Two-quarter	0.50	0.37	0.28	0.28	0.57 (6)
Four-quarter	0.62	0.47	0.41	0.41	0.69 (13)
Eight-quarter	0.71	0.60	0.62	0.61	0.75 (15)
VAR variables: forward-looking index, four-quarter GDP growth					
One-quarter	1.04	0.81	0.71	0.71	0.34 (2)
Two-quarter	1.11	0.87	0.79	0.79	0.35 (3)
Four-quarter	1.59	1.28	1.19	1.19	0.50 (5)
Eight-quarter	2.21	2.08	2.16	2.16	0.63 (12)

[a] Columns one and two give conventional root mean-squared errors (RMSEs) and mean absolute errors (MAEs). Columns three and four contain median-based RMSEs and MAEs (RMedSEs and MedAEs). Column five gives Theil's U, which equals a scale-adjusted RMSE. Numbers within parentheses in this column are rankings.

Table 5

Alternative forecasts of GDP growth: relative RMSEs for coincident index vs. unfiltered BTS variables[a]

	One-quarter	Two-quarter	Four-quarter
Consecutive quarterly GDP growth			
Median	1.15 (1.16)	1.07 (1.07)	1.03 (1.03)
Mean	1.16 (1.17)	1.08 (1.08)	1.02 (1.03)
Best one-quarter	0.93 (0.93)	0.99 (0.99)	0.99 (0.99)
Best two-quarter	1.03 (1.03)	0.93 (0.93)	0.97 (0.97)
Best four-quarter	1.01 (1.04)	1.00 (0.99)	0.84 (0.85)
Four-quarter GDP growth			
Median	1.23 (1.20)	1.24 (1.24)	1.08 (1.07)
Mean	1.25 (1.22)	1.25 (1.23)	1.08 (1.08)
Best one-quarter	0.96 (0.96)	1.19 (1.19)	1.09 (1.09)
Best two-quarter	1.06 (1.07)	0.89 (0.92)	0.77 (0.79)
Best four-quarter	1.06 (1.07)	0.89 (0.92)	0.77 (0.79)

[a] All numbers are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the models based on the unfiltered BTS variables. In the rows labelled "Median" and "Mean" the RMSEs of the models based on the unfiltered BTS variables are central-tendency moments of empirical distributions. The distributions are generated from the forecasts of all possible VAR models of dimension five or less (including the variable to be forecast) using the feasible set of BTS variables outlined in Table 1. In the rows "Best *x*-quarter" the RMSEs of the models based on the unfiltered BTS variables are optimised such that they are at their minima at the *x*-quarter horizon (again making use of the empirical distributions). The numbers in brackets are results that condition the forecasting models on satisfying certain residual diagnostics criteria (see the text and Table 3 for details). The shares of the models that are excluded when subjected to the residual diagnostics criteria are 20.4 percent in the case of consecutive quarterly GDP growth and 31.1 percent in the case of four-quarter GDP growth. The lag lengths of the VARs are determined by minimising the BIC (see the text for details).

Table 6

Alternative forecasts of GDP growth: relative RMSEs for forward-looking index vs. unfiltered BTS variables[a]

	One-quarter	Two-quarter	Four-quarter
Consecutive quarterly GDP growth			
Median	1.20 (1.20)	1.12 (1.12)	1.08 (1.08)
Mean	1.19 (1.20)	1.12 (1.12)	1.08 (1.09)
Best one-quarter	1.08 (1.09)	1.05 (1.03)	0.98 (1.14)
Best two-quarter	1.10 (1.10)	1.01 (1.01)	1.14 (1.14)
Best four-quarter	1.10 (1.20)	1.06 (1.16)	0.94 (1.02)
Four-quarter GDP growth			
Median	1.23 (1.23)	1.27 (1.28)	1.13 (1.13)
Mean	1.23 (1.23)	1.28 (1.28)	1.13 (1.13)
Best one-quarter	1.11 (1.11)	1.14 (1.14)	0.96 (0.96)
Best two-quarter	1.11 (1.11)	1.14 (1.14)	0.96 (0.96)
Best four-quarter	1.11 (1.11)	1.15 (1.15)	0.95 (0.95)

