Oesterreichische Nationalbank

Eurosystem

Workshops

Proceedings of OeNB Workshops

Macroeconomic Models and Forecasts for Austria

November 11 to 12, 2004

No. 5

The Economic Indicator of the OeNB: Methods and Forecasting Performance

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Abstract

The Oesterreichische Nationalbank (OeNB) has been publishing a quarterly short-term forecast of real GDP since April 2003 (OeNB's Economic Indicator, OEI). Its aim is to forecast growth of real GDP in Austria in the current and the consecutive quarter. It is based on a combination of the forecasts of an unobserved component model and a dynamic factor model, supplemented by judgement. Out-of-sample-simulations have shown that the OEI performs significantly better than naive benchmark models. Although the record in real-time forecasting is very short, the available results indicate that the OEI seems to be a valuable tool for forecasting short-term economic developments in Austria.

1. Introduction

Obtaining timely information about the current state and future prospects of the economy is of crucial importance for policy making. Quarterly National Accounts data provide a comprehensive overview about the economy. However, they are available only with a considerable delay. This raises the need for short-term forecasts not only for forthcoming quarters, but also to fill the gap until the first release of the data.

This was the motivation for the Oesterreichische Nationalbank (OeNB) to produce its own quantitative assessment of the conjunctural situation in Austria on a quarterly base. The *OeNB's Economic Indicator (OEI)* is published since the second quarter of 2003. Its objective is to forecast growth of real GDP in Austria in the current and the consecutive quarter.

Whereas medium- and long-term forecasts are usually based on structural macroeconometric models, short-term forecasts are produced utilizing non-structural time series models. The battery of available methods range from single regression equations and simple time series models (ARIMA, VAR, BVAR) over trend extrapolation methods (smoothing methods) to more complex methods. The *OEI* is based on the forecasts stemming from two up-to-date econometric methods, a dynamic factor model and an unobserved component model.

There are many reasons why combining forecasts from different models may be a fruitful approach. Since the seminal work of Bates and Granger (1969) it is well known that the combination of different forecasts often improves forecasting performance. In theory it is possible to build a model that encompasses all rivalling models, i.e. it pools all relevant information used in these models and hence performs best in forecasting. Although pooling of information is preferable to pooling of forecasts from a theoretical perspective (Diebold and Lopez, 1996), it is often hard to find an encompassing model in practice[1]. This clearly indicates that all models are miss-specified, which is an important rationale for forecast combination. Besides miss-specification, substantial gains from combination can be expected in the case of structural breaks and non-stationarities (see Hendry and Clements 2002 for a detailed discussion). Combining usually reduces the variance of the forecast. Forecasts can be combined in different ways. The simplest possibility is to assign equal weights to all forecasts. Using the median forecast instead of the mean makes the combined forecast less sensitive to outliers. Forecasts can also be combined with methods that assign the weights based on a ranking of the forecasts. More elaborated methods include the variance-covariance method and the regression-based method (Diebold and Lopez, 1996). Although the literature suggests that no specific combination method performs best in all situations, simple methods such as an averaging often perform as well as more statistically sophisticated methods (Clemen, 1989).

The combination method utilized in the OEI is to assign equal weights to both forecasts. In addition, judgement is added wherever deemed appropriate. The use of judgement is widely-used in short- and medium-term forecasting. The Bank of Canada and the Reserve Bank of New Zealand use judgement in their short-term projections, just to mention two of the numerous examples (Drew and Frith, 1998, Coletti and Murchison, 2002). The reasons for including judgement are manifold. First, every model is a simplification of reality and does not capture all information which may be relevant. Especially qualitative information is used to complement the model forecasts. Second, expected persistence of forecast errors may justify the use of judgement. If, for example, an unpredicted weakness of GDP growth is likely to continue, a negative add-factor might be added. Third, data quality plays a role. Each model that exploits statistical relationships is only as good as the data it

[1] Forecast combination is closely related to the concept of forecast encompassing. The latter concept would suggest incorporating superior features of rivalling models until combining the forecasts brings no gains. So testing for forecast encompassing is exactly the same as testing if there are gains from combination.

uses. Finally, discretionary policy measures have to be included in the form of judgement.

