2008 | 23

Working Paper

Research Department

Estimating the output gap in real time: A factor model approach

by Knut Are Aastveit and Tørres Trovik

NORGES BANK

Working papers fra Norges Bank kan bestilles over e-post:
tjenestetorget@norges-bank.no
eller ved henvendelse til:
Norges Bank, Abonnementsservice
Postboks 1179 Sentrum
0107 Oslo
Telefon 22 31 63 83, Telefaks 22 41 31 05

Fra 1999 og senere er publikasjonene tilgjengelige på www.norges-bank.no.

Working papers inneholder forskningsarbeider og utredninger som vanligvis ikke har fått sin endelige form.
Hensikten er blant annet at forfatteren kan motta kommentarer fra kolleger og andre interesserte.
Synspunkter og konklusjoner i arbeidene står for forfatternes regning.

Working papers from Norges Bank can be ordered by e-mail:
tjenestetorget@norges-bank.no
or from Norges Bank, Subscription service
P.O.Box. 1179 Sentrum
N-0107Oslo, Norway.
Tel. +47 22 31 63 83, Fax. +47 22 41 31 05

Working papers from 1999 onwards are available on www.norges-bank.no

Norges Bank's working papers present research projects and reports (not usually in their final form) and are intended inter alia to enable the author to benefit from the comments of colleagues and other interested parties.
Views and conclusions expressed in working papers are the responsibility of the authors alone.

ISSN 0801-2504 (printed) 1502-8143 (online)
ISBN 978-82-7553-476-5 (printed) 978-82-7553-477-2 (online)

Estimating the Output Gap in Real Time: A Factor Model Approach

Knut Are Aastveit† and Tørres G. Trovik‡ *

† University of Oslo and Norges Bank

‡ The World Bank and Norges Bank

December 9, 2008

*We have received helpful comments from Hilde C. Bjørnland, Jean Boivin, Domenico Giannone, Michele Modugno, Ragnar Nymoen and Shaun Vahey as well as conference participants at The 28th International Symposium on Forecasting in Nice, The 14th International Conference on Computing in Economics and Finance in Paris and The 4th Annual CIRANO Workshop on Data Revision in Macroeconomic Forecasting and Policy in Montreal and seminar participants at Norges Bank, University of Oslo and Universitat Pompeu Fabra. Views expressed are those of the authors and do not necessarily reflect the views of Norges Bank and The World Bank. E-mail: Knut Are Aastveit (corresponding author) at k.a.aastveit@econ.uio.no and Tørres G. Trovik at ttrovik@worldbank.org

Abstract

An approximate dynamic factor model can substantially improve the reliability of real time output gap estimates. The model extracts a common component from macroeconomic indicators, which reduces errors in the gap due to data revisions. The model's ability to handle the unbalanced arrival of data, also yields favorable nowcasting properties and thus starting conditions for the filtering of data into trend and deviations from trend. Combined with the method of augmenting data with forecasts prior to filtering, this greatly reduces the end-of-sample imprecision in the gap estimate. The increased precision has economic significance for real time policy decisions.

Keywords: Output gap, Real time analysis, Monetary policy, Forecasting, Factor model

JEL Classification: C33, C53, E52, E58

1 Introduction

Measurement of the output gap in real time is very unprecise. When additional information subsequently becomes available, one often sees large ex post revisions in the output gap. This poses a challenge for monetary policy which depends on a correct real time assessment of the current state of the economy. Monetary policy actions based on an erroneous output gap estimate could destabilize the economy.

There are several reasons for why the correct output gap in real time is so elusive. Macroeconomic data are released with a substantial time delay, and important data series are subsequently revised when less timely information becomes available. Moreover, most methods of computing the output gap allow the trend of the GDP series, i.e., the proxy for potential output, to vary over time. Thus, in real time it becomes challenging to allocate recent changes in the gap to changes *in* trend or to deviations *from* trend. That allocation will become more precise for one particular point in time when the subsequent observations become available. This end-of-sample problem is an important source of real time imprecision in the output gap.

In this paper, we study the potential of a dynamic factor model to improve the reliability of real time output gap estimates through two mechanisms. First, we proceed by using the factor model to extract a series for the common component in GDP from a large panel of related data. This series will be immune to revisions to the extent that these are due to unbiased measurement errors or idiosyncratic news. Indeed, we show that the factors obtained from the real time data set and from the final data set are almost identical, thus producing close to identical GDP estimates. Next, we calculate the output gap of the common component series, and show that these series now are almost invariant to data revisions. Using the factor model in this way we reduce the errors due to data revisions to a mere 8 per cent of revision errors in the standard approach. That factor models are robust to revision errors was conjectured in Giannone, Reichlin, and Small (2008).

