Forecasting Dutch GDP and inflation using Alternative Factor Model Specifications Based on Large and Small Datasets*

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Abstract

We compare the factor forecasting performance of nested specifications of the generalized factor model based on various configurations of a large macroeconomic data set. The forecast simulation design involves in-sample model selection, factor estimation, parameter estimation and, finally, generating factor forecasts and factor augmented autoregressive forecasts. In order to empirically determine the importance of the size and the structure of the data set, we run the forecast simulation design for different configurations of the data set. We compare the factor model diagnostics of each specification and data configuration with the corresponding forecast performance.

The results favour the factor structure as the specification that imposes the factor structure to the least extent and, hence, is allowed most flexibility to adapt to the data, is significantly being outperformed. Moreover, the results show that size matters as though

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smaller macroeconomic data sets exhibit stronger coherence, the factors being well fit do, however, generally not show improved forecasting performance.

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1 Introduction

Empirical research on forecasting macroeconomic key variables aims to provide fiscal and monetary policymakers with the most accurate predictions. The univariate and low order vector autoregressive (VAR) models have for a long time been the standard small-scale models for short term macroeconomic forecasting. These models include only a small number of variables while policymakers and applied forecasters are keen to extract information from many more series describing economic activity at a more disaggregate level. For instance, Svensson (2005) describes what central bankers do in practice: "Large amounts of data about the state of the economy and the rest of the world, including private-sector expectations and plans, are collected, processed, and analyzed before each major decision." The increase in the quantitity and quality of readily available economic data stimulates a macroeconometric literature that explicitly incorporates information from a large number of macroeconomic variables into formal statistical models. For example, Garcia-Ferrer et al. (1987) apply pooling techniques to establish a relationship between annual output growth and leading indicators such as real stock return and real money supply growth using a multi-country data set (see also Hoogstrate et al., 2000).

As an alternative strategy to handle large data sets, Bates and Granger (1969) propose to combine the forecasts of many low-order equations exclusively employing one of the available predictors. Moreover, Palm and Zellner (1992) relate to the relative merit between combination and selection to attain optimal forecasts.

The study adopts the notion that the essential characteristics of macroeconomic motions are captured by a few driving aggregate forces and that the information contained in all potentially available economic key variables at an aggregate level are individually less informative about macroeconomic behaviour. The related empirical literature suggests that factor-based forecasts tend to outperform small-scale rival models, although the evidence is not overwhelming, see Eickmeier and Ziegler (2008) for an overview of the empirical macroeconomic factor forecasting literature and for instance Rünstler et al. (2009) for a comparison over data sets for different European countries.

This paper applies the static factor model proposed by Stock and Watson (2002a) and its dynamic equivalent of Forni et al. (2000; 2001; 2001; 2004; 2005) to Dutch quarterly data with the aim of forecasting the growth rates of Gross Domestic Product (GDP) and inflation as measured by the the Consumer Price Index (CPI) for an horizon up to 4 quarters ahead. Like Boivin and Ng (2005) and D'Agostino and Giannone (2006), we compare nested specifications of the factor models and forecast equation. The data are a subset of the series underlying the Dutch central bank´s macroeconomic structural model for the Netherlands (cf. Van Els and Vlaar, 1996) supplemented with leading indicator variables. The data set consists of 124 series that can be classified into six categories. Boivin and Ng (2006) and Jacobs et al. (2007) show that enlarging a big data set not necessarily improves the factor forecasting performance if the additional series are noisy or unrelated to the target variable. In order to empirically determine the importance of the size and the structure of the data set, we generate forecasts for different configurations of the data set. We compare the factor model diagnostics of each specification and data configuration with the corresponding forecast performance.

This paper is organised as follows. Section 2 introduces the factor model and shows the specifications for which the cyclical dynamic factor collapses to a static one. Section 3 describes the out-of-sample forecast simulation design, the diagnostics of the factor model fit and the data set. Finally, section 4 reports the empirical results, documents the diagnostics of the model specifications and data configurations and, eventually, shows the best performing outcomes.

2 The factor model

Factor models are a tool to cope with many variables without running into problems of too little degrees of freedom often faced in regression based analysis.

2.1 Factor model representation

Consider a stationary stochastic vector process $\left\{\mathbf{x}_t = (x_{1t}...x_{nt})'\right\}$ with zero mean and finite second-order moments $\mathbf{\Gamma_X}(k) = E\left[\mathbf{x}_t\mathbf{x}'_{t-k}\right]$. Each variable x_i, $i = 1...n$ can be decomposed as the sum of two mutually orthogonal unobserved components: the common component χ_i and the idiosyncratic component ξ_i. The common components depend on a q-dimensional orthonormal white noise process $\mathbf{f}_t = (f_{1t}...f_{qt})'$ driven by a small number of q dynamic factors f_{it} with $q \ll n$. The factor model reads as

$$\mathbf{x}_t = \boldsymbol{\chi}_t + \xi_t = \mathbf{B}_n(L)\,\mathbf{f}_t + \xi_t, \tag{1}$$

where the dynamic loadings are represented by a $(n \times q)$-polynomial of order $m : \mathbf{B}_n(L) = (b_{i1}(L), ..., b_{iq}(L))' = \mathbf{B}_0^n + ... + \mathbf{B}_m^n L^m$ with the lag operator $L^s x_t = x_{t-s}$. The factors and idiosyncratic disturbances are assumed to be uncorrelated at all leads and lags, that is $E[\mathbf{f}_t\xi_{il}] = 0\ \forall i, l$. Clearly, if we let $\mathbf{F}_t = \left(\mathbf{f}'_t...\mathbf{f}'_{t+m}\right)'$ and $\mathbf{\Lambda}_n = (\mathbf{B}_0^n...\mathbf{B}_m^n)$, the dynamic factors obey the static representation:[1] $\boldsymbol{\chi}_t = \mathbf{B}_n(L)\,\mathbf{f}_t = \mathbf{\Lambda}_n\mathbf{F}_t$. A model with q dynamic factors $\mathbf{f}_t$ thus consists of $r = q(m+1)$ common static factors $\mathbf{F}_t$. The dynamic nature of (1) implies that $\mathbf{F}_t$ has a special structure: if $m > 0$ the rank of the spectral density matrix of $\mathbf{F}_t$ (namely q) is smaller than the rank of the covariance matrix of $\mathbf{F}_t$ (namely r).

The common component in (1) can be further decomposed into a cyclical medium- and long-run component $\boldsymbol{\chi}_t^c$ and a non-cyclical seasonal and irregular part $\boldsymbol{\chi}_t^{nc}$, similarly to Altissimo et al.'s (2010) coincident indicator of the euro area, €urocoin. This orthogonal decomposition is based on the two-sided, symmetric, square summable bandpass filter $\beta(L)$ (cf. p 275 in Priestley, 1982), which separates waves of periodicity larger than a given critical number of periods τ :

[1] Moreover, the orthonormality assumption for the common dynamic factors $\mathbf{f}_t$ is effectively an identifying assumption. Consider a nonsingular $(q \times q)$ −lag polynomial $\mathbf{A}(L)$ of order $M \leq m + 1$. Then, $\mathbf{B}_n(L)\,\mathbf{f}_t = \mathbf{B}_n(L)\,[\mathbf{A}(L)]^{-1}\,\mathbf{A}(L)\,\mathbf{f}_t = \widetilde{\mathbf{B}}_n(L)\,\widetilde{\mathbf{f}}_t$ shows that the factors and factor loadings can only be identified up to a rotation.

$$\chi^c_{ij,t} = \sum_{k=-\infty}^{\infty} \beta_k \chi_{ij,t-k}, \ \beta_k = \begin{cases} \frac{1}{k\pi} \sin(2k\pi/\tau) & \text{for } k \neq 0, \\ 1/\tau & \text{for } k = 0. \end{cases}$$

Note that in a forecasting context, the finite sample approximation of $\beta(L)$ consists of truncating the tails such that the filter becomes effectively one-sided, i.e. $\beta_k = 0$ for $k < 0$. Now, each variable can be decomposed into three orthogonal parts. When referring to the cyclical dynamic factor model, however, we define the common cyclical signal as $\boldsymbol{\chi}^c_t$ and redefine the idiosyncratic part as $\xi_t = \mathbf{x}_t - \boldsymbol{\chi}^c_t$. The cyclical medium- and long-run component $\boldsymbol{\chi}^c_{ij,t}$ is thereby filtered for short-run fluctuations with frequencies up to one year similarly to Altissimo et al.'s (2010) coincident indicator of the euro area, €urocoin.

2.2 Factor model estimation

Denote by $\mathbf{X}^{nT} = (x_{it})_{i=1...n,t=1...T}$ an $n \times T$ rectangular array of standardized observations from the stationary vector process $\mathbf{x}_t$. Let $\widehat{\mathbf{\Gamma}}^{nT}_{\mathbf{X}}(k) = \frac{1}{T-k}\sum_{t=k+1}^{T} \mathbf{x}^{nT}_t \mathbf{x}^{nT\prime}_{t-k}$ be the k-lag sample covariance of $\mathbf{X}^{nT}$. Moreover, let $\widehat{\mathbf{\Gamma}}^{nT}_{\mathbf{XY}}(k) = \frac{1}{T-k}\sum_{t=k+1}^{T} \mathbf{y}^{nT}_t \mathbf{x}^{nT\prime}_{t-k}$, with $\mathbf{y}$ the non-standardized correspondent of $\mathbf{x}$. The common factors $\mathbf{F}_t$ are latent and can be estimated by generalized principal components. More precisely, let $\mathbf{F}^{nT} = \mathbf{S}^{nT}\mathbf{X}^{nT}$, where $\mathbf{S}^{nT} = \left(S^{nT\prime}_1 ... S^{nT\prime}_r\right)'$ is the $(r \times n)-$matrix containing r generalized eigenvectors of the couple of matrices $\left(\mathbf{\Gamma}^{nT}_{\mathbf{X}}(0), \mathbf{\Gamma}^{nT}_{\xi}(0)\right)$ with normalization such that $S^{nT\prime}_i \mathbf{\Gamma}^{nT}_{\xi}(0) S^{nT\prime}_j = 1$ if $i = j$ and zero otherwise. Orthogonal projection of the data $\mathbf{x}_t$ on the factors $\mathbf{F}_t$ yield the factor loadings $\mathbf{\Lambda}_n = \mathbf{S}^{nT}$ and the common component $\chi^{nT} = \mathbf{S}^{nT\prime}\mathbf{S}^{nT}\mathbf{X}^{nT}$.