The OeNB uses currently two models in the OEI: an unobserved components model and dynamic factor model. Both models refer in their nature to the problem of optimal filtering but from a different perspective. The unobserved components model uses the Kalman filter technique to estimate the unobserved state of a system based on ‘noisy’ observations of a small number of time series. At the contrary, the dynamic factor model uses a very large number of time series and utilizes a filtering technique in the frequency domain aiming to extract the factors of the data set which explain the major part of the frequency spectrum. Thus, the two models can be seen as providing natural complements in the construction of a short-term indicator.

The structure of the paper is as follows. section 2 presents the unobserved components model. In section 3, the dynamic factor model is described. In section 4, the forecasting performance of the OEI is assessed. Emphasis is laid on a simulated out-of-sample forecasting experiment. In addition, the currently available forecasting record (which consists of seven forecasts) is subject to a first assessment. Section 5 concludes.

2. The Unobserved Components Model

The main challenge consists in finding an efficient econometric framework to use monthly conjunctural indicators to predict quarterly National Account GDP figures. A straightforward solution would be the aggregation of monthly to quarterly data. But this method is associated with a considerable loss of information as the dynamics within a quarter are no longer explicit. Furthermore, it does not solve the problem how the latest information from monthly indicators can be used if observations are available only until the first or second month within a quarter. Finally, the method should allow for a quick update of the forecast in case new monthly information becomes available.

State space models represent an efficient way of dealing with these kinds of problems. Based on a Kalman filter technique exogenous monthly indicators are used as explanatory variables to estimate a monthly GDP series as an unobserved component. A special feature of the model is the aggregation procedure to derive quarterly GDP growth rates from monthly GDP growth rates. The aggregation procedure makes clear that quarterly growth rates are not independent from the dynamics within the previous quarter.[2] This phenomenon is closely associated with the well known carry-over effect in macroeconomic forecast exercises.

[2] Given that the mean value theorem holds, one third of a quarterly growth rate is determined by the monthly dynamics within the previous quarter. If the observation-frequency within a quarter tends towards infinity the ratio approaches one half. In the

The basic idea of state space models is that an observable time series (Y_t) under study can be explained by a vector of unobserved components (α_t). The unobserved components are linked to the observed variable via a measurement equation, i.e. from the observed variable conclusions on the unobserved components can be drawn. A typical example from economics is the decomposition of GDP in a trend, a seasonal and an irregular component. In the present paper the aim is to extract unobservable monthly GDP growth rates from the quarterly GDP ESA95 series. The estimation of the unobserved component, i.e. monthly GDP growth, is based on an autoregressive term and exogenous monthly conjunctural indicators. This relation is formulated in the so called transition equation. The evaluation of this estimation takes place in the measurement equation. Each third month, at the end of a quarter, the quarterly GDP growth rate is calculated as a weighted sum of past and current monthly GDP growth rates and can be compared to the actual outcomes.

2.1 The Model

In general a state space model consists of an observation (measurement) and a transition equation.[3] In the present model the observation equation which compares the actual and the estimated quarterly GDP growth rates takes the simple form:

$$\Delta \ln y_\tau^Q = \Delta \ln y_\tau^{Qe} \quad \tau = 1 \ldots T/3; \quad t = 1,2,3 \ldots T \quad \textit{(Observation equation)} \qquad (U.1)$$

where $\Delta ln\, y_\tau^Q$ denotes the actual growth rate of real GDP, $\Delta ln\, y_\tau^{Qe}$ the estimated growth rate of real GDP and t and τ the index of months and the index of quarters, respectively. The estimated growth rate of real GDP is a weighted sum of the present and the past four estimated monthly growth rates of real GDP where the weights are given by $(1/3 \quad 2/3 \quad 1 \quad 2/3 \quad 1/3)$.[4] Thus, the estimated growth rate of real GDP is given by:

$$\Delta ln\, y_\tau^{Qe} = \tfrac{1}{3}\Delta ln\, y_t^m + \tfrac{2}{3}\Delta ln\, y_{t-1}^m + \Delta ln\, y_{t-2}^m + \tfrac{2}{3}\Delta ln\, y_{t-3}^m + \tfrac{1}{3}\Delta ln\, y_{t-4}^m \qquad \text{(U.2)}$$

$$\tau = 1 \ldots T/3; \quad t = 1,2,3 \ldots T$$

case of quarterly and annual observations the ratio equals 3/8. (see Fenz and Spitzer, 2003).