[a] All numbers are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the models based on the unfiltered BTS variables. In the rows labelled "Median" and "Mean" the RMSEs of the models based on the unfiltered BTS variables are central-tendency moments of empirical distributions. The distributions are generated from the forecasts of all possible VAR models of dimension five or less (including the variable to be forecast) using the feasible set of BTS variables outlined in Table 1. In the rows "Best *x*-quarter" the RMSEs of the models based on the unfiltered BTS variables are optimised such that they are at their minima at the *x*-quarter horizon (again making use of the empirical distributions). The numbers in brackets are results that condition the forecasting models on satisfying certain residual diagnostics criteria (see the text and Table 3 for details). The shares of the models that are excluded when subjected to the residual diagnostics criteria are 9.0 percent in the case of consecutive quarterly GDP growth and 5.0 percent in the case of four-quarter GDP growth. The lag lengths of the VARs are determined by minimising the BIC (see the text for details).

Table 7

Alternative forecasts of GDP growth: relative RMSEs for coincident index vs. macro variables[a]

	One-quarter	Two-quarter	Four-quarter	Eight-quarter
Consecutive quarterly GDP growth				
Median	1.23 (1.22)	1.09 (1.03)	0.91 (0.98)	0.87 (0.73)
Mean	1.22 (1.19)	1.09 (1.04)	0.92 (0.98)	0.86 (0.80)
Best one-quarter	1.00 (1.00)	0.96 (0.96)	0.93 (0.93)	0.94 (0.94)
Best two-quarter	1.25 (1.00)	0.95 (0.96)	0.98 (0.93)	0.70 (0.94)
Best four-quarter	1.25 (1.24)	1.11 (1.05)	0.86 (0.91)	0.87 (0.88)
Best eight-quarter	1.30 (1.30)	1.14 (1.15)	1.06 (1.06)	0.67 (0.67)
Four-quarter GDP growth				
Median	1.27 (1.26)	1.21 (1.20)	0.92 (0.92)	0.75 (0.76)
Mean	1.28 (1.27)	1.21 (1.21)	0.93 (0.95)	0.76 (0.77)
Best one-quarter	1.16 (1.16)	1.09 (1.09)	0.93 (0.93)	0.86 (0.86)
Best two-quarter	1.23 (1.23)	1.08 (1.08)	0.84 (0.84)	0.84 (0.84)
Best four-quarter	1.31 (1.23)	1.19 (1.08)	0.79 (0.84)	0.82 (0.84)
Best eight-quarter	1.30 (1.41)	1.26 (1.27)	0.93 (1.10)	0.60 (0.63)

[a] All numbers are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the models based on the macro variables. In the rows labelled "Median" and "Mean" the RMSEs of the models based on the macro variables are central-tendency moments of empirical distributions. The distributions are generated from the forecasts of all possible VAR models of dimension five or less (including the variable to be forecast) using the following eight macro variables (in addition to GDP growth): inflation according to headline CPI and the underlying measure UND1X; effective exchange-rate growth; unemployment; employment growth; short- and long-term interest rates; wage inflation. In the rows "Best *x*-quarter" the RMSEs of the models based on the macro variables are optimised such that they are at their minima at the *x*-quarter horizon (again making use of the empirical distributions). The numbers in brackets are results that condition the forecasting models on satisfying certain residual diagnostics criteria (see the text and Table 3 for details). The shares of the models that are excluded when subjected to the residual diagnostics criteria are 88.4 percent in the case of consecutive quarterly GDP growth and 53.7 percent in the case of four-quarter GDP growth. The lag lengths of the VARs are determined by minimising the BIC (see the text for details).

Table 8

Alternative forecasts of GDP growth: relative RMSEs for forward-looking index vs. macro variables[a]