Forni et al.(2000; 2001; 2001; 2004; 2005) propose to estimate $\widetilde{\mathbf{F}}^{nT}$ by generalized principal components $\widetilde{\mathbf{S}}^{nT}\mathbf{X}^{nT}$, for which the (cyclical) generalized eigenvectors[2] $\widetilde{\mathbf{S}}^{nT}$ are obtained with $\mathbf{\Gamma}^{nT}_{\xi}(0)$ being determined in the

[2]More precisely, they propose the generalized eigenvectors of the couple of matrices $\left(\widetilde{\mathbf{\Gamma}}^{nT}_{\chi}(0), \widetilde{\mathbf{\Gamma}}^{nT}_{\xi}(0)\right)$. Given the factor model assumption of orthogonality between χ and ξ, then $\widetilde{\mathbf{S}}^{nT}$ are also the generalized eigenvectors of the couple $\left(\widetilde{\mathbf{\Gamma}}^{nT}_{\chi}(0) + \widetilde{\mathbf{\Gamma}}^{nT}_{\xi}(0), \widetilde{\mathbf{\Gamma}}^{nT}_{\xi}(0)\right) = \left(\widehat{\mathbf{\Gamma}}^{nT}_{\mathbf{X}}(0), \widetilde{\mathbf{\Gamma}}^{nT}_{\xi}(0)\right)$, with eigenvalues $\lambda^{nT}_j + 1$. Although

first step of a two-step procedure, see appendix A.1.1 for details. The off-diagonal elements of $\mathbf{\Gamma}_{\xi}^{nT}(0)$ are set to zero as they are ill-conditioned in case n is large. Stock and Watson(2002a; 2002b) obtains the estimate $\widehat{\mathbf{F}}^{nT}$ by ordinary principal components $\widehat{\mathbf{S}}^{nT}\mathbf{X}^{nT}$ being a special case with $\mathbf{\Gamma}_{\xi}^{nT}(0) = \mathbf{I}_n$, i.e. the identity matrix. Computing the generalized principal components of $\mathbf{x}$ is equivalent to computing the standard principal components of $\mathbf{y} = H\mathbf{x}$ with $\det(H) \neq 0$ and H such that $H\xi_{nt}\xi_{nt}'H' = \mathbf{I}_n$. The transformation H amounts to downweighing x by the standard deviation of its idiosyncratic component.

2.2.1 Factor model specification

Estimating the factors by (generalized) principal components as described in the former section only requires to specify the number of factors r. Bai and Ng's (2002) information criteria (BNIC) determine r as a trade-off between goodness-of-fit and an overfitting penalty. The goodness-of-fit is measured by the log of the residual sum of squares and different specifications of the penalty function that increase with sample size n and time series length T are proposed. We employ the criterion that shows good performance in Monte Carlo studies and whose penalty function is defined as $r\left(\frac{n+T}{T}\right)\ln\left(\min\{n,T\}\right)$. Note that in case $n = T$, this penalty function becomes $2r\frac{\ln T}{T}$, which is 2 times the penalty factor of the usual Bayesian Information Criterion (BIC).

The number of factors r is the only parameter that needs to be specified for the static factor method. The dynamic factor method estimates in the first step of a two-step procedure the idiosyncratic covariance matrix $\mathbf{\Gamma}_{\xi}^{nT}(0)$, which requires the specification of the number of dynamic factors q, the parameter m that determines the maximum lag of the auto-covariance matrix and the cyclicality parameter τ. We follow Forni et al.'s (2000) approach and select $q = 3$ in the finite-sample as the marginal explained variance of the q^{th} dynamic eigenvalue is larger than 10% and the $(q+1)^{th}$ one is smaller than 10%. Moreover, we employ a data dependent rule to set the

this equivalence holds in population, it breaks down in sample.

maximum lead and lag of m periods, that is $b_{ik,\pm n}L^{\pm n}f_{kt} = 0$ for $n > m$, at $m(T) = \text{ROUND}\left(2T^{(1/2)}\right)$. Finally, we set $\tau = 4$, so all seasonality, which by definition entails a duration shorter than 1 year, or 4 quarters, is filtered out. Note that the cyclical dynamic factor model nests the dynamic factor model, i.e. by setting $\tau = 1$, which by itself nests the static factor model, i.e. by setting $m = 0$ and $q = r$.

2.3 Factor model forecasting

The object of interest is the h-step ahead forecast of the stationary time series variable $y_{i,T+h|T}$, whose standardized correspondent is x_i with mean μ_i and standard deviation σ_i. The factor forecasts read as $y_{i,T+h|T} = \mu_{i|T} + \sigma_{i|T}\chi_{i,T+h|T} = \mu_{i|T} + \sigma_{i|T}\beta_h\mathbf{\Lambda}_{n,i}\mathbf{f}_T$.

As the parameters are not observed and, hence, need to be estimated, the equivalence in population of the different forecast specifications breaks down in sample, so $\widehat{\sigma_{i|T}\boldsymbol{\beta}_h\mathbf{\Lambda}}_{n,i}\widehat{\mathbf{f}}_T \neq \left(\widehat{\sigma_{i|T}\beta_1\mathbf{\Lambda}}_{n,i}\right)^h\widehat{\mathbf{f}}_T \neq \widehat{\sigma}_{i|T}\widehat{\beta}_h\widehat{\mathbf{\Lambda}}_{n,i}\widehat{\mathbf{f}}_T$. Using the same horizon for estimating and forecasting can modify the potential impact of the model specification error (cf. Clements and Hendry, 1998). Therefore, we disregard the parameter estimates that result from h times iterated one step ahead forecasts $\left(\widehat{\sigma_{i|T}\beta_1\mathbf{\Lambda}}_{n,i}\right)^h$. Moreover, as the stochastic process driving the factors is generally not known, potential misspecification of $\widehat{\beta}_h$ can also be avoided by determining $\widehat{\sigma_{i|T}\beta_h\mathbf{\Lambda}}_{n,i}$ as one parameter.

Therefore, the unrestricted χ_y, respectively restricted factor forecasts χ_χ are obtained by a linear projection of the h-step ahead observations $y_{i,t+h}$, respectively the common component $\chi_{i,t+h}^{nT}$on the t-dated factors $\mathbf{f}_t^{nT}$. The corresponding h-step ahead factor forecasts of the common component of the i-th variable given T observations of n time series variables reads as:

$$\begin{aligned}
\chi_{y_i,T+h|T}^{nT} &= \left[\widehat{\mathbf{\Gamma}}_{\mathbf{XY}}^{nT}(h)\right]_i \mathbf{S}^{nT\prime}\left(\mathbf{S}^{nT}\widehat{\mathbf{\Gamma}}_{\mathbf{X}}^{nT}(0)\,\mathbf{S}^{nT\prime}\right)^{-1}\mathbf{S}^{nT}\mathbf{X}^{nT} \\
\chi_{\chi_i,T+h|T}^{nT} &= \widehat{\mu}_{i|T} + \widehat{\sigma}_{i|T}\left[\mathbf{\Gamma}_\chi^{nT}(h)\right]_i \mathbf{S}^{nT\prime}\left(\mathbf{S}^{nT}\widehat{\mathbf{\Gamma}}_{\mathbf{X}}^{nT}(0)\,\mathbf{S}^{nT\prime}\right)^{-1}\mathbf{S}^{nT}\mathbf{X}^{nT}.
\end{aligned} \tag{2}$$

with sample mean $\widehat{\mu}_{i|T}$ and standard deviation $\widehat{\sigma}_{i|T}$. The static and dynamic factor forecasts can be obtained by employing $\widehat{\mathbf{S}}^{nT}$ and $\widehat{\mathbf{\Gamma}}_{\chi}^{nT}(h)$, respectively $\widetilde{\mathbf{S}}^{nT}$ and $\widetilde{\mathbf{\Gamma}}_{\chi}^{nT}(h)$. As Boivin and Ng (2005) noted, the restricted factor forecasts χ_{χ} adhere stronger to the factor structure as the matrix $\mathbf{\Gamma}_{\chi}^{nT}(h)$ is involved instead of the data driven matrix $\widehat{\mathbf{\Gamma}}_{\mathbf{XY}}^{nT}(h)$. This latter matrix also contains the first moment μ and second moment σ. So, the unrestricted (dynamic) factor forecasts χ_y are obtained as $\sigma_{i|T}\beta_h\mathbf{\Lambda}_{n,i}\mathbf{f}_T + \mu_{i|T} = \left[\widehat{\Gamma}_{\mathbf{XY}}^{nT}(h)\right]\mathbf{S}^{nT'}\left(\mathbf{S}^{nT}\widehat{\Gamma}_{\mathbf{X}}^{nT}(0)\,\mathbf{S}^{nT'}\right)^{-1}\mathbf{S}^{nT}\mathbf{X}^{nT}$. Finally, D'Agostino and Giannone (2006) point out that $\mathbf{\Gamma}_{\mathbf{XY}}(0)$ is the unrestricted equivalent of $\mathbf{\Gamma}_{\chi}(0)$ namely for $q = n$, i.e. if the number of factors equals the number of variables.[3]