[3] For a complete set up of the state space model see Fenz and Spitzer (2003).

[4] For a derivation of the weights see Fenz and Spitzer (2003).

where $\Delta ln\, y_t^m$ denotes the unobserved monthly GDP growth rates.

The transition equation describes the path of the unobserved component, i.e. monthly GDP growth rate. As is generally the case in state space models the unobserved component is assumed to follow a first order Markov process. Monthly GDP growth additionally depends on a number of stationary exogenous variables (i.e. explanatory monthly indicators) denoted by $x_{n,t}^m$, where $n = 1 \ldots N$.

$$\Delta ln\, y_t^m = \zeta \cdot \Delta ln\, y_{t-1}^m + \beta_1 \cdot x_{1,t}^m + \ldots + \beta_N \cdot x_{N,t}^m + e_t \quad \text{(Transition equation) (U.3)}$$

Equations (1) to (3) describe how monthly indicators can be combined with quarterly GDP growth rates for forecasting purposes. Once the parameters of the model are estimated using the Kalman filter, observations of the monthly indicators can be used to derive forecasts of quarterly GDP growth rates. Depending on the leading indicator properties of each single indicator and the time lags of data releases, the available observations of monthly indicators may not be sufficiently long to cover the whole forecasting horizon. In this case of missing observations monthly indicators are forecast using ARIMA models.

2.2 Estimation Results

The forecasting performance of more than 300 variables from various sectors and markets was analysed and compared. Variables tested cover the labour market, external trade, confidence indicators, prices, financial variables, whole and retail sales, industrial production and exchange rates. The selection of explanatory variables is based on the following principles: (a) leading indicator properties; (b) estimation properties; (c) forecasting performance; (d) time lag of data releases; (e) probability of data revisions; (f) coverage of different sectors.

According to these criterions the following six monthly indicators were selected as explanatory variables in the transition equation of the state space form to estimate monthly GDP growth rates: Ifo-index (*ifo*), outstanding loans to the domestic non financial sector (*loans*), number of vacancies (*vac*), real exchange rate index (*exrate*), number of employees (*empl*) and new car registrations (*cars*). All explanatory variables are in logarithm and enter the equation system in first differences with the exception of the number of employees where we used second differences.

$$\begin{aligned}\Delta \ln y_t^m = \zeta \cdot \Delta \ln y_t^m + \beta_1 \Delta \ln ifo_{t-1} + \beta_2 \Delta \ln loans_{t-4} + \beta_3 \Delta \ln vac_t + \beta_4 \Delta \ln exrate_{t-3} \\ + \beta_5 \Delta\Delta \ln empl_{t-1} + \beta_6 \Delta \ln cars_{t-2} + e_t\end{aligned} \quad \text{(U.4)}$$

The error term e_t follows an AR(1) process. The inclusion of the parameter σ^2 is due to computational convenience. u_t represents the innovations of the equation system which are calculated each third month via the measurement equation.

$$e_t = \rho_1 \cdot e_{t'-1} + \sigma^2 u_{t-1} \tag{U.5}$$

Table1: Estimation Results for Monthly GDP Growth Rates

	Δln / ΔΔln	**Lag**	**Coefficient**	**t-value**
Ifo-index business climate for West Germany	Δln	1	0.17	2.34
Outstanding credits to domestic non financial sector, current prices	Δln	4	0.17	2.25
Number of vacancies	Δln	0	0.13	2.29
Real exchange rate	Δln	3	–0.19	–2.63
Number of employees	ΔΔln	1	0.45	2.65
New car registrations	Δln	2	0.61	3.26
Dummy94_4			–3.87	–5.02
Dummy95_1			3.18	4.13
Dummy97_1			–2.09	–2.77
ζ			–0.40	–2.36
ρ_1			–0.63	–3.04

Note: All variables are standardized.
Δln / ΔΔln indicate first and second differences, respectively.
Lag: number of lags of the exogenous variable – indicates leading indicator properties.
Source: Authors' calculations.