	One-quarter	Two-quarter	Four-quarter	Eight-quarter
Consecutive quarterly GDP growth				
Median	1.31 (1.30)	1.16 (1.10)	1.01 (1.10)	0.82 (0.69)
Mean	1.29 (1.26)	1.15 (1.10)	1.02 (1.09)	0.81 (0.75)
Best one-quarter	1.06 (1.06)	1.02 (1.02)	1.04 (1.04)	0.89 (0.89)
Best two-quarter	1.32 (1.06)	1.01 (1.02)	1.09 (1.04)	0.66 (0.89)
Best four-quarter	1.32 (1.32)	1.18 (1.11)	0.96 (1.01)	0.82 (0.83)
Best eight-quarter	1.38 (1.38)	1.21 (1.21)	1.18 (1.18)	0.63 (0.64)
Four-quarter GDP growth				
Median	1.20 (1.19)	1.24 (1.23)	1.04 (1.05)	0.71 (0.72)
Mean	1.20 (1.20)	1.25 (1.24)	1.05 (1.07)	0.72 (0.73)
Best one-quarter	1.10 (1.10)	1.12 (1.12)	1.05 (1.05)	0.81 (0.81)
Best two-quarter	1.16 (1.16)	1.11 (1.11)	0.95 (0.95)	0.79 (0.79)
Best four-quarter	1.23 (1.16)	1.23 (1.11)	0.89 (0.95)	0.78 (0.79)
Best eight-quarter	1.23 (1.33)	1.29 (1.31)	1.05 (1.25)	0.57 (0.60)

[a] All numbers are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the models based on the macro variables. In the rows labelled “Median” and “Mean” the RMSEs of the models based on the macro variables are central-tendency moments of empirical distributions. The distributions are generated from the forecasts of all possible VAR models of dimension five or less (including the variable to be forecast) using the following eight macro variables (in addition to GDP growth): inflation according to headline CPI and the underlying measure UND1X; effective exchange-rate growth; unemployment; employment growth; short- and long-term interest rates; wage inflation. In the rows “Best *x*-quarter” the RMSEs of the models based on the macro variables are optimised such that they are at their minima at the *x*-quarter horizon (again making use of the empirical distributions). The numbers in brackets are results that condition the forecasting models on satisfying certain residual diagnostics criteria (see the text and Table 3 for details). The shares of the models that are excluded when subjected to the residual diagnostics criteria are 88.4 percent in the case of consecutive quarterly GDP growth and 53.7 percent in the case of four-quarter GDP growth. The lag lengths of the VARs are determined by minimising the BIC (see the text for details).

Table 9

Alternative forecasts of GDP growth: relative RMSEs for coincident index vs. popular summary indices[a]

	One-quarter	Two-quarter	Four-quarter
Consecutive quarterly GDP growth			
BTS confidence indicator, manufacturing	1.02	0.98	0.93
BTS confidence indicator, construction	1.17	1.17	0.96
Consumer survey, own personal economy†	1.04	1.06	0.90
Consumer survey, whole economy†	1.06	1.06	0.94
Consumer survey, unemployment	1.08	1.09	1.04
Consumer survey, backward-looking†	1.08	1.08	0.91
Activity index (consecutive quarterly change)	1.12	1.08	0.96
Four-quarter GDP growth			
BTS confidence indicator, manufacturing	1.20	1.15	0.94
BTS confidence indicator, construction	1.27	1.23	1.03
Consumer survey, own personal economy†	1.15	1.05	0.82
Consumer survey, whole economy	1.14	1.08	0.91
Consumer survey, unemployment	1.15	1.18	1.04
Consumer survey, backward-looking†	1.18	1.11	0.89
Activity index (four-quarter change)	1.17	1.05	0.98

[a] All numbers are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the models based on the other popular summary indices. † means that the models based on the other popular summary indices do not pass the residual diagnostics criteria (see the text and Table 3 for details). All models are bivariate VARs, whose lag lengths have been determined using the BIC (see the text for details).

Table 10

Alternative forecasts of GDP growth: relative RMSEs for forward-looking index vs. popular summary indices[a]

	One-quarter	Two-quarter	Four-quarter
Consecutive quarterly GDP growth			
BTS confidence indicator, manufacturing	1.08	1.04	1.03
BTS confidence indicator, construction	1.24	1.24	1.06
Consumer survey, own personal economy†	1.10	1.12	1.00
Consumer survey, whole economy†	1.12	1.12	1.05
Consumer survey, unemployment	1.14	1.16	1.16
Consumer survey, backward-looking†	1.14	1.14	1.02
Activity index (consecutive quarterly change)	1.18	1.14	1.06
Four-quarter GDP growth			
BTS confidence indicator, manufacturing	1.13	1.18	1.07
BTS confidence indicator, construction	1.19	1.26	1.16
Consumer survey, own personal economy†	1.09	1.08	0.92
Consumer survey, whole economy	1.08	1.11	1.03
Consumer survey, unemployment	1.09	1.21	1.18
Consumer survey, backward-looking†	1.12	1.14	1.01
Activity index (four-quarter change)	1.11	1.08	1.11

[a] All numbers are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the models based on the other popular summary indices. † means that the models based on the other popular summary indices do not pass the residual diagnostics criteria (see the text and Table 3 for details). All models are bivariate VARs, whose lag lengths have been determined using the BIC (see the text for details).