Secondly, we address the end-of-sample problem by using the factor model to augment the time series for GDP with a nowcast. The factor model is able to handle a jagged edge in the data and incorporate new information on non-synchronized variables as they become available, i.e it can handle the unbalanced arrival of data. This improves the nowcasting performance of the model, and could thus reduce the end-of-sample problem in the output gap estimation. To the best of our knowledge this is the first paper to substantiate the importance of high quality nowcasts for output gap estimation in a real time data environment. We show that this information is indeed important for improving the reliability of real time output gap estimates. Furthermore, our approach can be combined with the augmentation method suggested by Mise, Kim, and Newbold (2005), where it is shown that augmenting the time series for GDP with forecasts up to 28 quarters ahead will improve the Hodrick and Prescott (1997) [HP] filter estimate of the trend and cycle towards the last observations of the series.[1] We focus on the HP filter as the detrending method of choice because it is widely used, it is simple and it allows for time variation in the trend estimate. Mise, Kim, and Newbold (2005) show that the HP filter is optimal for a wide class of time series. The overall performance of our suggested approach reduce total errors to about 25 percent of that of the standard approach.

Bernanke and Boivin (2003) was among the first to use a factor model on real time

[1]Watson (2007) finds similar results when estimating the trend with a Band-Pass filter.

data; confirming the usefulness, also on real time data, of using a large data set in forecasting. They used a factor model developed by Stock and Watson (2002b). Giannone, Reichlin, and Sala (2004) use a factor model to study monetary policy in real time and argues that a limited number of factors captures sufficient inference about the state of the economy needed to conduct monetary policy. Other related literature includes Garratt et al. (2008). While we use a dynamic factor model to moderate the effect of revisions, they attempt to model the revision process, or changes in vintages, through a cointegrating VAR model. Our approach is based upon the alternative assumption that revisions are idiosyncratic in nature and do not display a systematic pattern.

The reliability of estimates of the output gap in real time is studied by Orphanides and van Norden (2002). They find that across a wide selection of methods, the reliability of estimates are quite low. The estimation error for real time estimates are of the same magnitude as the gap itself and are highly volatile. Attribution of the error to various causes indicate that the end-of-sample problem is the most important reason for the estimation error. Cayen and van Norden (2005) and Bernhardsen et al. (2005) find similar results for respectively the Canadian and the Norwegian economy.

The factor model we use is similar to Giannone, Reichlin, and Small (2008). This model is a recent addition to the nowcasting literature. An approximate dynamic factor model is used to distill information from a very large cross section into factors, and then produce back-, now-, and forecasts with those factors as independent variables. The model performs well both on this US data set as well as for other economies, see e.g. Aastveit and Trovik (2008) for an application to Norway.

This paper is organized as follows: In the following section we present the factor model.

Section three presents our data and discuss model selection issues. Empirical results are discussed in section four. We first assess how much we can improve the imprecision due to data revisions, and then how much we can improve the imprecision due to the end-of sample problem. Section five illustrates the economic implications of our method by studying the magnitude of the interest rates implied by a simple Taylor rule. Finally, section six summarizes and concludes.

2 Model

We assume that the data, X_t, can be described by an approximate dynamic factor model similar to Giannone, Reichlin, and Small (2008). Let

$$X_t = \chi_t + \xi_t = \Lambda F_t + \xi_t \tag{1}$$

where χ_t is a common component driving the variation in X_t and ξ_t is a non-forecastable idiosyncratic component.[2] Λ is a $(n \times r)$ matrix of factor loadings and $F_t = \begin{pmatrix} f_{1t}, & \ldots, & f_{rt} \end{pmatrix}'$ are the factors. Typically the number of factors, r, is much smaller than the number of variables, n, thus securing a parsimonious model. The idiosyncratic component, $\xi_t = \begin{pmatrix} \xi_{1t}, & \ldots, & \xi_{nt} \end{pmatrix}'$, have zero expectation and a covariance matrix equal to $\Psi_t = E\left[\xi_t \xi_t'\right]$.

The factors evolve through time according to the vector autoregression

$$F_t = AF_{t-1} + Bu_t, \tag{2}$$

[2]The model is an approximate factor model, since in contrast to the strict factor model, the idiosyncratic terms in Equation 1 are allowed to be weakly correlated. See Chamberlain and Rothschild (1983), Forni et al. (2000) and Stock and Watson (2002a) for details.

where A is an $r \times r$ parameter matrix where all roots of $\det(I_r - Az)$ lie outside the unit circle, B is $r \times q$ of full rank q, and q is the number of common shocks in the economy, i.e., the dimension of u_t. We assume that the common shocks, u_t, follows a white-noise process and that $Q = E\left[Bu_t(Bu_t)'\right]$. In this model an r larger than q captures the lead and lag relations between common factors and common shocks. Equation (1) and (2) together define a state-space representation of an approximate dynamic factor model. See e.g. Forni et al. (2005) for details.