The ifo-index is a good indicator of business confidence in Austria and additionally mirrors the latest developments on Austria's most important export market. Outstanding loans to the domestic non financial sector capture financing conditions and credit standards in the banking sector. The number of vacancies is a well known early indicator for the labour market. The real exchange rate index affects the price competitiveness of Austrian exports. Second differences in the number of employees indicate new labour market developments relatively early. Finally, new car registrations are known to react sensitive to economic fluctuations. Furthermore, three dummies were introduced to control for outliers in the GDP time series in 1994Q4, 1995Q1 and 1997Q1.

The in sample one step ahead performance of the UOC model is shown in chart 1. The estimated quarter-on-quarter GDP growth rates tend to be less volatile than the original series as is typically the case in forecasting exercises.

3. The Generalized Dynamic Factor Model

During the last two years, factor models became increasingly popular as tools to forecast macroeconomic variables (see e.g., Stock and Watson, 1998, Gosselin and Tkacz 2001, Artis, Banerjee and Marcellino, 2002). These models promise to offer a tool to summarize the information available in a large data set by a small number of factors. The basic idea that stands behind a factor model is that the movement of a time series can be characterized as the sum of two mutually orthogonal components: The common component which should explain the main part of the variance of the time series as a linear combination of the common factors. The second component, the idiosyncratic component, contains the remaining variable specific information and is only weakly correlated across the panel.

The approach utilized in this paper is the frequency domain analysis as proposed by Forni and Reichlin (1998), Forni and Lippi (1999) and Forni, Hallin, Lippi and Reichlin (2000) (referred to as 'FHLR' thereafter). It has been increasingly used for business cycle analysis and forecasting (e.g. 'EuroCoin', Altissimo et al., 2001 or Cristadoro et al., 2001). The main difference of the FHLR approach to the widely-used approach of Stock and Watson (1998) is that it allows richer dynamics, since both contemporaneous and lagged correlations between variables are incorporated.

3.1 The Model

In our approximate dynamic factor model, each variable x_{it} for $i=1,...,N$ and $t=1,...,T$ of the panel is assumed to be a realization of a zero mean, wide-sense stationary process $\{x_{it}, t \in \mathbb{Z}\}$. Each process of the panel is thought of as an element from an infinite sequence, indexed by $i \in \mathbb{N}$. All processes are co-stationary, i.e. stationarity holds for any of the n-dimensional vector processes $\{x_{nt} = (x_{1t}...x_{nt})'; t \in \mathbb{Z}, n \in \mathbb{N}\}$. Each series is decomposed into two components

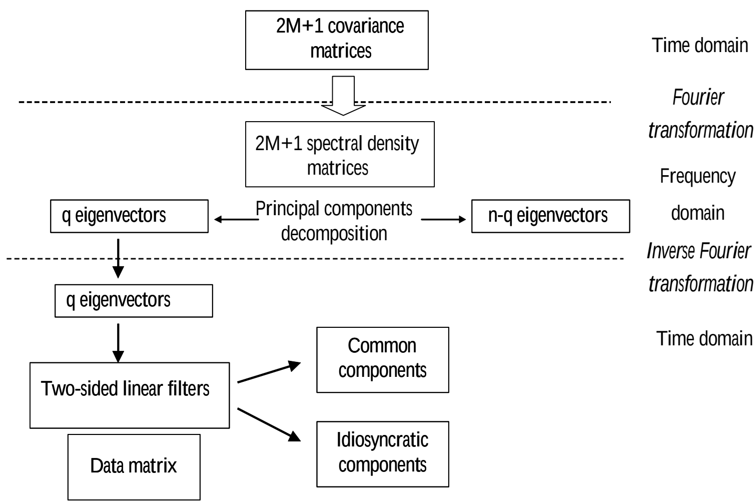
$$x_{it} = \chi_{it} + \xi_{it} = \lambda_i(L)F_t + \xi_{it} \tag{F.1}$$

where χ_{it} is the common component, ξ_{it} the idiosyncratic component and $\lambda_i(L) = \lambda_{i1}(L),...,\lambda_{ik}(L)$ is a $1\times(k+1)$ vector of finite lag polynomials of factor loadings of order k. $F_t = (f_{1t},...,f_{qt})'$ is a $1\times q$ vector of q common factors. Each series is therefore expressed as the sum of moving averages of the factors plus an idiosyncratic component. There is a limited amount of cross-correlation between the idiosyncratic components allowed.