The sampling error of the factor estimates enters the forecasts and might even dominate the information gain in the factors. The forecast error is then affected both by the estimation of the factors and by the equation relating the estimated factors to the target variable. Rewriting the forecast equation $x_{i,T+h|T} = \chi_{i,T+h|T} + \xi_{i,T+h|T} = \beta_h\mathbf{\Lambda}_{n,i}\mathbf{f}_T + \rho_i(L)\,\xi_{i,T} = \left(1-\rho_i(L)\,L^h\right)\beta_h\mathbf{\Lambda}_{n,i}\mathbf{f}_T + \rho_i(L)\,x_{i,T}$ shows that forecasting the components separately is equivalent to forecasting the sum plus one of the two components separately. Boivin and Ng's (2005) factor augmented autoregressive forecasts (FAAR) simply augment lags of the estimated factors to an autoregressive forecast equation of the non-standardized target variable:

$$\widehat{y}_{i,T+h|T} = \widehat{\mu}_{i,h} + \widehat{\theta}_{i,h}(L)\,\widehat{\mathbf{f}}_T + \widehat{\gamma}_{i,h}(L)\,y_{iT} \tag{3}$$

The parameters $\widehat{\mu}_{i,h}$, $\widehat{\theta}_{i,h}(L)$ and $\widehat{\gamma}_{i,h}(L)$ are obtained by regressing $y_{i,t+h}$ on b_f lags of $\widehat{\mathbf{f}}_t$ and b_y lags of y_{it}. A likewise forecast $\widetilde{y}_{i,T+h|T}$ is obtained using the generalized dynamic factors $\widetilde{\mathbf{f}}_T$. The lags are chosen by the BIC out of $1 \leq b_f \leq 4$ and $0 \leq b_y \leq 4$. So, the smallest candidate model that BIC can produce includes a constant, a single contemporaneous factor and no autoregressive lags. The parameter $\widehat{\mu}_{i,h}$ is the estimated mean of the stationary variable. Since $\widehat{\theta}_{i,h}(L)$ is not constrained to equal $\left(1-\widehat{\rho}_i(L)\,L^h\right)\widehat{\sigma_i\beta_h\mathbf{\Lambda}_{n,i}}$, $\widehat{\mu}_{i,h}$ is not restricted to equal the sample mean $\widehat{\mu}_{i|T}$ and no restrictions are

[3]Moreover, the equivalence $q = n$ holds in population and only also in sample if a rectangular estimation window is employed to estimate the spectral density matrix $\sum_{\mathbf{X}}^{nT}(\theta_h)$, see appendix A.1.1.

imposed on the coefficients of the b_f lags of $\widehat{\mathbf{f}}_t$ and b_y lags of y_{it}, the FAAR specification (3) nests the factor forecast specification (2) and is allowed more flexibility to adapt to the data.

3 Forecasting Dutch GDP and inflation

3.1 Out-of-sample forecast simulation design

The aim is to generate forecasts $y_{i,T+h|T}$ for GDP and inflation for the Netherlands over a forecast horizon of $h = 1, ..., 4$ quarters ahead. The stationarity inducing transformations concerning GDP consist of the first difference of the log of GDP measured in constant prices, i.e. quarter-on-quarter real GDP growth rates, while the transformation for inflation consists of the first difference of the fourth difference of the log of the CPI index, i.e. quarterly changes of inflation rates. The forecasting exercise involves in-sample model selection, factor estimation, parameter estimation and, finally, generating factor forecasts (2) and FAAR forecasts (3). The in-sample selection of the factor models and the specification of the forecast equation are performed according to the various information criteria as explained in the previous sections. The precise specifications are based on data that cover the first half of the sample of observations, which runs from 1980Q2 until 1991Q1, and consists of 46 observations for each time series variable. Given the selected factor model and the factor forecast specification, the forecast $\widehat{y}^h_{1991Q1+h}$ is generated in the first round. In the subsequent iteration, the factors and the parameters of the selected factor model and forecast specification are reestimated and utilized to generate the forecast $\widehat{y}^h_{1991Q2+h}$. The iteration repeats 46 times and results in the final forecast $\widehat{y}^h_{2002Q4+h}$. The factors and the parameters of the selected specifications are iteratively reestimated based on a rolling window scheme, which as we will show takes better into account the presence of structural breaks in the data set than a recursive window scheme.

3.2 Factor model diagnostics

The extracted factors represent the underlying specific data set, which then should capture correctly the main forces that drive the variable of interest, in our case GDP and CPI. Boivin and Ng (2006) refer to oversampling as the situation in which the data are more informative about some factors than about the others. Including more variables in an oversampled data set could result in more precise factor estimates, which do however not improve the forecasting performance for the variables that depend on the less dominant factors. Let the commonality ratio $R_i^2 = \sum_{t=1}^{T} \chi_{it}^2 / \sum_{t=1}^{T} x_{it}^2$ indicate the relative importance of the common component of variable i and let the average commonality ratio of a specific data set be $\overline{R}^2 = \sum_{i=1}^{n} R_i^2$. A below average commonality ratio for the variable of interest, $R_i^2 < \overline{R}^2$, $i \in \{gdp, cpi\}$ is then an indication of an oversampled data set.

In absence of oversampling, the features of the data that improve the precision of the factor estimates relate to the importance and disperson of the common component. The estimation precision improves when the common component, as measured by $\overline{R}^2$, is important, but deteriorates with a larger dispersion of the importance of the common component. The cross-sectional dispersion R_q^2 is measured by the difference between the R_i^2 in the 90^{th} and the 10^{th} percentile: $R_q^2 = R_{.9N}^2 - R_{.1N}^2$. So, adding data with large idiosyncratic errors or weak factor loadings deteriorates the factor diagnostics.

3.3 Dutch data

The data set provides a balanced representation of the Dutch economy and of the forces it is exposed to. For this purpose, the data set of the macroeconometric model MORKMON of De Nederlandsche Bank for the Dutch economy (cf Van Els and Vlaar, 1996) is supplemented with variables potentially possessing valuable information from a forecasting perspective. The data cover the Dutch national accounts on the expenditure components of GDP and describe the behaviour of the macro actors in the economy: households, firms, monetary financial sector, government and foreign sector. The data set is screened on variables that are only available at a yearly frequency, especially related to the government sector, social security and the flow of funds like tax funds, insurance and pension premiums. The data set is supplemented with a more detailed extension of macro-wide variables and leading indicators.

The final data set consists of 124 time series variables, which can be divided into six different categories. The first category labeled 'GDP' consist of GDP, its expenditure components, labour market variables, real wages and the housing market. The second category labeled 'industrial production' consists of sectorally disaggregated time series on manufacturing turnover and capacity utilization. The third category labeled 'prices' consists of consumer, producer and commodity prices. The fourth category labeled 'financial' covers the financial developments captured by interest rates, exchange rates and the stock market. The fifth category labeled 'external' represents the external sector as recorded on the balance of payments in variables such as income transfers, direct and portfolio investment. The sixth and final category labeled 'surveys' consists of business expectations, assessments of stocks and order arrivals and confidence indicators.

The details of the data including the preprocessing are explained in appendix B. The preprocessing includes outlier detection, removing seasonality and stationarity inducing transformations, rendering standardized time series variables of quarterly frequency. As the focus is on the size and structure of the data set, we abstract from the release timing of the different variables. Moreover, the entire data set was collected in the second quarter of 2004 and consists of the fully revised historical series available as of this date. The collected data set is the 2004Q2 snapshot of the variables and in this regard the forecasting results will be different from the results using real-time data. Finally, the sample period runs from 1980Q1 until 2003Q4.

4 Empirical results

We employ the out-of-sample forecast simulation design on different configurations of the data set, one of which consists of preselected targeted predictors along the lines of Bai and Ng (2008). Targeting predictors means that the preselection is based on the relationship between the forecast variable y and the indicator variables $\mathbf{X}$. Bai and Ng (2008) use penalized regression techniques and the most promising method for preselection is least-angle regression with elastic net (LARS-EN). Zou and Hastie's (2005) EN criterion in a regression problem allows simultaneously for shrinkage of coefficients, elimination of regressors and efficient selection of representatives within groups of highly correlated regressors. Consider the regression $y_{t+h} = \alpha_1 + \alpha_2 * y_t + \beta' \mathbf{X}_t + \epsilon_{t+h}$ where β represents the regression coefficients corresponding to the standardized stationary predictor variables. Denoting by RSS the residual sum of squares, then Zou and Hastie's (2005) EN crition looks like

$$\min_{\beta} RSS + \kappa_1 \sum_i |\beta_i| + \kappa_2 \sum_i \beta_i^2 \tag{4}$$

Efron et al.'s (2004) LARS is an efficient solution to compute the regression coefficients β subject to the EN-criterion (4), which we will refer to as LARS-EN. The algorithm starts with all coefficients β set to zero and then, successively, the most important one of the remaining indicator variables is selected according to criterion (4) while taking into account the correlation with the already selected indicator variables. Bai and Ng (2008) show that the algorithm provides a soft threshold ranking of the predictors as it takes the presence of the other predictor variables into account. Moreover, the algorithm avoids strongly correlated predictors, since if one of the correlated predictors is already included, the new residual will have a low correlation with the predictor variables that are strongly correlated with the one already included. For specifying LARS-EN, one fixes the shrinkage parameter κ_2 and the number of active regressors. Following Bai and Ng (2008), we set $\kappa_2 = 0.25$ and a stopping rule for the number of active regressors replaces specifying κ_1. Our main interest is not so much in the point estimates β, but in the ordering of the variables and we set the number of active regressors at 62 corresponding to half the size of the complete data set.