In Giannone, Reichlin, and Small (2008), equations (1) and (2) are estimated by a two-step procedure. First, parameters are estimated by OLS on principal components from the balanced part of the data set, i.e., the data set up to the last date for which there exists observations of all variables. These parameters and factors are used as initial values in a Kalman-filter re-estimation of the now possibly non-orthogonal factors. Moreover, the unbalanced part of the data set can be incorporated through use of the Kalman-filter. Missing observations are interpreted to have an infinitely large noise to signal ratio.[3] The ability to handle non-synchronized data makes it possible to evaluate the relative importance of blocks of new data releases in real time. The estimator is consistent under general assumptions and feasible for a very large cross section. There are no restrictions on the number of variables, N, relative to number of observations, T. Thus a parsimonious model is obtained. See Doz, Giannone, and Reichlin (2007) for details about the properties of the estimator.

Having obtained an estimate of the factors conditioned on all available information up to t, GDP growth is estimated as a simple projection, i.e., quarterly GDP growth is

[3]This is done by parameterazing the variance of the idiosyncratic component of the missing observations to infinity at the end of the sample.

regressed on the factors using OLS.[4] [5] Hence, we assume that the common factors capture the dynamic interaction among the dependent variables as well as the dynamics in GDP. Further, the estimated GDP growth series is transformed to levels. Finally, we obtain an estimate of the output gap by detrending the estimated GDP series in levels. In this final step various detrending methods can be applied. We choose to focus on HP filter as our method of choice for the detrending procedure because it is widely used, it is simple and it allows for time variation in the trend estimate.

We re-estimate our model once every quarter. The vintages corresponds to the information available at the middle of each quarter.

3 Data and Model selection

3.1 Data

We use the real time macroeconomic variables for the USA collected by Federal Reserve Bank of Philadelphia, see Croushore and Stark (2001) for details. In addition we use

[4]In this step, we have to bridge the monthly data from the factor model with the quarterly GDP growth. This is done by averaging the factors to obtain quarterly series. The time aggregation is such that the quarterly series corresponds to the third month of the quarter. Series in differences will then enter the factor model in terms of three month changes. This will be consistent with defining quarterly GDP growth as the three month average of monthly latent observations. See Giannone, Reichlin, and Small (2008) and Angelini et al. (2008) for details on this.

[5]Note that in this specification, lagged values of GDP are not included as a predictor.

real time financial and consumer price data.[6] In total we have a panel of 54 variables collected in real time vintages. While most of the variables, like the financial data, are not subject to revision after the initial release, 11 macro variables are subsequently revised. All variables have or are aggregated into a monthly frequency, but some variables are released in quarterly intervals. Hence in our analysis we use quarterly vintages of monthly real time data.

The first vintage we use is the 1984q1 vintage which we fill with data from 1970m1 to 1984m1. The last vintage we use is 2007q3, but its sample covers 1970m1 to 2003m10 only, to exclude observations that may subsequently be revised in the future. The database from Federal Reserve Bank of Philadelphia contains observations prior to 1970 as well but then only on a limited set of variables.

Financial data such as equity prices (returns), dividend yields, interest rates, currency rates and commodity prices are constructed as monthly averages of daily observations. All variables are transformed to induce stationarity and normalized to have expectations equal to zero and variance equal to one.[7] The full details of the data set and the

[6]CPI data do generally not undergo revisions similar to the other macroeconomic variables. Revisions are mainly due to changes in seasonal factors. We therefore use the final vintage of CPI data as a real time variable.

[7]This is crucial when estimating the factors with principal components.

transformations are reported in Appendix A.1.[8]

3.2 Number of factors

When using factor models, the number of factors is usually exogenously determined. Formal information criteria to elicit the optimal number of factors have been suggested, see e.g. Bai and Ng (2002), trading off good fit and parsimony. Applying the Bai and Ng (2002) criterium to our data yields a very high number of factors. This indicates that the method gives high importance to the fit of the model. We thus complement this method by the standard approach of gauging the marginal increase in total variance explained by including an additional factor or principal component.[9]

In Table 1 the percentage of the total variance explained by up to ten principal components is shown:

[8]Note that the model performs slightly worse on the real time data set that we use in this paper than on the quasi real time data set used in Giannone, Reichlin, and Small (2008). One reason may be that the number of data series available in real time is limited. While Giannone, Reichlin, and Small (2008) use a panel of 192 variables, we use the real time data available from the Federal Reserve Bank of Philadelphia together with macro variables and financial variables that are not subject to revisions, in total 54 variables.

[9]We have also tried to select the number of factors by applying the Bayesian Information Criteria (BIC) to the OLS regression of GDP growth on the factors. The resulting number of factors are rather unstable during the recursive estimation. It is unlikely that the number of factors driving the economy changes much during our sample period.