3.2 Estimating the Common Component

Forni, Hallin, Lippi and Reichlin (2000, 2001 and 2003) proposed an estimation method for model (1). The method relies on a *dynamic principal components* analysis. This approach exploits the dynamic covariance structure of the data, i.e. the relation between different variables at different points in time. This information is contained in $k=2m+1$ covariance matrices, where m denotes the number of leads and lags.

Chart 1: The Dynamic Factor Model: Estimation of the Common and Idiosyncratic Components



These covariance matrices are transformed from the time domain into the frequency domain by Fourier transformations. Each of the resulting spectral density matrices is decomposed by applying principal components. The resulting first q eigenvectors and eigenvalues are summed up over frequencies and are then transformed back to the time domain by an inverse Fourier transformation resulting in a two-sided linear filter. Applying these filters to the data matrix gives the common and the idiosyncratic component for each variable in the data set.

3.3 Forecasting the Common Component

The common and the idiosyncratic component of a variable are mutually orthogonal. Thus, forecasting a variable in a dynamic factor model can be split into two separate forecasting problems, forecasting the common component and forecasting the idiosyncratic component. Since the idiosyncratic components are mutually orthogonal or only weakly correlated, they can be forecast easily using standard univariate or low-dimensional multivariate methods like ARIMA of VAR models. The remainder of the subsection concentrates on the task of forecasting the common component.

The forecasting strategy used in the FHLR approach exploits the information contained in the lagged covariances between the variables to construct the factor space. The dynamic principal components which can be obtained by decomposing the spectral density matrix are based on two-sided filters of the data matrix. This is a major drawback for forecasting, since these filters cannot be used directly to construct a forecast. The basic idea to overcome that problem is to use the covariance matrices of the common and the idiosyncratic component obtained by the dynamic principal component analysis to construct a static factor space which may be a better approximation for the factor space than usual static principal components (Forni, Hallin, Lippi and Reichlin, 2003). The factors are given by

$$F_n^t = X_n^{t'} Z_n^T \tag{F.2}$$

Forni, Hallin, Lippi and Reichlin (2003) show that Z_{nl}^T can be obtained as the solution of the following generalized eigenvalue problem:

$$Z_{nl}^T \equiv \arg\max a\Gamma_{n0}^{\chi T}\tilde{a} \tag{F.3}$$

subject to $a\Gamma_{n0}^{\chi T}\tilde{a} = 1$,

$$a\Gamma_{n0}^{\xi T}\tilde{Z}_{nm}^T = 0 \; for \, 1 \le m < l, l \le l \le n \, .$$

a denotes the eigenvalues resulting from the solution of the generalized eigenvalue problem and $\Gamma_{n0}^{\chi T}$ and $\Gamma_{n0}^{\xi T}$ denote the variance-covariance matrices of the common and the idiosyncratic components, respectively. The intuition behind this approach is that the solution of the generalized eigenvalue problem gives us weights Z_{nl}^T that maximize the ratio between the variance of the common and the idiosyncratic component in the resulting aggregates. In other words, the two variance-covariance matrices can help to construct averages of the data matrix which put a larger weight on variables that have a larger 'commonality' (Forni, Hallin, Lippi and Reichlin, 2003).

The *h*-step ahead forecast for the common component $\chi_{it} (= \phi^{n,t}_{i,T+h|T})$ can be obtained by projecting the future value, $\chi_{it,T+h}$ onto the approximate factor space

$$\phi_{i,T+h|T} \equiv proj(\chi_{i,T+h} \mid G(F_{nq})) = F_t (F_t' F_t)^{-1} F_t' F_t' x_{nT} \qquad \text{(F.4)}$$

The factor space $G(F_{nq}))$ is spanned by the static principal components $F_t = (f_{1t}, \ldots, f_{nt})'$. As $n \to \infty$ the approximate factor space, i.e. the space spanned by the first q principal components, denoted by $G(F_{nq},t)$ converges to the factor space $G(Fq,t)$[5].

Inserting equation (F.2) into equation (F.4) and rearranging gives us the proposed projection formula

$$\phi_{i,T+h|T} = \Gamma^{\chi T}_{nh} Z^{T}_{n} (Z^{'T}_{n} \Gamma^{xT}_{n0} Z^{T}_{n\,t})^{-1} Z^{'T}_{n} x_{nT} \qquad \text{(F.5)}$$

As the sample size increases, the estimate $\phi_{i,T+h|T}$ converges in probability to χ_{it}. A more detailed explanation of the estimation and the forecasting procedure can be found in Schneider and Spitzer (2004).