Table 11

Forecasts of other macro variables: relative RMSEs, coincident index and data in consecutive quarterly growth[a]

	Inflation		Exch. rate		Unemploy.		Employment		Interest rate		Wages	
	One	Two	One	Two	One	Two	One	Two	One	Two	One	Two
Unfiltered	1.34	1.51	1.00	0.99	1.21	1.17	1.10	1.11	1.09	0.98	1.09	1.07
BTS	**1.37**	**1.55**	**1.00**	**0.99**	**1.22**	**1.18**	**1.10**	**1.11**	**1.14**	**1.01**	**1.08**	**1.07**
	0.79	*0.79*	*0.00*	*0.00*	*0.38*	*0.38*	*0.08*	*0.08*	*0.34*	*0.34*	*0.19*	*0.19*
Macro	1.13	1.14	1.06	1.03	1.05	1.03	1.21	1.07	1.04	0.87	0.84	0.99
variables	**1.11**	**1.06**	**1.06**	**1.02**	**0.95**	**1.03**	**1.21**	**1.07**	**1.04**	**0.87**	**0.85**	**1.00**
	0.57	*0.57*	*0.02*	*0.02*	*0.82*	*0.82*	*0.02*	*0.02*	*0.02*	*0.02*	*0.38*	*0.38*
CI, manuf.	0.97	0.91	0.99	0.98	0.96††	0.96††	0.96	0.96	1.07	1.11	1.17	1.16
CI, constr.	1.17††	1.37††	1.03	1.01	0.96††	0.96††	0.96	0.96	0.98	0.99	1.00	1.06
CS, own	1.17††	1.34††	1.09	1.08	0.92††	0.88††	0.92	0.88	0.98	1.03	1.03	1.10
CS, whole	1.13††	1.29††	1.00	1.00	0.96††	0.92††	0.92	0.92	0.98	1.01	0.96	1.03
CS, unemp.	1.17††	1.40††	1.01	1.01	1.12††	1.04††	1.12	1.04	1.07	1.08	1.08	1.13
CS, back	1.20	1.40	1.11	1.09	0.92††	0.94††	0.92	0.94	1.02	1.06	1.11	1.12
Activity in.	1.17	1.23	1.04	1.03	0.85	0.84	0.85	0.84	1.09	1.11	0.90	0.97

[a] All numbers (except in italics) are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the rival models. To save space, the results for headline CPI inflation and the short-term interest rate have been left out (but are available upon request). Column "One" evaluates forecasts one quarter ahead. Column "Two" evaluates forecasts two quarters ahead. The (nominator of the) relative RMSEs in the rows "Unfiltered BTS" and "Macro variables" are based on medians of empirical distributions (see the Notes of Tables 5–6 and Tables 7–8 for details). Numbers in bold in those rows are relative RMSEs that condition the forecasting models on satisfying certain residual diagnostics criteria (see the text and Table 3 for details). Numbers in italics in those rows show the shares of the rival models that are excluded when subjected to the residual diagnostics criteria. The remaining rows are comparisons with other popular summary indices (see the Notes of Tables 9–10). † means that the models based on the common factor do not pass the residual diagnostics criteria; †† means that the rival models do not pass the residual diagnostics criteria; ††† means that neither the models based on the common factor nor the rival models pass the residual diagnostics criteria.