Number of PCs:	1	2	3	4	5	6	...	10
Percentage of total variance explained	0.30	0.52	0.60	0.67	0.72	0.77	...	0.87

Table 1: *Percentage of total variance explained by the first r static principal components. Based on data from 1970 to 2003.*

A few principal components explain a non-trivial fraction of the total variance in the data set, thus indicating collinearity between the transformed variables. A cut-off for marginal explanation of the next consecutive factor of less than five percentage points, implies a choice of six static factors. This number is in line with studies of Bai and Ng (2002), Stock and Watson (2002b), Bernanke and Boivin (2003) and Stock and Watson (2005). However the number is somewhat larger than what is used in Giannone, Reichlin, and Small (2008).

In the present application we will utilize both in-sample fit as well as forecasting, thus we will use a somewhat high number of factors like $r = 6$ when the model is used to estimate the ex-post GDP. However, the number of dynamic factors, i.e., shocks in the economy, may be smaller.[10] For a given $r = 6$, we apply the test of Bai and Ng (2007) to determine the number of dynamic factors. The resulting number of dynamic factors

[10]See for instance Bai and Ng (2007) for a detailed discussion of the relationship between static and dynamic factors.

are 2 to 3.[11] However, the combination $q = 3$ and $r = 6$, shows evidence of first order autocorrelation in the final projection of GDP on the factors. Autocorrelation is not evident when choosing $q = 2$ and $r = 6$. Hence, we chose this factor combination, but check other combinations for robustness of our results.

4 Empirical Results

Our conjecture is that a factor model can improve the precision of a real time output gap through two channels. First, a factor model can allocate a large data set into a common component and idiosyncratic noise. We will investigate whether this feature can be used to reduce imprecision in the output gap due to subsequent revision of macroeconomic data.

Second, the present factor model can make use of new information as it is released, i.e., the model can handle a jagged edge in the data set. This is useful when updating lagging variables like GDP with related information from more frequent and less lagging variables. Hence, this factor model's proven ability to produce good nowcasts, see Giannone, Reichlin, and Small (2008), can perhaps improve real time precision of the output gap by reducing the end-of-sample problem associated with many methods used to distinguish between trend and cycle in the GDP series.

We will address these two topics in sequence, first we discuss how to measure the precision of a real time output gap.

[11] Bai and Ng (2007) selects q as the smallest value that satisfies $D_1 = \frac{\widehat{\lambda}_{q+1}}{\sum_{i=1}^{r} \widehat{\lambda}_i} < q_{crit}$ or $D_2 = \frac{\sum_{i=q+1}^{r} \widehat{\lambda}_i}{\sum_{i=1}^{r} \widehat{\lambda}_i} < q_{crit}$, where $\widehat{\lambda}_i$ are the ordered eigenvalues from the sample covariance matrix of Bu_t and q_{crit} an appropriate critical value. In our application, D_1 and D_2 yields a different number of dynamic factors.

4.1 Benchmarking the real time output gap

The output gap represents the difference between current production and the economy's potential output. The gap is computed as the cycle obtained when decomposing a time series of GDP into a trend and cycle. There are several methods available for such a decomposition or detrending. In the following we use the term "standard approach" when detrending the log of GDP by the HP filter. See Canova (1998) for an overview of alternative detrending methods.

A key issue in this exercise is the choice of benchmark representing the true or final output gap. The real time literature has no definite answer to offer, e.g. Stark and Croushore (2002) use gaps computed on three alternative vintages of data: the most recent data, the last vintage before a structural revision (called benchmark vintages) and finally the vintage that is released a fixed period of time after the real time date.

We follow Orphanides and van Norden (2002) and choose the gap measured from the most recent vintage to represent the true gap estimate. That is, we compare the gap computed recursively on real time data up to the relevant point in time with a gap using the full sample of data currently available. Hence this latter full sample gap is computed on data which are finalized in terms of revisions and that cover the largest available time span. We use the vintage data of 2007q3 as final data, recognizing that final is very much an ephemeral concept in the measurement of macroeconomic variables. To reduce the probability of subsequent revisions of the last observations in what we define as the final vintage, we exclude the last 15 quarters of data. The last observation we use from the current 2007q3 vintage is thus the value for 2003q3. The benchmark has thus a forward bias in the sense that it uses information not available in real time. We will denote the output gaps computed on this vintage for $\texttt{GAP}_{\texttt{FIN}}$, and use that as a benchmark for comparison with various real time gap measures. We will denote gaps computed with the standard real time approach for $\texttt{GAP}_{\texttt{RT}}$.

Our benchmark $\texttt{GAP}_{\texttt{FIN}}$ could still change in the future, as pointed out in Croushore and Stark (2003). They divide data revisions into information-based revisions and structural revisions. The first captures revisions that occur because statistical agencies have additional source of information and update their estimates. The second capture revisions due to changes in the structure of the data accounting system, such as changes in aggregation methods and changes in base years. While our procedure of omitting the last 15 quarters of data would reduce the first type of revisions, it is not immune to the second type. However, to base the benchmark on the last vintage before a structural revision (i.e., a benchmark release) would neglect the fact that the latest observations in that vintage will be revised.