3.3 Estimation Results

The data set includes 105 variables of monthly or quarterly frequency. Some variables have been included in the model in levels as well as in differences. So the total number of series included in the factor model is 143. The quarterly data set ranges from the first quarter of 1988 until the second quarter of 2003, i.e. it contains 62 observations.

Missing monthly observations within the last quarter are forecast by a monthly factor model. These monthly series are aggregated to quarters and are then concatenated to the quarterly data to build the final data set.

Extensive simulations (Schneider and Spitzer, 2004) have shown that the forecasting performance of the dynamic factor models can be increased considerably when it is based on a handful of carefully selected series instead of the full data set of 143 series. The best performance can be obtained with small models with 11 variables (forecast of the current quarter) respectively 13 variables (forecast of the consecutive quarter). Table 2 lists the variables of these two

[5] For a proof see Forni, Hallin, Lippi and Reichlin (2003), Lemma 3.

models, which have been selected in order to minimise the root mean squared error (RMSE).

Table 2: Variables Used in the Dynamic Factor Model

Forecast of the current quarter	Forecast of the consecutive quarter
GDP, real	GDP, real
Exports of commodities into the EU	Vacancies
Production expectations in industry	Dax-Index
Imports – SITC 7 (machines and transport equipment)	M1
M2	Exports of commodities into the U.S.A.
Unemployment rate (national definition)	USD/EUR exchange rate
Dax-Index	Yield spread
Secondary market yield (maturity 9–10 years)	HICP energy
Changes in inventories	Assessment of the present business situation – construction
Dow Jones Index	Wholesale prices for consumer goods
Direct credits to private firms	GDP deflator
	Total exports
	HICP commodities

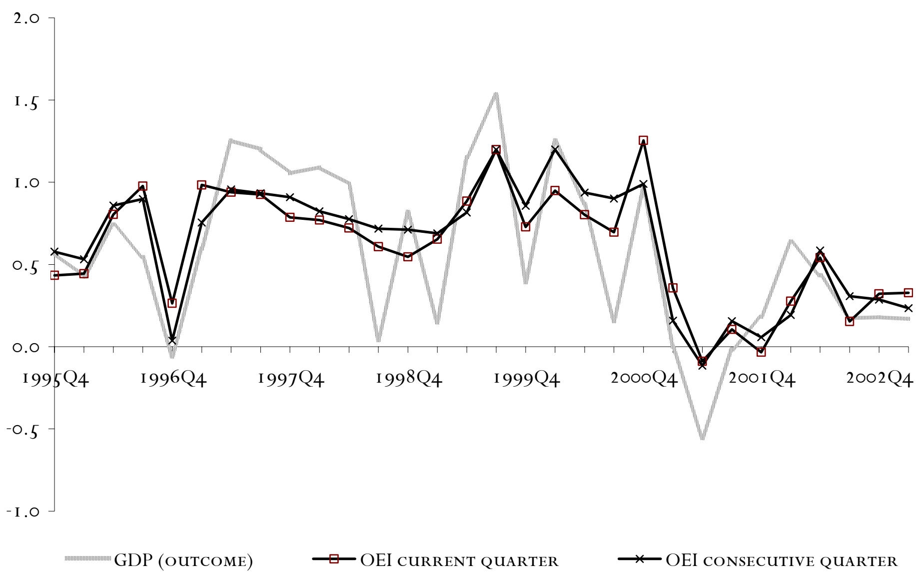
4. Assessing the Forecasting Performance

This section assesses the forecasting performance of the OEI. In the first subsection, a simulated out-of-sample forecasting exercise evaluates the forecasting performance of the OEI and its two models relative to two simple benchmark models. This out-of-sample exercise is purely model-based. In the second subsection, efforts are made to provide a first provisional assessment of the seven publications of the OEI (which also include judgement).