Table 12

Forecasts of other macro variables: relative RMSEs, coincident index and data in four-quarter growth[a]

	Inflation		Exch. rate		Unemploy.		Employment		Interest rate		Wages	
	One	Two	One	Two	One	Two	One	Two	One	Two	One	Two
Unfiltered	0.94	0.92	1.06	1.14	1.21	1.17	1.19	1.24	1.09	0.98	1.06	1.18
BTS	**0.92**	**0.89**	†	†	**1.22**	**1.18**	**1.20**	**1.25**	**1.14**	**1.01**	**1.07**	**1.18**
	0.62	*0.62*	*1.00*	*1.00*	*0.38*	*0.38*	*0.29*	*0.29*	*0.34*	*0.34*	*0.39*	*0.39*
Macro	0.98	0.97	1.13	1.29	1.06	1.09	1.11	1.19	1.11	1.01	0.87	0.86
variables	**0.97**	**0.97**	†	†	**0.96**	**1.03**	**1.13**	**1.18**	**1.11**	**1.01**	**0.87**	**0.88**
	0.22	*0.22*	*0.93*	*0.93*	*0.92*	*0.92*	*0.81*	*0.81*	*0.44*	*0.44*	*0.40*	*0.40*
CI, manuf.	1.05	0.97	1.06†††	1.11†††	1.04††	1.02††	1.24	1.20	1.07	1.11	1.07	1.06
CI, constr.	0.83	0.72	1.09†††	1.15†††	1.04††	1.02††	1.20	1.17	0.98	0.99	0.99	1.02
CS, own	0.95	0.89	1.19†††	1.27†††	1.00††	0.93††	1.06	1.10	0.98	1.03	0.93	0.98
CS, whole	0.95	0.91	1.08†††	1.15†††	1.04††	0.98††	1.14††	1.05††	0.98	1.01	0.93	0.96
CS, unemp.	0.98	0.86	1.07†††	1.14†††	1.21††	1.11††	1.19††	1.25††	1.07	1.08	1.00	1.05
CS, back	0.93	0.86	1.21†††	1.29†††	1.00††	1.00††	1.12	1.08	1.02	1.06	0.99	1.04
Activity in.	1.05	1.09	0.87†††	0.94†††	0.92	0.89	1.17	1.25	1.09	1.11	0.89	0.89

[a] All numbers (except in italics) are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the rival models. To save space, the results for headline CPI inflation and the short-term interest rate have been left out (but are available upon request). Column "One" evaluates forecasts one quarter ahead. Column "Two" evaluates forecasts two quarters ahead. The (nominator of the) relative RMSEs in the rows "Unfiltered BTS" and "Macro variables" are based on medians of empirical distributions (see the Notes of Tables 5–6 and Tables 7–8 for details). Numbers in bold in those rows are relative RMSEs that condition the forecasting models on satisfying certain residual diagnostics criteria (see the text and Table 3 for details). Numbers in italics in those rows show the shares of the rival models that are excluded when subjected to the residual diagnostics criteria. The remaining rows are comparisons with other popular summary indices (see the Notes of Tables 9–10). † means that the models based on the common factor do not pass the residual diagnostics criteria; †† means that the rival models do not pass the residual diagnostics criteria; ††† means that neither the models based on the common factor nor the rival models pass the residual diagnostics criteria.

Table 13

Forecasts of other macro variables: relative RMSEs, forward-looking index and data in consecutive quarterly growth[a]

	Inflation		Exch. Rate		Unemploy.		Employment		Interest rate		Wages	
	One	Two	One	Two	One	Two	One	Two	One	Two	One	Two
Unfiltered	1.18	1.21	0.99	0.96	1.15	1.10	1.02	1.04	1.12	0.91	0.87	1.00
BTS	**1.18**	**1.17**	**0.99**	**0.96**	†	†	**1.01**	**1.04**	**1.13**	**0.94**	**0.87**	**1.00**
	0.49	*0.49*	*0.03*	*0.03*	*0.23*	*0.23*	*0.03*	*0.03*	*0.60*	*0.60*	*0.03*	*0.03*
Macro	1.09	1.14	1.03	0.98	1.13	1.10	1.01	0.97	1.04	0.83	0.65	0.89
variables	**1.08**	**1.06**	**1.03**	**0.98**	†	†	**1.01**	**0.97**	**1.04**	**0.83**	**0.66**	**0.89**
	0.57	*0.57*	*0.02*	*0.02*	*0.82*	*0.82*	*0.02*	*0.02*	*0.02*	*0.02*	*0.38*	*0.38*
CI, manuf.	0.94	0.91	0.96	0.94	0.96†††	0.96†††	0.98	0.95	1.07	1.06	0.93	0.94
CI, constr.	1.13††	1.37††	1.00	0.96	0.96†††	0.96†††	1.00	1.00	0.98	0.94	0.86††	0.90††
CS, own	1.13††	1.34††	1.06	1.02	0.92†††	0.88†††	0.99	0.93	0.98	0.98	0.82	0.87
CS, whole	1.10††	1.29††	0.97	0.96	0.96†††	0.92†††	1.04	1.04	0.98	0.96	0.81	0.84
CS, unemp.	1.13††	1.40††	0.98	0.96	1.12†††	1.04†††	0.94	0.97	1.07	1.02	0.88	0.93
CS, back	1.16	1.40	1.07	1.03	0.92†††	0.94†††	0.99	0.93	1.02	1.01	0.87	0.91
Activity in.	1.13	1.23	1.01	0.98	0.85†	0.84†	0.96	0.91	1.09	1.06	0.78	0.78