In order to empirically determine the importance of the size and structure of the data set, we run the out-of-sample forecast simulation design for different configurations of the data set. Apart from the complete data set and the data set consisting of targeted predictors, we perform the forecast simulation on each of the six groups separately and on the complete data set excluding consecutively each one of the six groups. The forecasting performance is summarized by the relative mean squared forecast error (ReMSFE), which is the mean squared forecast error (MSFE) of the particular forecast specification divided by the MSFE of the AR(1)-process. The different factor forecast specifications (2) consist of the unrestricted factor forecasts χ_y versus the restricted ones χ_χ. Moreover, the factor forecasts employ static factors $\widehat{\chi}$, dynamic factors $\widetilde{\chi}$ or cyclical dynamic factors $\widetilde{\chi}^c$. Table 1 reports the factor model diagnostics and the forecasting performance for the different forecast specifications. The results in the left part of the table are based on the complete data set, while the results of the forecast specifications represented with a bar, $\overline{\chi}$ are averages over the 14 different configurations of the data.

Table 1: Diagnostics for different factor model specifications

	h	$\widehat{\chi}_\chi$	$\widehat{\chi}_y$	$\widetilde{\chi}_\chi$	$\widetilde{\chi}_y$	$\widetilde{\chi}^c_\chi$	$\widetilde{\chi}^c_y$	$\overline{\widehat{\chi}}_\chi$	$\overline{\widehat{\chi}}_y$	$\overline{\widetilde{\chi}}_\chi$	$\overline{\widetilde{\chi}}_y$	$\overline{\widetilde{\chi}}^c_\chi$	$\overline{\widetilde{\chi}}^c_y$
R^2_{gdp}	0	1.80	1.80	0.86	1.30	0.74	1.27	2.44	2.44	1.33	1.78	0.58	1.05
(*10)	1	0.72	0.75	0.21	0.30	0.50	0.47	0.57	0.65	0.25	0.30	0.37	0.36
	2	0.20	0.25	0.26	0.22	0.26	0.29	0.20	0.31	0.23	0.24	0.18	0.22
	3	0.04	0.10	0.14	0.28	0.12	0.31	0.12	0.30	0.12	0.25	0.08	0.22
	4	0.03	0.07	0.01	0.05	0.05	0.11	0.08	0.19	0.07	0.14	0.05	0.12
R^2_{cpi}	0	0.30	0.30	0.19	0.24	0.33	0.41	1.41	1.41	0.99	1.30	0.87	1.31
(*10)	1	0.12	0.70	0.05	0.04	0.20	0.13	0.37	1.20	0.59	0.74	0.71	0.73
	2	0.03	0.76	0.15	0.19	0.15	0.29	0.26	1.09	0.61	0.82	0.52	0.76
	3	0.01	0.62	0.09	0.14	0.14	0.24	0.20	1.06	0.45	0.75	0.37	0.68
	4	0.00	0.41	0.02	0.03	0.10	0.11	0.23	0.86	0.28	0.59	0.26	0.54
$\overline{R}^2$	0	1.00	1.00	0.76	1.00	0.66	0.99	2.33	2.33	1.80	2.24	0.80	1.48
(*10)	1	0.40	0.52	0.48	0.56	0.52	0.61	0.54	0.70	0.64	0.73	0.61	0.67
	2	0.11	0.25	0.23	0.30	0.27	0.36	0.28	0.44	0.33	0.44	0.29	0.40
	3	0.02	0.18	0.12	0.21	0.14	0.24	0.20	0.36	0.21	0.36	0.14	0.29
	4	0.02	0.16	0.10	0.23	0.10	0.23	0.15	0.29	0.16	0.33	0.10	0.24
R^2_q	0	0.34	0.34	0.25	0.36	0.23	0.31	0.43	0.43	0.37	0.47	0.23	0.43
	1	0.14	0.10	0.15	0.17	0.19	0.21	0.12	0.13	0.15	0.17	0.18	0.19
	2	0.04	0.06	0.06	0.08	0.07	0.08	0.06	0.10	0.07	0.10	0.07	0.10
	3	0.01	0.05	0.03	0.05	0.03	0.06	0.03	0.08	0.04	0.08	0.03	0.07
	4	0.01	0.04	0.03	0.06	0.02	0.06	0.03	0.06	0.03	0.07	0.02	0.06
ReMSFE	1	0.84	0.85	0.87	0.87	0.87	0.88	0.90	0.90	0.92	0.93	0.89	0.91
GDP	2	0.90	0.92	0.95	0.96	0.91	0.94	0.95	1.00	0.98	0.99	0.94	0.95
	3	0.96	0.93	0.99	1.01	0.96	0.99	0.96	1.02	1.02	1.05	0.97	1.01
	4	0.98	1.05	0.95	0.98	0.96	0.97	0.99	1.08	0.95	0.98	0.96	0.97
ReMSFE	1	0.85	0.85	0.92	0.93	0.88	0.91	0.89	0.95	0.91	0.92	0.88	0.90
cpi	2	0.92	0.89	0.94	0.94	0.96	0.95	0.96	0.95	0.97	0.99	0.96	0.96
	3	0.94	0.89	1.00	1.04	1.00	1.05	0.96	1.00	1.03	1.08	1.00	1.06
	4	0.96	1.06	1.01	1.04	1.01	1.05	1.00	1.13	1.01	1.06	1.00	1.04
ReMSE	1	0.85	0.82	0.91	0.90	0.91	0.91	0.88	0.85	0.88	0.87	0.89	0.88
GDP	2	0.94	0.95	0.96	0.97	0.96	0.98	0.93	0.94	0.95	0.96	0.94	0.95
	3	0.94	0.92	0.95	0.95	0.94	0.96	0.96	0.97	0.95	0.96	0.94	0.96
	4	0.94	0.96	0.93	0.95	0.95	0.96	0.96	0.96	0.93	0.94	0.95	0.94
ReMSE	1	0.93	0.74	1.03	1.04	0.98	1.01	0.96	0.79	0.95	0.93	0.89	0.88
cpi	2	0.97	0.71	0.95	0.93	1.00	0.92	0.98	0.78	0.92	0.89	0.90	0.84
	3	0.97	0.77	1.02	1.02	1.00	1.00	0.95	0.79	0.97	0.94	0.93	0.89
	4	0.97	0.81	0.92	0.90	0.89	0.86	0.96	0.84	0.93	0.87	0.88	0.80

Notes.
$\widehat{\chi}_y$ is the unrestricted static factor-forecast, $\widehat{\chi}_\chi$ is the restricted static factor forecast, $\widetilde{\chi}_y$ is the unrestricted dynamic factor forecast, $\widetilde{\chi}_\chi$ is the restricted dynamic factor forecast, $\widetilde{\chi}^c_y$ is the unrestricted cyclical dynamic factor-forecast, $\widetilde{\chi}^c_\chi$ is the restricted cyclical dynamic factor forecast. The results of the forecast specifications are based on the complete data set of 124 variables. Moreover, the forecast specifications represented with a $\overline{bar}$ present the average results over the 14 different configurations of the data. R^2_{gdp}, R^2_{cpi} and $\overline{R^2}$ indicate the relative importance of the common component of GDP, CPI respectively the average relative importance of the common component of all the variables in the data set. R^2_q measures the cross-section dispersion of the common component. Finally, ReMSFE is the mean squared forecast error relative to the mean squared forecast error of the AR(1) process and ReMSE is the mean squared forecast of the rolling versus recursive window specification.

The results in the table clearly shows that the average commonality ratio of the complete data set $\overline{R}^2$ is lower than its equivalent that is averaged over the 14 different configurations of the data $\overline{\overline{R}}^2$, i.e. $\overline{R}^2 < \overline{\overline{R}}^2$, while simultaneously it holds that ReMSFE$<\overline{\text{ReMSFE}}$ for all forecast horizons h. Smaller macroeconomic data sets exhibit stronger coherence, which is captured by the factors explaining a larger part of the correlation between the variables. However, the higher explanatory power of the factors does not lead to improved forecasting performance. One explanation is that the better factor fit does not relate to the variable of interest as shown by $\overline{R_i^2} < \overline{\overline{R}}^2$ for $i \in \{gdp, cpi\}$, for which the upper bar denotes the average over the 14 different data configurations. Here, oversampling, or rather missampling, refers to the misrepresentation of a small data set exhibiting a strong factor structure.

Comparing the diagnostics of the different factor forecast specifications, the table clearly shows that the unrestricted factor forecasts χ_y exhibit a better fit than its restricted equivalent χ_χ for the different specifications, horizons h and data set sizes. Comparing the diagnostics of employing static factors $\widehat{\chi}$ as compared to dynamic factors $\widetilde{\chi}$ does not reveal structural differences, excepting that the static method seems to exhibit a better factor fit and forecasting performance at horizon $h = 1$. Comparing the diagnostics of employing dynamic factors $\widetilde{\chi}$ as compared to cyclical dynamic factors $\widetilde{\chi}^c$ only shows a worse fit of the cyclical factors in case of small data sets. Finally, the last eight rows in Table 1 benchmarks the forecasting performance concerning GDP and inflation relative to employing a recursive window scheme. The results confirm that correcting for structural breaks by applying a rolling window scheme overcompensates the loss of data at the beginning of the sample period, see Eickmeier and Ziegler's (2008) meta-analysis of the empirical factor forecasting literature.