We check the robustness of our results with respect to different definitions of final data in two ways. First, we check if our results change by using the vintages 2004q3, 2005q3 or 2006q3 as final data, always excluding the last 15 quarters of observations. Second, we explore the effects of defining final data as the vintage one, two or three years after the real time date. We find that our results are robust to these different definitions of final data. Results are shown in Table A-2 and A-3 in the appendix.

We can decompose the difference between $\texttt{GAP}_{\texttt{RT}}$ and $\texttt{GAP}_{\texttt{FIN}}$ into one part due to revisions of data, and one part due to the end-of-sample effect. We introduce a second benchmark computed by using data that are finalized in terms of revisions but we use only the data spanning the same time period as $\texttt{GAP}_{\texttt{RT}}$, i.e., this is what is often called a quasi real time gap. We will call this benchmark for $\mathtt{GAP_{QRT}}$. Now the difference between $\mathtt{GAP_{RT}}$ and $\mathtt{GAP_{QRT}}$ will be imprecision due to data revisions only.

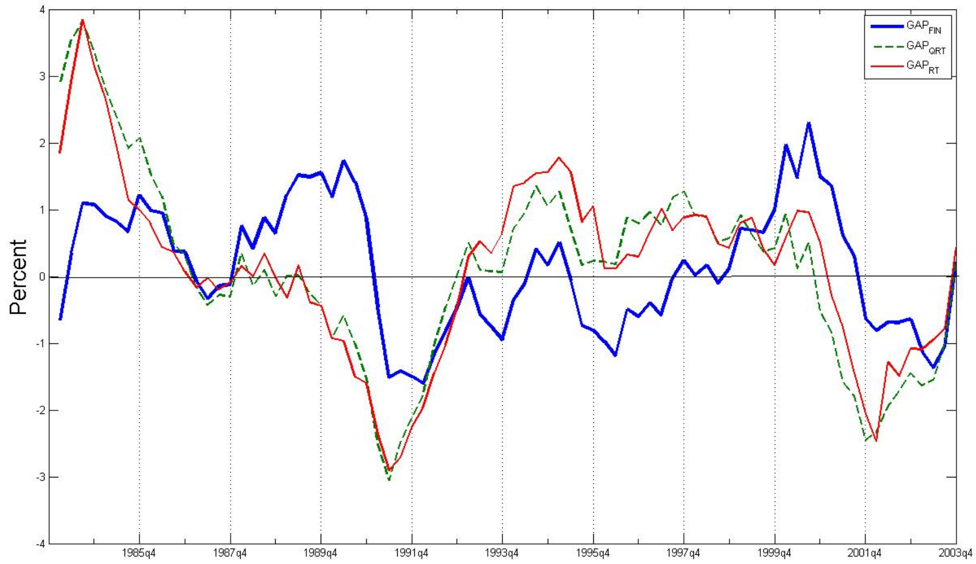

Figure 1: *Output gaps produced with the standard approach. The real time gap, $\mathtt{GAP_{RT}}$; quasi real time gap, $\mathtt{GAP_{QRT}}$; and the ex-post benchmark, $\mathtt{GAP_{FIN}}$. Output gaps produced with the HP-filter on data corresponding to vintages from 1984q1 through 2003q4.*

Figure 1 compares the standard approach for the real time gap ($\mathtt{GAP_{RT}}$), the quasi real time gap ($\mathtt{GAP_{QRT}}$) and the ex-post gap ($\mathtt{GAP_{FIN}}$) using a HP-filter as detrending method. This is similar in scope to the exercise done in Orphanides and van Norden (2002), but our data sample is different. Our data sample covers the period 1970q1 - 2003q4, with recursive simulations of the real time gap for the period 1984q1 - 2003q4.[12] Similar to Orphanides and van Norden (2002), we find that there is a considerable difference

[12]Orphanides and van Norden (2002) use a data sample for the period 1959q1 - 1997q4, with recursive simulations for the period 1965q1 - 1997q4.

between the three measures. However, it should be noted that the data revision problem is somewhat smaller in our sample.

To assess the difference between these measures we deviate from Orphanides and van Norden (2002) by focusing on the Mean Squared Error of the differences obtained from the recursive exercise rather than the mean of the differences. The mean of the differences can be small, despite large positive and negative errors data point by data point.

4.2 Imprecision due to the data revision problem

When we use the factor model to address the revision problem we use the model in the following way: We use our full panel of data and compute the dynamic factors as described in section 2. Note that GDP itself is not a part of the panel. This step will remove idiosyncratic noise from the panel and we are left with factors capturing the core movement in the panel variables. These factors are then regressed against real time GDP growth in a standard OLS. The estimated GDP growth from this OLS is transformed to levels and then detrended. Hence we use the in-sample estimated GDP from our factor model rather than the raw GDP data as input to the detrending method. We do not make any changes to the detrending method as such. We call the resulting real time output gap $\mathtt{GAP}_{\mathtt{RT-FM}}$, where subscript $\mathtt{FM}$ indicates that it is computed by using the factor model.