[a] All numbers (except in italics) are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the rival models. To save space, the results for headline CPI inflation and the short-term interest rate have been left out (but are available upon request). Column "One" evaluates forecasts one quarter ahead. Column "Two" evaluates forecasts two quarters ahead. The (nominator of the) relative RMSEs in the rows "Unfiltered BTS" and "Macro variables" are based on medians of empirical distributions (see the Notes of Tables 5–6 and Tables 7–8 for details). Numbers in bold in those rows are relative RMSEs that condition the forecasting models on satisfying certain residual diagnostics criteria (see the text and Table 3 for details). Numbers in italics in those rows show the shares of the rival models that are excluded when subjected to the residual diagnostics criteria. The remaining rows are comparisons with other popular summary indices (see the Notes of Tables 9–10). † means that the models based on the common factor do not pass the residual diagnostics criteria; †† means that the rival models do not pass the residual diagnostics criteria; ††† means that neither the models based on the common factor nor the rival models pass the residual diagnostics criteria.

Table 14

Forecasts of other macro variables: relative RMSEs, forward-looking index and data in four-quarter growth[a]

	Inflation		Exch. rate		Unemploy.		Employment		Interest rate		Wages	
	One	Two	One	Two	One	Two	One	Two	One	Two	One	Two
Unfiltered	1.00	1.86	1.06	1.06	1.15	1.10	1.17	1.22	1.12	0.91	1.00	1.01
BTS	**1.00**	**0.86**	†	†	†	†	†	†	**1.13**	**0.94**	**1.00**	**1.01**
	0.37	*0.37*	*0.98*	*0.98*	*0.23*	*0.23*	*0.29*	*0.29*	*0.60*	*0.60*	*0.15*	*0.15*
Macro	1.00	0.97	1.10	1.16	1.15	1.17	1.05	1.10	1.11	0.96	0.76	0.76
variables	**1.00**	**0.97**	†	†	†	†	†	†	**1.11**	**0.96**	**0.76**	**0.77**
	0.22	*0.22*	*0.93*	*0.93*	*0.92*	*0.92*	*0.81*	*0.81*	*0.44*	*0.44*	*0.40*	*0.40*
CI, manuf.	1.07	0.97	1.03†††	0.99†††	1.04†††	1.02†††	1.17†	1.11†	1.07	1.06	0.91	1.03
CI, constr.	0.85	0.72	1.06†††	1.03†††	1.04†††	1.02†††	1.14†	1.08†	0.98	0.94	0.77	0.95
CS, own	0.98	0.89	1.16†††	1.14†††	1.00†††	0.93†††	1.01†	1.02†	0.98	0.98	0.80	0.98
CS, whole	0.98	0.91	1.05†††	1.03†††	1.04†††	0.98†††	1.08†††	0.97†††	0.98	0.96	0.74	0.92
CS, unemp.	1.00	0.86	1.05†††	1.02†††	1.21†††	1.11†††	1.13†††	1.15†††	1.07	1.02	0.84	1.01
CS, back	0.95	0.86	1.18†††	1.15†††	1.00†††	1.00†††	1.06†	1.00†	1.02	1.01	0.86	1.00
Activity in.	1.07	1.09	0.85†††	0.84†††	0.92†	0.89†	1.11†	1.15†	1.09	1.06	0.69	0.86