4.1 A Simulated Out-of-Sample Forecasting Exercise

We have conducted a simulated out-of-sample forecasting exercise to assess the forecasting performance of the OEI and its two sub models. The forecasting performance for each model was obtained by performing out-of-sample forecasts for 30 rolling windows. The first window contained data until the second quarter of 1995. The last two observations were used for evaluating the out-of-sample forecasts. After computing the one and the two-steps-ahead forecasts, one new observation of the data set was added, the model was reestimated and new forecasts were computed. This procedure was repeated for all remaining windows until the second quarter of 2002. Chart 1 gives a visual impression of the forecasting performance of the OEI. It shows that the OEI predicts most of the turning points correctly (even two-steps ahead). Even the steep slow down of economic activity in the first two quarters of 2001 was predicted (although not to its full extent).

Chart 2: Simulated Out-of-Sample Forecasts of the OEI for the Current and the Consecutive Quarter



Note: Change in % to previous quarter, GDP corrected for outliers.
Source: OeNB's Economic Indicator.

A couple of different tests have been utilized to quantify the forecast performance. The results can be found in table A-1 to A-4 in the appendix. First, it has to be assessed whether the forecasts $\hat{y}_t$ have the same mean as the realizations $y_t (= \mu)$. This can be done by testing the null hypothesis $\hat{y}_t - y_t = \mu + u_t$ using a simple t-test. The results (table A-1) show that there is no significant deviation of the mean of forecasted series to the realizations. Hence, the forecasts are unbiased. In order to asses the forecasting performance of our two models relative to some simple benchmark models, we have compared them with a 'naive' (no-change) and an ARIMA forecast. Both OEI models perform remarkably better then the benchmark forecasts (table A-2). The combination of the two model forecast (OEI) performs slightly better than the model with the lower RMSE[6]. The average RMSE of the

6 A direct comparison of the forecasting performance of these two models is critical since the dynamic factor model was optimized in order to minimise the forecasting error over

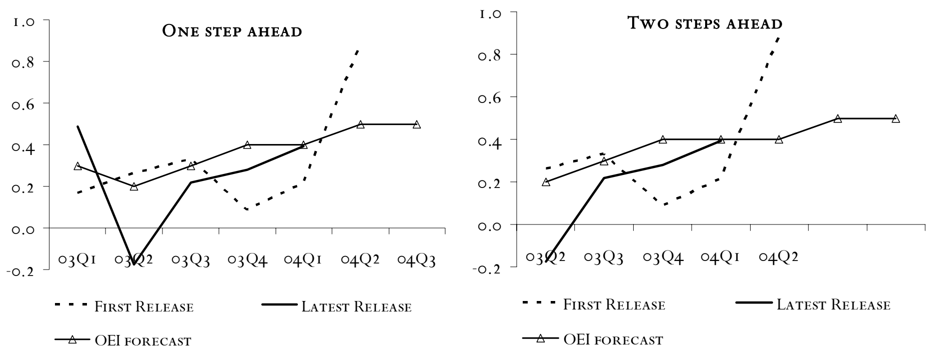
OEI for the forecasts of the current and the consecutive quarter (0.63) lies well below the naive forecast (1.24) and the ARIMA forecast (1.03). A crucial question is whether these differences are statistically significant. This has been tested by the Diebold and Mariano (1995) test for equal forecasting accuracy. It tests the null hypothesis of equal forecasting accuracy of two rivalling forecasts. Table A-4 presents the results. It can be seen that the gains of the OEI against the two benchmark forecasts ('naive' forecast and ARIMA forecast) are highly significant. Table A-4 give the results of the Harvey test for model encompassing (see Harvey, Leybourne and Newborn, 1998). It tests the null that forecast A encompasses forecast B, i.e. forecast B adds no predictive power to forecast A. The null can be rejected for all forecast combinations with the exception of one.

4.2 Forecasting Record

Till now the *OEI* has been published seven times. Consequently, there are six observations available for an assessment of the forecasting performance of the current quarter and five observations for the consecutive quarter. Given the small number of observations the assessment can not be done with the same accuracy as in the simulated out-of-sample experiment with 30 observations. Instead, only tentative conclusions from descriptive analyses may be drawn.

30 quarters (which are used in the exercise), whereas the unobserved components model was optimized for 10 quarters only (due to less degrees of freedom). Hence, the direct comparison between the two models should not be taken literally.

Chart 3: Performance of the First Data Release and the OEI Relative to the Latest Data Release



Note: Change in % to previous quarter.
Source: Authors' calculations, WIFO.