4.1 Forecast accuracy of various model specifications

In order to systematically analyse the forecasting performance of the different factor forecasts (2) and the FAAR forecasts (3), we apply Giacomini and

White's (2006) (GW) pairwise test of equal forecast accuracy. This test statistic can be applied to compare two competing series of forecasts generated from estimated and, possibly, nested models under a rolling window scheme. Under the null hypothesis, the squared difference between the forecast errors of two competing models is not statistically different from zero. We report the (symmetric) p-values of the GW-statistic that reject the null hypothesis.

As an additional summary statistic for the relative forecast accuracy over time, we follow Schumacher (2007) and pairwise count the number of time periods for which model A has a smaller squared forecast error than model B. The counted number of time periods as a fraction of the total time span for which forecasts are generated provides a summary statistic, denoted as $I_{A<B}(h)$, for each forecast horizon h. So, if $I_{A<B}(h) > 0.5$ then in more than half of the forecast occasions, model A manages to outperform model B. Note that if, at the complementary occasions, model B outperforms model A with much smaller forecast errors, then it holds simultaneously that $MSE_A > MSE_B$ and $I_{A<B}(h) > 0.5$. So, $I_{A<B}(h)$ is a complementary statistic to MSE.

Table 2: Forecast accuracy of different model specifications for GDP; one quarter ahead forecast horizon

	$\widehat{\chi}_\chi$	$\widehat{\chi}_x$	$\widehat{y}$	$\widetilde{\chi}_\chi$	$\widetilde{\chi}_x$	$\widetilde{\chi}^c_\chi$	$\widetilde{\chi}^c_x$	$\widetilde{y}$
$\widehat{\chi}_\chi$		*0.62*	*0.09*	*0.29*	*0.28*	*0.35*	*0.34*	*0.14*
$\widehat{\chi}_x$	0.45		*0.11*	*0.69*	*0.73*	*0.64*	*0.59*	*0.17*
$\widehat{y}$	0.34	0.34		*0.18*	*0.15*	*0.21*	*0.23*	*0.81*
$\widetilde{\chi}_\chi$	0.45	0.51	0.57		*0.65*	*0.98*	*0.87*	*0.25*
$\widetilde{\chi}_x$	0.47	0.53	0.60	0.47		*0.83*	*0.72*	*0.22*
$\widetilde{\chi}^c_\chi$	0.45	0.49	0.60	0.51	0.55		*0.76*	*0.29*
$\widetilde{\chi}^c_x$	0.51	0.53	0.55	0.51	0.53	0.47		*0.31*
$\widetilde{y}$	0.40	0.47	0.40	0.40	0.43	0.40	0.40	

Notes.
See Table 1 for the explanation of the different factor forecast specifications. The results are based on the complete data set consisting of 124 variables. Moreover, $\widehat{y}$ and $\widetilde{y}$ represent the unrestricted static respectively dynamic factor augmented autoregressive forecasts as defined in 3. The p-values of the (symmetric) GW-test of pairwise equal forecast accuracy are presented in *italics* in the upper part of the table. The summary statistics of forecast accuracy over time $I_{A<B}(h)$ are presented in the lower part of the table for which model A is represented in the row and model B in the column.

Table 3: Forecast accuracy of different model specifications for CPI; one quarter ahead forecast horizon

	$\widehat{\chi}_\chi$	$\widehat{\chi}_x$	$\widehat{y}$	$\widetilde{\chi}_\chi$	$\widetilde{\chi}_x$	$\widetilde{\chi}^c_\chi$	$\widetilde{\chi}^c_x$	$\widetilde{y}$
$\widehat{\chi}_\chi$		*0.91*	*0.43*	*0.03*	*0.04*	*0.13*	*0.09*	*0.48*
$\widehat{\chi}_x$	0.46		*0.45*	*0.23*	*0.19*	*0.49*	*0.31*	*0.51*
$\widehat{y}$	0.43	0.46		*0.69*	*0.73*	*0.54*	*0.63*	*0.30*
$\widetilde{\chi}_\chi$	0.33	0.41	0.54		*0.19*	*0.07*	*0.39*	*0.78*
$\widetilde{\chi}_x$	0.35	0.41	0.57	0.48		*0.05*	*0.07*	*0.83*
$\widetilde{\chi}^c_\chi$	0.50	0.41	0.61	0.57	0.59		*0.09*	*0.61*
$\widetilde{\chi}^c_x$	0.50	0.41	0.59	0.61	0.63	0.41		*0.71*
$\widetilde{y}$	0.41	0.43	0.43	0.39	0.39	0.37	0.39	

Notes.
See Table 2

The p-values of the GW-statistic and the forecast accuracy statistic over time $I_{A<B}(h)$ at horizon $h = 1$ for the different forecast specifications are reported in Table 2 for GDP in Table 3 for CPI. The results are based on the complete data set consisting of 124 time series variables. The table show that the FAAR specifications y for both GDP and CPI are clearly being outperformed according to the statistic of forecast accuracy over time $I_{A<B}(h)$. Moreover, the cyclical dynamic factor forecast $\widetilde{\chi}^c$ outperforms almost all other specifications, even significantly so in case of CPI according to the GW-statistic. The model specification that impose the factor structure most, i.e. the restricted factor forecasts employing cyclical dynamic factors, shows best forecasting performance despite showing among the weakest factor model diagnostics. Boivin and Ng's (2005) FAAR specifications, which of all the possible specifications imposes the factor structure to the least extent and therefore allows the forecast equation most flexibility to adapt to the data, show worst forecasting performance. As shown in section 2.2, the more complex dynamic factor model weighs down the variables with a larger idiosyncratic variance, which improves upon the forecasting performance (cf. rules SWa and SWb in Boivin and Ng, 2006). D'Agostino and Giannone (2006) argue though that the outperformance of the dynamic method is rather due to the rolling window estimation scheme. Finally, the result based on Dutch data that imposing factor structure improves forecasting performance is in line with Eickmeier and Ziegler's (2008) meta-analysis of the empirical factor forecasting literature.

4.2 Forecast accuracy of various data configurations

The factor model diagnostics and forecasting performance at horizon $h = 1$ of the best performing dynamic $\widetilde{\chi}^c_\chi$ and static $\widehat{\chi}_\chi$ factor forecast specifications and the FAAR specifications $\widetilde{y}$, respectively $\widehat{y}$, for different configurations of the data set are presented in Table 4 regarding GDP and in Table 5 regarding CPI. The different configurations of the data set consist of each of the six groups separately, the complete data set consisting of 124 variables, the LARS-EN data set consisting of 62 targeted predictors and the complete data set excluding consecutively each one of the six groups.

Table 4: Forecasting performance of different data sets for GDP: one quarter forecast horizon

Group	**Dynamic**	**Method**		**ReMSFE**		**Static**	**Method**		**ReMSFE**		**Ranking**				**Forecast**	**accuracy**		
	R^2_{gdp}	$\overline{R^2}$	R^2_q	$\widetilde{\chi}^c_\chi$	$\widetilde{y}$	R^2_{gdp}	$\overline{R^2}$	R^2_q	$\widehat{\chi}_\chi$	$\widehat{y}$	$\widetilde{\chi}^c_\chi$	$\widetilde{y}$	$\widehat{\chi}_\chi$	$\widehat{y}$	$\widetilde{\chi}^c_\chi$	$\widetilde{y}$	$\widehat{\chi}_\chi$	$\widehat{y}$
1	0.33	0.11	0.32	0.93	1.08	0.57	0.12	0.32	0.95	1.14	10	10	11	12	0.45	0.57	0.47	0.45
2	0.23	0.38	0.83	0.87	1.07	0.26	0.38	0.77	0.94	1.11	3	13	10	14	0.51	0.43	0.47	0.36
3	0.07	0.53	0.74	1.02	1.12	0.19	0.63	0.51	0.87	1.07	14	14	7	8	0.45	0.49	0.47	0.34
4	0.10	0.69	0.77	0.95	1.12	0.13	0.69	0.77	1.04	1.12	12	11	13	11	0.45	0.47	0.43	0.53
5	0.12	0.14	0.33	0.94	1.07	0.13	0.15	0.33	0.97	1.11	11	9	12	10	0.47	0.57	0.51	0.49
6	0.56	0.47	0.68	0.96	0.98	0.57	0.48	0.56	1.05	1.00	13	2	14	4	0.40	0.51	0.47	0.53
Total	0.13	0.10	0.36	0.89	0.95	0.18	0.10	0.34	0.84	0.95	4	5	5	6				
LARS-EN	0.20	0.10	0.29	0.88	1.03	0.27	0.10	0.28	0.92	1.01	5	6	9	5	0.40	0.70	0.36	0.68
Total -/- 1	0.11	0.11	0.39	0.89	0.97	0.15	0.11	0.38	0.86	0.96	8	1	6	2	0.34	0.45	0.45	0.45
Total -/- 2	0.09	0.09	0.27	0.90	0.99	0.18	0.09	0.32	0.81	0.97	9	12	1	13	0.45	0.47	0.55	0.49
Total -/- 3	0.13	0.11	0.38	0.88	0.97	0.17	0.12	0.34	0.87	0.96	7	8	8	7	0.36	0.30	0.51	0.51
Total -/- 4	0.11	0.11	0.44	0.86	1.03	0.17	0.11	0.37	0.83	0.93	1	7	3	9	0.62	0.45	0.57	0.51
Total -/- 5	0.12	0.11	0.40	0.88	0.98	0.17	0.11	0.35	0.84	0.95	6	3	4	1	0.55	0.43	0.49	0.43
Total -/- 6	0.19	0.09	0.30	0.86	0.99	0.26	0.09	0.34	0.82	0.97	2	4	2	3	0.57	0.45	0.55	0.49

Notes.
The results are based on forecast horizon $h = 1$. R^2_{gdp} and $\overline{R^2}$ indicate the relative importance of the common component of GDP respectively the average relative importance of the common component in the data group. R^2_q measures the cross-section dispersion of the common component across the variables in the respective data groupings. ReMSFE is the mean squared forecast error relative to the AR(1)-process. The section "Ranking" represents the ranking of the different configurations of the data set according to the ReMSFE of the various forecasting methods. The section "Forecast accuracy" refers to the accuracy of the forecasts $I_{A<B}(h)$, where A refers to the corresponding data configuration and B to the complete data set. $\widehat{\chi}_\chi$ represents the restricted static factor-forecast, $\widetilde{\chi}^c_\chi$ is the restricted cyclical dynamic factor-forecast, $\widetilde{y}$ represents the dynamic factor augmented autoregressive forecast and $\widehat{y}$ represents the static factor augmented autoregressive forecast.