An important motivation for introducing the factor model is its scope for reducing the revision problem. To investigate the properties of $\mathtt{GAP}_{\mathtt{RT-FM}}$ in this respect we need to introduce a quasi real time output gap computed the same way as $\mathtt{GAP}_{\mathtt{RT-FM}}$, with the factor model. We call this benchmark for $\mathtt{GAP}_{\mathtt{QRT-FM}}$.

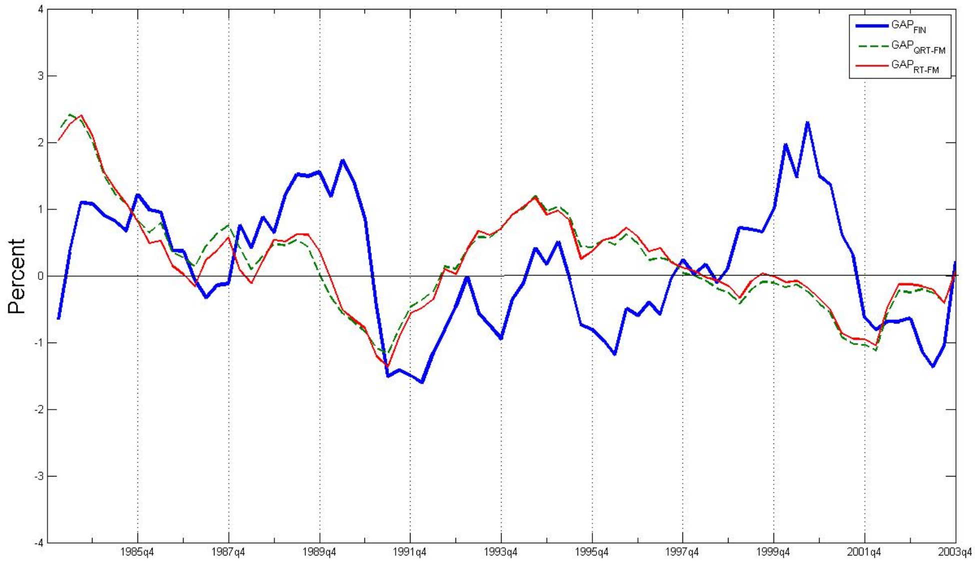

Figure 2: *Output gaps produced with the factor model approach. The real time gap, $GAP_{RT\text{-}FM}$; the quasi real time gap, $GAP_{QRT\text{-}FM}$; and the ex-post benchmark, GAP_{FIN}. Output gaps produced with the HP-filter on data corresponding to vintages from 1984q1 through 2003q4.*

Figure 2 shows the real time gap, $\mathtt{GAP}_{\mathtt{RT\text{-}FM}}$, and quasi real time gap, $\mathtt{GAP}_{\mathtt{QRT\text{-}FM}}$, produced with the factor model, together with the ex-post benchmark, $\mathtt{GAP}_{\mathtt{FIN}}$. Comparing the distance between the real time and quasi real time gaps in Figure 2 and Figure 1, we see that our factor model based output gap is much more robust relative to data revisions than the standard approach depicted in Figure 1. This result is confirmed in Table 2, where errors due to data revisions are only 8 per cent of what it is in the standard approach. Hence, we obtain a superior data revision performance when using the factor model. This confirms empirically the conjecture in Giannone, Reichlin, and Small (2008) that factor models are robust to data revisions.

Measure	Formula	HP
True real time performance	$\frac{mean((\texttt{GAP}_{\texttt{RT-FM}} - \texttt{GAP}_{\texttt{FIN}})^2)}{mean((\texttt{GAP}_{\texttt{RT}} - \texttt{GAP}_{\texttt{FIN}})^2)}$	0.71
Data revision performance	$\frac{mean((\texttt{GAP}_{\texttt{RT-FM}} - \texttt{GAP}_{\texttt{QRT-FM}})^2)}{mean((\texttt{GAP}_{\texttt{RT}} - \texttt{GAP}_{\texttt{QRT}})^2)}$	0.08
Quasi real time performance	$\frac{mean((\texttt{GAP}_{\texttt{QRT-FM}} - \texttt{GAP}_{\texttt{FIN}})^2)}{mean((\texttt{GAP}_{\texttt{QRT}} - \texttt{GAP}_{\texttt{FIN}})^2)}$	0.68

Table 2: *Relative Mean Squared Error between output gaps and their relevant benchmarks. Gaps are computed with the Hodrick-Prescott filter. A value below 1 indicates better performance of the gap to the left in the numerator of the formula. Time subscripts are suppressed. Based on vintages from 1984q1 to 2007q3, spanning time series from 1970m1 to 2003m10.*