An assessment of the forecasting performance is hampered by the fact that all forecasts published fall into an exceptional phase. Compared to past downswings the slowdown lasted considerably longer. The high degree of uncertainty surrounding this period is also reflected in the pronounced revisions of first releases of GDP growth figures. Chart 2 shows that according to first data releases the cyclical trough was reached in the fourth quarter of 2003, whereas the latest release suggests that the trough already took place in the second quarter. Chart 2 also shows the typical result that forecasts are less volatile than actual outcomes. Table 5 quantifies the forecasting performance of the OEI in terms of the RMSE (root mean squared error). The OEI (including judgement) and the pure model results (without judgement) are compared with the first and the latest data releases. In addition, the first data release is compared relative to the latest release. For both the forecast of the current and the consecutive quarter, the second quarter of 2004 (which is already available) has been omitted since only the first data release exists for it.

Table 5: Performance of the First Data Release and the OEI Relative to the Latest Data Release

Series to be compared	Relative to	Period: 03Q1–04Q1	Period: 03Q2–04Q1
		Forecast of the current quarter	Forecast of the consecutive quarter
OEI	First data release	0.176	0.185
OEI	Latest data release	0.198	0.200
Pure model results	First data release	0.235	0.279
Pure model results	Latest data release	0.258	0.188
First data release	Latest data release	0.273	0.260

Note: Root mean squared error.
Source: Authors' calculations.

Four main results can be mentioned. First, there are gains from adding judgement to the pure model results. The forecasting errors of the OEI are about 20 to 30% lower then the pure model results (with one exception). Second, the RMSE of the OEI is smaller than the RMSE of the first release (both with respect to the final release of GDP growth figures). This result holds both for the forecast of the current and of the consecutive quarter. Third, there is only a negligible difference when comparing the OEI with the first and the latest data release. Fourth, the forecasting performance of the current and the consecutive quarter are roughly equal. As the number of observations is too small to conduct statistical tests, this conclusion is very tentative.

5. Summary

The aim of this paper was to present the framework developed at the Oesterreichische Nationalbank for short-term forecasting of real GDP in Austria. Out-of-sample-simulations have shown that the OEI performs significantly better than naive benchmark models. Up to now, the *OeNB's Economic Indicator (OEI)* has been published seven times. Although the number of observations is by far too small to make well-founded statements about the forecasting accuracy, the results suggest that it predicts the latest data release with accuracy comparable to the first data release. The OEI seems to be a valuable tool for forecasting short-term economic developments in Austria.

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Appendix

Table A1: Test on Unbiasedness

	Realisation	Current quarter (h=1)	Consecutive quarter (h=2)
Mean	0.61	0.59	0.64
p-value	-	0.42	0.23

Source: Authors' calculations.

Table A2: Simulated Out-of-Sample Forecasting Performance

	Current quarter (h=1)	Consecutive quarter (h=2)	Mean
'Naive' forecast	1.18	1.30	1.24
ARIMA	1.01	1.05	1.03
Dynamic factor model	0.65	0.65	0.65
Unobserved components model	0.77	0.76	0.76
OeNB's economic indicator	**0.63**	**0.63**	**0.63**

Note: Root mean squared error, computed for 30 windows.
Source: Authors' calculations.

Table A3: Results of the Diebold-Mariano Test for Equal Forecasting Accuracy

	Current quarter (h=1)		Consecutive quarter (h=2)	
Unobserved components model	*p-values*		*p-values*	
'Naive' forecast	0.003	***	0.005	***
ARIMA	0.037	**	0.081	*
Dynamic factor model				
'Naive' forecast	0.000	***	0.000	***
ARIMA	0.000	***	0.009	***
OeNB's economic indicator				
'Naive' forecast	0.000	***	0.000	***
ARIMA	0.001	***	0.013	**

Source: Authors' calculations.

Table A4: Results of the Harvey Test for Model Encompassing

Null hypothesis	p-value
Forecast of the current quarter	
H0: Factor model encompasses unobserved components model	0.148
H0: Unobserved components model encompasses factor model	0.000
Forecast of the consecutive quarter	
H0: Factor model encompasses unobserved components model	0.039
H0: Unobserved components model encompasses factor model	0.000

Source: Authors' calculations.