Table 5: Forecasting performance of different data sets for CPI: one quarter forecast horizon

Group	**Dynamic**	**Method**		**ReMSFE**		**Static**	**Method**		**ReMSFE**		**Ranking**				**Forecast**	**accuracy**		
	R^2_{cpi}	$\overline{R^2}$	R^2_q	$\widetilde{\chi}^c_{\mathcal{X}}$	$\widetilde{y}$	R^2_{cpi}	$\overline{R^2}$	R^2_q	$\widehat{\chi}_{\mathcal{X}}$	$\widehat{y}$	$\widetilde{\chi}^c_{\mathcal{X}}$	$\widetilde{y}$	$\widehat{\chi}_{\mathcal{X}}$	$\widehat{y}$	$\widetilde{\chi}^c_{\mathcal{X}}$	$\widetilde{y}$	$\widehat{\chi}_{\mathcal{X}}$	$\widehat{y}$
1	0.26	0.09	0.28	0.91	0.82	0.31	0.12	0.32	1.10	0.82	9	1	12	1	0.45	0.55	0.32	0.53
2	0.08	0.24	0.77	0.90	0.92	0.12	0.39	0.75	0.85	0.95	6	7	2	5	0.57	0.62	0.45	0.53
3	0.47	0.68	0.79	0.87	0.89	0.47	0.69	0.77	0.87	0.98	4	5	7	9	0.47	0.60	0.47	0.49
4	0.27	0.52	0.71	0.98	1.13	0.24	0.63	0.53	1.28	1.09	14	14	14	14	0.40	0.49	0.30	0.53
5	0.13	0.14	0.32	0.86	0.84	0.09	0.15	0.31	0.94	0.83	2	2	11	2	0.45	0.60	0.36	0.60
6	0.43	0.37	0.72	0.81	0.86	0.53	0.48	0.57	1.20	1.00	1	4	13	13	0.51	0.57	0.47	0.40
Total	0.02	0.10	0.36	0.88	0.97	0.03	0.10	0.33	0.85	0.99	8	12	4	10				
Targ. Pred.	0.02	0.11	0.41	0.94	0.92	0.01	0.12	0.36	0.94	0.95	11	8	10	7	0.38	0.57	0.40	0.55
Total -/- 1	0.01	0.11	0.38	0.94	0.93	0.02	0.11	0.37	0.85	0.96	12	10	5	8	0.43	0.55	0.47	0.57
Total -/- 2	0.00	0.09	0.27	0.88	0.84	0.01	0.09	0.32	0.91	0.86	5	3	8	3	0.47	0.62	0.38	0.47
Total -/- 3	0.03	0.11	0.39	0.91	0.98	0.04	0.12	0.34	0.85	1.00	10	13	3	12	0.43	0.43	0.62	0.45
Total -/- 4	0.08	0.11	0.44	0.86	0.94	0.08	0.11	0.38	0.83	1.00	3	11	1	11	0.55	0.43	0.52	0.49
Total -/- 5	0.02	0.11	0.40	0.91	0.92	0.02	0.11	0.36	0.86	0.95	7	9	6	6	0.57	0.55	0.47	0.55
Total -/- 6	0.00	0.09	0.29	0.95	0.90	0.01	0.09	0.35	0.91	0.89	13	6	9	4	0.34	0.51	0.30	0.55

Notes.
The results concern the one quarter ahead forecasts for CPI. See Table 4 for further explanation.

The results in Table 4 show that size matters as the complete data set of 124 series outperforms in terms of ReMSFE for almost all specifications the data configurations consisting of each of the six individual groups, which amounts to a size of around 20 variables. While the individual groups exhibit a strong factor structure (high $\overline{R}^2$), most are prone to missampling ($R^2_{GDP} < \overline{R}^2$). Moreover, the forecast accuracy statistic $I_{A<B}(1)$ tells that the complete data set generally more often than half of the times outperforms the data configurations consisting of the individual data sets, especially so for the factor model specifications. The complete data set configuration also outperforms data set configuration consisting of targeted predictors according to both the ReMSFE and forecast accuracy statistics. The results in Table 5 regarding CPI are less pronounced. The complete data set configuarion generally outperforms the individual data group configurations for the factor model specifications, though not for the unrestricted specifications y, according to both the forecast accuracy and the ReMSFE statistics. The data configuration regarding group 2 consisting of industrial production series seems to possess good forecasting performance, even though it is particularly prone to missampling ($R^2_{CPI} < \overline{R}^2$).

Considering the restricted factor model specifications and taking the big sized complete data set configuration as the benchmark, then Table 4 and Table 5 show that factor model diagnostics matter. Excluding a particular group of variables such that the remaining data set shows a better factor model fit, as revealed by the factor model diagnostics, corresponds with improved forecasting performance. For instance, factor diagnostics improve, especially an enhanced R^2_i, $i \in \{gdp, cpi\}$ and lower dispersion R^2_q, regarding GDP by excluding group 6 consisting of survey variables and regarding CPI by excluding group 4 consisting of financial variables. The better factor model fit does for both forecast variables corresond with a better forecasting performance as shown by a lower ReMSFE and a higher $I_{A<B}(1)$. Apparently, the respective groups of variables expose the data compilation to oversampling, thereby hampering forecast improvement.

From an intra-quarter sampling perspective, however, surveys and financial variables possess an early signal as they are more timely released than, for instance, the industrial production series. Rünstler et al. (2009) and Caggiano et al. (2011) employ data sets sampled at a monthly frequency to generate factor forecasts for, amongst others Dutch, GDP. The monthly data sets of the two studies include more timely available, but also more idiosyncratically erratic series as money and financial series, surveys and price indices. As pointed out by Rünstler et al. (2009), a one quarter ahead forecast for GDP entails seven consecutive monthly forecasts considering that GDP is published only six weeks after the corresponding quarter has ended. The Dutch results in Rünstler et al. (2009) and Caggiano et al. (2011) show that mainly only the one month ahead forecasts, which are effectively backcasts generated after the ending of the concerning quarter but before its corresponding GDP release, outperform the one-quarter ahead forecasts as reported in Table 4. For the other horizons, the forecasting performance as reported in Table 1 compare quite well. The forecasts are based on the data set of section 3.3, which is sampled at a quarterly frequency and essentially encompasses the National Accounts data that compiles GDP itself. Finally, Caggiano et al. (2011) confirm the result for Dutch data that size matters as preselecting the variables does not particularly lead to an improvement in the forecast performance.

5 Conclusions

This study compares the forecasts of inflation and GDP growth rates for the Netherlands over a forecast horizon up to 4 quarters ahead based on alternative factor model specifications and various data set configurations. Based on each possible combination of models and data, the aim is to determine a relationship between the factor diagnostics and the forecasting performance.

Regarding the model specifications, the factor forecasts outperform the FAAR specifications consistently for all specifications for both target variables. Of all the possible specifications considered in this study, the FAAR specification imposes the factor structure to the least extent and therefore allows the forecast equation most flexibility to adapt to the data. According to the statistic of forecast accuracy over time, the best performing specification is the restricted cyclical dynamic factor forecast. This specification rests upon the most comprehensive factor design, which encompasses both dynamics and cyclicality, and moreover, imposes the factor structure on the forecast equation.

Despite the better forecasting performance, the diagnostics of the restricted factor forecasts do however not compare favourably to their unrestricted counterparts for different specifications, forecast horizons and data set configurations. Comparing the diagnostics of employing static factors, dynamic factors and cyclical dynamic factors does not reveal structural differences, excepting that the static method represents the target variables better at the first horizon.

Regarding the data set configurations, the results show that size matters as the complete data set of 124 series outperforms regarding the factor specifications for both variables, but especially GDP, all the data configurations consisting of each of the six individual groups separately. This result also holds with respect to the data configuration consisting of targeted predictors, which consists of the best performing half of all the variables according to a penalized regression. Even though smaller macroeconomic data sets exhibit stronger coherence, the factors being well fit do, however, generally not relate to the variable of interest. Here, oversampling, or rather missampling, refers to the misrepresentation of a small data set exhibiting a strong factor structure. Starting with the big sized complete data set, however, then excluding a particular group of variables such that the remaining data set shows a better factor model fit corresponds with improved forecasting performance.

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A Appendix

A.1 The estimator

In this appendix, we show in more detail how the common component χ can be estimated in a stepwise procedure. Moreover, we will highlight the parameter condition that makes the static factor model a special case of the dynamic one. Finally, we show in more detail the estimator for the factor model forecasts in case the forecast equation is restricted to admit the factor model structure.