[a] All numbers (except in italics) are relative RMSEs. The models that make use of the common-factor index appear in the denominator so that numbers greater (smaller) than unity mean that the models based on the common factor outperform (are outperformed by) the rival models. To save space, the results for headline CPI inflation and the short-term interest rate have been left out (but are available upon request). Column "One" evaluates forecasts one quarter ahead. Column "Two" evaluates forecasts two quarters ahead. The (nominator of the) relative RMSEs in the rows "Unfiltered BTS" and "Macro variables" are based on medians of empirical distributions (see the Notes of Tables 5–6 and Tables 7–8 for details). Numbers in bold in those rows are relative RMSEs that condition the forecasting models on satisfying certain residual diagnostics criteria (see the text and Table 3 for details). Numbers in italics in those rows show the shares of the rival models that are excluded when subjected to the residual diagnostics criteria. The remaining rows are comparisons with other popular summary indices (see the Notes of Tables 9–10). † means that the models based on the common factor do not pass the residual diagnostics criteria; †† means that the rival models do not pass the residual diagnostics criteria; ††† means that neither the models based on the common factor nor the rival models pass the residual diagnostics criteria.

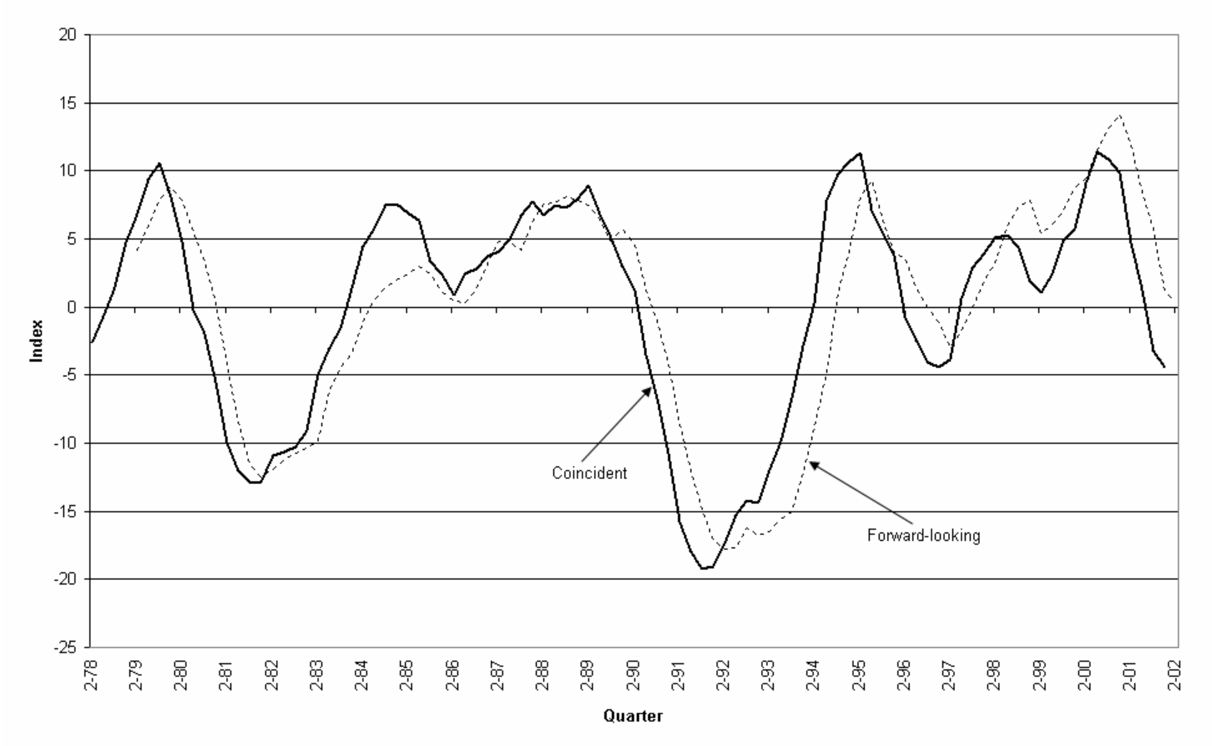

Fig. 1. One-sided estimates of common factors using model (1)–(2) and survey variables in Table 1.