Figure 3 compares the real time output gap calculated by the standard approach, $\texttt{GAP}_{\texttt{RT}}$, the real time gap for the estimated series, $\texttt{GAP}_{\texttt{RT-FM}}$, and the ex-post benchmark, $\texttt{GAP}_{\texttt{FIN}}$. Measured by Mean Square Error (MSE), we find that the MSE of $\texttt{GAP}_{\texttt{RT-FM}}$ versus $\texttt{GAP}_{\texttt{FIN}}$ is 71 percent of the MSE of $\texttt{GAP}_{\texttt{RT}}$ versus $\texttt{GAP}_{\texttt{FIN}}$. Hence, also the overall performance of our gap measure is superior to that of the standard approach. Notice, that $\texttt{GAP}_{\texttt{RT-FM}}$ performs especially well during the period from 1987 throughout 1995. It seems to capture both the productivity growth during the early 90s as well as the boom in the late 80s quite well. However, the good performance decrease towards the end of the sample. This indicates that our model has problems capturing the consumption driven boom starting in the late 1990s. There could be several reasons for this. First, it may indicate instability

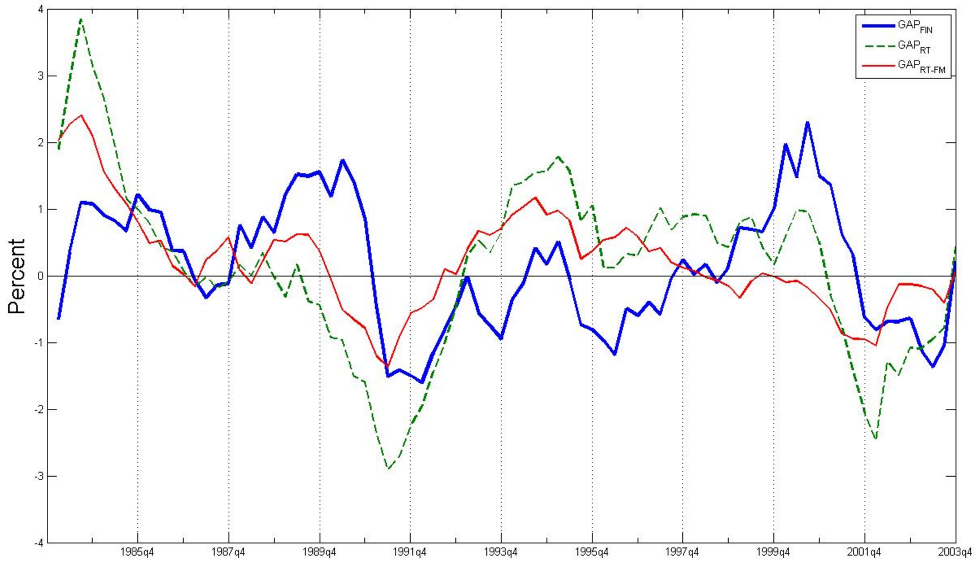

Figure 3: *The real time output gap calculated by the standard approach,* GAP_{RT}*; the real time gap for the estimated series,* GAP_{RT-FM}*; and the ex-post benchmark,* GAP_{FIN}*. Output gaps produced with the HP-filter on data corresponding to vintages from 1984q1 through 2003q4.*

in the OLS regression of GDP growth on the factors.[13] However, the coefficients from the recursive estimation of the OLS equation, are stable over time. Figure A-1 in the appendix, shows the coefficients from a recursive estimation using the final data vintage.[14] Second, it might be the case that the factors simply do not capture all the relevant information for this boom. Since we are using a real time data set, our data set is very

[13]Results in Banerjee, Marcellino, and Masten (2008) and Stock and Watson (2008) indicate that instability in the forecasting equation is the most important reason for breakdowns in factor model forecasts. While both papers conclude that factor models in general seem more robust to structural breaks than other forecasting methods.

[14]This is a representative data vintage. Similar results hold for other data vintages. Note that it is only the two first factors that are statistical significant at a 5 percent significance level.

limited. For instance, variables from the housing and credit market are not included in our data set. These variables are expected to carry important information for the consumption driven boom.

The panel of data that we use contains 54 variables in total, of which only 11 are subject to revision. To test whether our result is due to our factor model allocating low weights to the variables that are revised, we compute factors on a reduced data set as well, where the 11 subsequently revised variables are excluded. Table 3 shows the correlation between all of the six factors used in our approach computed with and without the 11 variables. We see that the first factor is not very much affected by excluding the 11 variables, however these variables play a significant role in determining the remaining factors. Still, our approach seem to mask the effect of revisions in these variables, as our initial conjecture suggested.