A.1.1 The dynamic method

The dynamic method as outlined in Forni et al. (2000; 2001; 2001; 2004; 2005) (FHLR) consists of the frequency-domain counterpart of the static method. The dynamic factors[4] $\mathbf{u}_t = (u_{1t}...u_{qt})'$ are estimated by the dynamic principal components, which are the static principal components of the spectral density matrix as outlined by Brillinger (1981). Let $\mathbf{X}^{nT}$ be the observations and $\widehat{\mathbf{\Gamma}}_{\mathbf{X}}^{nT}(k)$ its k-lag sample correlation matrix. FHLR suggest the following stepwise procedure:

(i) estimate the spectral density matrix (cf. Brillinger, 1981) of $\mathbf{X}^{nT}$ as $\sum_{\mathbf{X}}^{nT}(\theta_h) = \sum_{k=-M}^{M} \widehat{\Gamma}_{\mathbf{X}}^{nT}(k)\,\omega_k e^{-ik\theta_h}$, $\theta_h = 2\pi h/(2M+1)$, $h = 0,...,2M$, where $\omega_k = 1 - |k|/(M+1)$ is the Bartlett window of size M. Like Forni et al. (2000), we set $M(T) = \text{ROUND}\left(2T^{(1/2)}\right)$ such that the convergence rate is $M(T)/T = O\left(T^{(1/2)}\right)$;

(ii) calculate from the spectral density matrix $\sum_{\mathbf{X}}^{nT}(\theta_h)$ the q largest dynamic eigenvalues $\lambda_j^{nT}(\theta_h)$ and the corresponding dynamic eigenvectors $\mathbf{p}_j^{nT}(\theta_h)$, $j = 1,...,q$ for $h = 0,...,2M$. We follow Forni et al.'s (2000) approach and select $q = 3$ in a finite-sample such that the marginal explained variance of the q^{th} dynamic eigenvalue is larger than 10% and the $(q+1)^{th}$ equivalent is smaller than 10%;

[4] The notation of the dynamic factors $\mathbf{u}_t$ differs with $\mathbf{f}_t$ in (1) as the latter notation is now employed for the generalized principal component estimator of the dynamic factors in step (v) below.

(iii) let $\underline{\mathbf{p}}_q^{nT}(\theta_h) = \left(\mathbf{p}_1^{nT'}(\theta_h)...\mathbf{p}_q^{nT'}(\theta_h)\right)'$ the $(q\times n)-$matrix of dynamic eigenvectors and $\underline{\lambda}_q^{nT}(\theta_h)$ a diagonal matrix with the q largest dynamic eigenvalues on the diagonal. Inverse Fourier transformation of $\widetilde{\sum}_\chi^{nT}(\theta_h) = \underline{\mathbf{p}}_q^{nT'*}(\theta_h)\underline{\lambda}_q^{nT}(\theta_h)\,\underline{\mathbf{p}}_q^{nT}(\theta_h)$ ($*$ denotes complex conjugate) results in the correlation matrix of the common component $\widetilde{\Gamma}_\chi^{nT}(k) = \frac{1}{(2M+1)}\sum_{k=-M}^{M}\widetilde{\sum}_\chi^{nT}(\theta_h)\,\omega_k e^{ik\theta_h}$ for $h = 0,...,2M$. Moreover, the estimated common dynamic factors are $\widetilde{\boldsymbol{u}}_t^{nT} = \frac{1}{(2M+1)}\sum_{k=-M}^{M}\sum_{h=0}^{2M}\underline{\mathbf{p}}_q^{nT}(\theta_h)\,e^{ik\theta_h}\mathbf{x}_{t-k}^{nT}$. Projecting the data on the common dynamic factors gives the estimator of the cyclical medium- and long-run common component:

$$\widetilde{\phi}_{nt}^{nT} = \frac{1}{(2M+1)}\sum_{k=-M}^{M}\sum_{h=0}^{2M}\beta_k\underline{\mathbf{p}}_q^{nT'*}(\theta_h)\,\underline{\mathbf{p}}_q^{nT}(\theta_h)\,e^{ik\theta_h}\mathbf{x}_{t-k}^{nT}, \qquad \text{(A.1)}$$

where the finite sample approximation of $\beta(L)$ consists of truncating the tails of the band-pass filter that involve unavailable data observations, i.e. $\beta_k = 0$ for $k > M$.

(iv) repeat step (iii) using the $(q+1)$ to n ordered eigenvalues to obtain $\widetilde{\Gamma}_\xi^{nT}(k)$;

(v) let $\widetilde{\mathbf{S}}^{nT} = \left(\widetilde{S}_1^{nT'}...\widetilde{S}_r^{nT'}\right)'$ the $(r\times n)$-matrix containing the r generalized eigenvectors of the couple of matrices $\left(\widetilde{\Gamma}_\chi^{nT}(0), \widetilde{\Gamma}_\xi^{nT}(0)\right)$ with the normalization that $\widetilde{S}_i^{nT'}\text{DIAG}\left(\widetilde{\Gamma}_\xi^{nT}(0)\right)\widetilde{S}_j^{nT'} = 1$ if $i = j$ and zero otherwise. We use Bai and Ng's (2002) information criteria (BNIC) to determine the r generalized static factors as a trade-off between the goodness-of-fit and overfitting. The factors can then be estimated by the generalized principal components, i.e. $\widetilde{\mathbf{F}}^{nT} = \widetilde{\mathbf{S}}^{nT}\mathbf{X}^{nT}$, with $\widetilde{\mathbf{F}}^{nT} = \left(\widetilde{\mathbf{f}}_1^{nT}...\widetilde{\mathbf{f}}_T^{nT}\right)$ a $(r\times T)-$matrix of the stacked estimated factors;

(vi) let $\widetilde{\chi}_{i,T+h|T}^{nT}$ be the h-step ahead factor forecasts of the common component of the i-th variable given T observations of n time series variables. The forecasts for the dynamic common component can be obtained by projecting the $(t+h)-$dated unobserved common component χ_{t+h}^{nT} on the t-dated factors $\widetilde{\mathbf{f}}_t^{nT}$, which for variable i results in:

$$\widetilde{\chi}_{i,T+h|T}^{nT} = \left[\widetilde{\Gamma}_{\chi}^{nT}(h)\right]_i \widetilde{\mathbf{S}}^{nT\prime} \left(\widetilde{\mathbf{S}}^{nT} \widetilde{\Gamma}_{\mathbf{X}}^{nT}(0) \widetilde{\mathbf{S}}^{nT\prime}\right)^{-1} \widetilde{\mathbf{S}}^{nT} \mathbf{X}^{nT} \tag{A.2}$$

Evidently, the in-sample estimator for the common component can be obtained by setting $h = 0$.

Step (i) until step (iii) allow to estimate the dynamic factor model. The estimated cyclical common component $\widetilde{\phi}_{nt}$ is calculated by applying time filters to the x´s before averaging along the cross-section. The dynamic estimation method consists of two-sided filters and cannot be applied at the end of the sample, which is the most important part for forecasting. By truncating the time filters, the performance of the estimator deteriorates as t approaches T. Therefore in step (v), FHLR construct generalized principal components $\mathbf{F}^{nT}$, which are contemporaneous averages of $\mathbf{X}^{nT}$ that minimize the ratio of the variance of the idiosyncratic to common component.

B Dutch data set

The appendix describes the data set for the Dutch economy. The aim is to construct an exhaustive collection covering different economic spheres, which gives a balanced representation of the economy and of the forces influencing it. For this purpose, the data set for the macroeconometric model MORKMON of De Nederlandsche Bank is screened and supplemented with a set of macro variables of forward looking nature. The data set consists of stock variables of five sectors, namely households, business, monetary financial institutions, government and external world, and the variables describing the flows between these sectors. The data set is screend on variables that are available only at a yearly frequency, especially within the sphere of public finance and social security, taxation and capital formation. This data set is supplemented with sectorally disaggregated production series, surveys and leading indicators, external economic developments and international financial developments as transmitted by equity prices, a broader set of interest rates, exchange rates and commodity prices. The data is preferably collected on a seasonally (and calender effects) adjusted basis at a quarterly sampling frequency. Some of the series available on a quarterly frequency are only disposable in raw format and are seasonally adjusted by applying the census-X12 method. Other series like interest rates, exchange rates and equity prices are kept in raw format.

Table B.1 lists all the series and the columns report respectively the description of the variable, unit of measurement, transformation code to render the variable stationary and the original data source. The automated procedure of TRAMO (cf Gómez and Maravall, 1996) is applied to correct the data for outliers and missing observations. Subsequently, the time series are rendered stationary by following one of the codes: 1 = no transformation for capacity utilization rates, unemployment rates, ratios and interest rate spreads, 2 = first difference for interest rates, surveys, sentiment indicators and, in general, (nonstationary) series possessing negative values like balance of payments statistics, 3 = first difference of logarithms producing quarterly growth rates for the vast majority of the series and 4 = second difference of logarithms for nonstationary series like wages, consumer prices, producer prices, commodity prices and monetary aggregates. These stationarity inducing transformations are imposed without employing formal unit root testing procedures following the practice of Stock and Watson (2002b).

As is required for factor estimation, the variables were standardized by subtracting their mean and then dividing by their standard deviation. This standardization is necessary to avoid overweighting of large variance series in the factor estimation. The full data set consists of 124 series that can be divided equally into six different categories labeled GDP, industrial production, prices, financial, external and surveys. The sample period runs from 1980Q1 until 2003Q4. Moreover, the data are collected in the second quarter of 2004 and represents therefore the fully revised historical series, or equivalently, the 2004Q2 snapshot of the data.

Table B.1: Description of data set (1)

#	Description	Unit	Transformation code[a]	Original source[b]
	Group 1: GDP, gross value added and real activity			
1	Gross domestic product by expenditure, constant prices	mil. euro 95	3	CBS
2	Private final consumption expenditure incl. NPI-h, constant prices	mil. euro 95	3	CBS
3	Government final consumption expenditure, constant prices	mil. euro 95	3	CBS
4	Gross fixed capital formation, constant prices	mil. euro 95	3	CBS
5	Gross fixed capital formation of dwellings, constant prices	mil. euro 95	3	CBS
6	Gross fixed captial formation of machinery and equipment, constant prices	mil. euro 95	3	CBS
7	Gross domestic product by expenditure, OECD (25), constant prices	index 1995=100	3	OECD, QNA
8	Compensation of employees	mil. euro	4	CBS
9	Unemployment	persons*1000	4	CBS
10	Number of jobs employees	jobs*1000	4	CBS
11	Negotiated wage (monthly base)	index 1995=100	4	CBS
12	Collective final consumption expenditure of general government	mil. euro	3	CBS
13	Capital formation excluding changes in inventories (sector), constant prices	mil. euro 95	3	CBS
14	Negotiated wage (monthly base)	index 1995=100	4	CBS
15	Residence permits granted	number	3	CBS
16	Houseprices	euro * 1000	4	Kadaster
17	Negotiated wage (all sectors: monthly base)	index 1995=100	4	CBS
18	hourly wages, industry	index 2000=100	4	CBS
19	issued vehicle registration certificates	number (end of period)	3	CBS
20	Composite Leading Indicator (trend restored)	indicator	2	DS
21	WO business cyle indicator NL	indicator	1	DNB - division WO
	Group 2: Industrial Production and capacity utilization			
22	Productive hours worked per employee in construction	index 1995=100	4	CBS
23	Capacity utilization in manufacturing industry	%	3	CBS
24	World capacity utilization in manufacturing industry	index 1995=100	3	OECD
25	production of consumptiongoods (average daily production)	index 2000=100	3	CBS
26	production of investementgoods (average daily production)	index 2000=100	3	CBS
27	average daily production - production industries	index 2000=100	3	CBS
28	average daily production - energycompanies and waterworks	index 2000=100	3	CBS
29	average daily production - mineral extraction	index 2000=100	3	CBS
30	average daily production - industry	index 2000=100	3	CBS
31	labour productivity, production per employed person	index 2000=100	3	CBS
32	earnings per employee, private businesses, general government and other sectors	index 1995=100	3	DNB/CBS
33	production per employee, private businesses, general government and other sectors	index 1995=100	3	DNB/CBS
34	labour costs per unit, private businesses, general government and other sectors	index 1995=100	3	DNB/CBS
35	capacity utilization manufacturing industry	percentage	2	DS
36	capacity utilization intermediate and final goods	percentage	2	CBS
37	capacity utilization consumer goods	percentage	2	CBS
38	capacity utilization investment goods	percentage	2	CBS
39	capacity utilization intermediate products	percentage	2	CBS
40	labour costs per unit product, processing industry	index 1995=100	3	EC
41	industrial turnover, foreign market, manufacturing	index 2000=100	3	CBS
42	industrial turnover, domestic market, manufacturing	index 2000=100	3	CBS

Notes.

[a]: 1 = no transformation; 2 = first differences; 3 = first difference of logarithms producing quarterly growth rates; and 4 = second difference of logarithms for nonstationary series.

[b]: BIS Bank of International Settlements; CBS Central Bureau of Statistics; DNB-FM De Nederlandsche Bank, divisie Financiële Markten; DS Datastream; EC European Commission; ECB European Central Bank; HWWA Institut fur Wirtschaftsforschung; OECD, QNA Organisation for Economic Co-operation and Development, Quarterly National Accounts.

Description of data set (2)

#	Description	Unit	Transformation code[a]	Original source[b]
	Group 3: Prices			
43	Large scale price of natural gas	eurocent p/m3	4	CBS
44	Foreign consumer price	index 1995=100	4	SIR
45	HICP component housing	index 1995=100	4	CBS
46	gas price index, small-scale, excl.vat	index 1990=100	4	CBS
47	spot crude oil UK Brent	US-dollar per barrel	4	OPEC
48	world market commodity prices, overall (euro area)	index 2000=100	4	HWWA
49	world market commodity prices, overall excl. energy (euro area)	index 2000=100	4	HWWA
50	world market commodity prices, food and luxury foods (euro area)	index 2000=100	4	HWWA
51	world market commodity prices, industrial materials (euro area)	index 2000=100	4	HWWA
52	world market commodity prices, agricultural-industrial materials (euro area)	index 2000=100	4	HWWA
53	world market commodity prices, metals (euro area)	index 2000=100	4	HWWA
54	world market commodity prices, energy-components (euro area)	index 2000=100	4	HWWA
55	Producer prices, sale, industry, dom.+for.market, total interm.+final products	Index 2000=100	4	CBS
56	Producer prices, large-scale gas consumption, dom.+for.market (index)	Index 1990=100	4	CBS
57	Consumerprice index NL, total CPI, all households	Index 2000=100	4	CBS
58	Consumerprice index NL, underlying inflation	Index 2000=100	4	CBS
59	Consumerprice index NL, energy	Index 2000=100	4	CBS
60	Consumerprice index NL, vegetables and fruit	Index 2000=100	4	CBS
	Group 4: Financial			
61	Short term interest rate	%-point	2	DNB-FM
62	Long term interest rate	%-point	2	DS
63	Exchange rate	dollar per euro	3	ECB
64	Domestic stock market prices	1983-IV=100 (end)	4	CBS
65	British pound per euro	number	3	ECB
66	Japanese yen per euro	number	3	ECB
67	Effective return om government bonds	percent	2	CBS
68	Effective return on national loan (3-5 year)	percent	2	CBS
69	Effective return on national loan (5-8 year)	percent	2	CBS
70	Effective return on bank-bonds	percent	2	CBS
71	Effective return on mortgage bonds	percent	2	CBS
72	M1	mil. euro	4	ECB
73	M3 (money in circulation inclusive)	mil. euro	4	ECB
74	spread (67 - 61)		1	calculation
75	spread (68 - 61)		1	calculation
76	spread (69 - 61)		1	calculation
77	spread (rl - 61)		1	calculation
78	Amsterdam Midkap-index	index 830103=45,4(EUR)	4	Euronext Amsterdam
79	stock prices, CBS General	index 1983=100	4	CBS
80	stock prices, internationals	index 1983=100	4	CBS
81	stock prices, inland (domestic)	index 1983=100	4	CBS
82	stock prices, financial institutions	index 1983=100	4	CBS
83	stock prices, non-financial institutions	index 1983=100	4	CBS
84	stock prices, general reinvestment index	index 1983=100	4	CBS

Notes. See Table B.1.

Description of data set (3)

#	Description	Unit	Transformation code[a]	Original source[b]
	Group 5: External Sector			
85	gdp germany	mil. euro 95	3	ECB
86	gdp belgium	mil. euro 95	3	ECB
87	gdp united kingdom	mil. Br. pound 95	3	ECB
88	gdp united states	bil. US-dollar 2000	3	BIS
89	gdp japan	bil. Jap. yen 95	3	BIS
90	gdp france	mil. euro 95	3	ECB
91	gdp italy	mil. euro 95	3	ECB
92	exports of goods	mil. euro	4	DNB, balance of payments section
93	imports of goods	mil. euro	4	DNB, balance of payments section
94	balance on goods	mil. euro	1	DNB, balance of payments section
95	exports of services	mil. euro	3	DNB, balance of payments section
96	imports of services	mil. euro	3	DNB, balance of payments section
97	balance on services	mil. euro	2	DNB, balance of payments section
98	receipts (income account)	mil. euro	3	DNB, balance of payments section
99	expenditures (income account)	mil. euro	3	DNB, balance of payments section
100	balance on income	mil. euro	2	DNB, balance of payments section
101	receipts (current transfers account)	mil. euro	3	DNB, balance of payments section
102	expenditures (current transfers account)	mil. euro	3	DNB, balance of payments section
103	net current transfers	mil. euro	2	DNB, balance of payments section
104	balance on current account	mil. euro	2	DNB, balance of payments section
105	inland volume of trade NCM	mil. euro	3	Nederlandse Crediet Maatschappij
106	IFO-indicator	index 2000=100	1	IFO-Institut
	Group 6: Surveys			
107	consumer confidence	percentage	2	DS
108	producer confidence	percentage	2	DS
109	nl business tendency survey: mfg. - export orders inflow	percentage	2	DS - OECD
110	nl business tendency survey: mfg. - finished goods stocks	percentage	2	DS - OECD
111	nl business tendency survey: mfg. - future production	percentage	2	DS - OECD
112	nl business tendency survey: manufacturing - order books	percentage	2	DS - OECD
113	nl business tendency survey: manufacturing - ordersinflow	percentage	2	DS - OECD
114	nl business tendency survey: manufacturing - production	percentage	2	DS - OECD
115	nl construction survey: order book position	index - diffusion	2	DS - EC
116	nl consumer opinion survey: confidence indicator	percentage	2	DS - OECD
117	nl industry survey: capacity utilisation	index - diffusion	2	DS - EC
118	nl industry survey: current production capacity	index - diffusion	2	DS - EC
119	nl industry survey: export expectation for mo. ahead	index - diffusion	2	DS - EC
120	nl industry survey: mth. prod. assured by order book	index - diffusion	2	DS - EC
121	nl industry survey: new order pstn. in recent months	index - diffusion	2	DS - EC
122	nl industry survey: order book position	index - diffusion	2	DS - EC
123	nl industry survey: prod.expectation for mth. ahead	index - diffusion	2	DS - EC
124	nl industry survey: stocks of finished goods	index - diffusion	2	DS - EC

Notes. See Table B.1. Bank of International Settlements; CBS Central Bureau of Statistics; DNB-FM De Nederlandsche Bank, divisie Financiële Markten; DS Datastream; EC European Commission; ECB European Central Bank; HWWA Institut fur Wirtschaftsforschung; OECD, QNA Organisation for Economic Co-operation and Development, Quarterly National Accounts.