Factor number:	1	2	3	4	5	6
Corr(full panel, reduced panel)	0.99	0.93	-0.55	0.93	0.49	-0.67

Table 3: *Correlation between factors computed on the full panel and factors computed with 11 potentially revised variables excluded. Correlations for the first six consecutive factors.*

4.3 Imprecision due to the end-of-sample problem

The end-of-sample problem is well illustrated for the HP filter in Figure 1. The difference between $\texttt{GAP}_{\texttt{QRT}}$ and $\texttt{GAP}_{\texttt{FIN}}$ is due to the extended, full sample being used in $\texttt{GAP}_{\texttt{FIN}}$, while $\texttt{GAP}_{\texttt{QRT}}$ is computed using data available up to each point in time only. All data points used are identical in the two benchmarks[15]. The problem arise because future data contain information about whether the current state represents a movement along a cycle or a change in the trend of the series. Figure 1 confirms the observation in Orphanides and van Norden (2002) that the end-of-sample problem is the most important cause of imprecision in real time output gap measures. There are at least three ways of addressing the end-of-sample problem.

First, detrending methods can rely on more or less ex-ante specified structure in the time series model for GDP. Estimation of a time series model that allows a stochastic trend as well as a stochastic cycle can be less sensitive to an extension of the sample than a method assuming the time series is well estimated by, say, a linear trend; the outcome depends on what the true data generating process for the series is. For an unknown data generating process, choice of detrending method is a trade off between the risk of over-fitting a general process versus having a large end-of-sample problem from a strong (and erroneous) structural assumption on the process.

Second, the output gap represents the business cycle. Some simple variables, like unemployment and real investments or coincident indexes like Stock and Watson (1989), might be good real time indicators of the true business cycle and requires at most only

[15]The ex-post benchmark is computed with data up to 2003. Hence there is a "leakage" from the end-of-sample problem into the benchmark for the last part of the sample.

a simple demeaning rather then a full detrending procedure. Combining the real time measure of the output gap with such additional information might improve the precision of the output gap. Relying on real time indicators made up of one or a few data series is a trade off between accepting possibly spurious signals versus dealing with a problematic detrending procedure of the much broader GDP data.

Third, by using forecasts of future data points in the GDP series the real time sample can be extended. If the forecasts contain any true information, such a procedure should on average decrease the end-of-sample problem over time, see Mise, Kim, and Newbold (2005) for an extensive study of this idea. Making use of forecasts is a trade-off between extending the sample but possibly adding more model and estimation risk. While Mise, Kim, and Newbold (2005) test the method on simulated data we combine their method with our factor model framework and test the procedure on real time data.

In the following we investigate using the dynamic factor model in the two latter ways described above. That is, using information from real time indicators as well as from forecasts of future data points. See Orphanides and van Norden (2002) for an evaluation of various detrending methods qua the end-of-sample problem.

The panel of data that we use to obtain factors contains several variables that are used as coincident indicators of the business cycle. In addition, the panel contains financial data that could reflect expectations about future states of the cycle. These factors are then connected to GDP growth through the OLS. Hence in our approach we filter potential information in the coincident variables through the factor model rather than incorporate such information directly.

We focus on the factor model's proven ability to produce good short term forecasts, see Giannone, Reichlin, and Small (2008). This performance is related to the model's ability to make use of a jagged edge in the data set, hence more timely information can be used to produce good back-, now- and near term forecasts. The performance deteriorates for longer term forecasts. In the present application we set ourselves at the 15th in the middle month of each quarter, hence there are no need for a backcast since it has been released at that time. The model allows a more detailed data structure than what is applied here, hence the nowcasting performance is not exploited fully. See Giannone, Reichlin, and Small (2008) for details.

To include longer term forecast we use the method of Mise, Kim, and Newbold (2005). While Mise, Kim, and Newbold (2005) test the method on simulated data we combine their method with our factor model framework and test the procedure on real time data. We do this in two ways. First, we use data from our factor model (including the nowcast) and expand the series with 28 periods of forecasts from an AR(1).[16] We call the resulting gap $\mathtt{GAP}_{\mathtt{RT\text{-}FM\text{-}AR}}$. Second, we use real time GDP series and include the nowcast from our factor model. We then expand the series with 28 periods of forecast from an AR(1). The resulting gap is called $\mathtt{GAP}_{\mathtt{RT\text{-}FM\text{-}NOW\text{-}AR}}$.

[16] Mise, Kim, and Newbold (2005) found it sufficient to expand the series with 28 periods of forecast for quarterly data.

Sample	True real time performance	Quasi real time performance
Observed data only	0.71	0.68
Factor model data and 28 forecast	0.43	0.42
Factor Model nowcast and 28 forecasts	0.26	0.25

Table 4: *Performance of the factor model approach and the effect of forecast augmentation before extracting the cycle, relative to the standard approach. Ratios of Mean Squared Error relative to $\texttt{GAP}_{\texttt{FIN}}$. The HP-filter is used as detrending method.*

Figure 4 and Table 4 show that the end-of-sample problem can be reduced by using the forecast augmented gaps explained above. Formulas behind the measures can be seen in Table 2. $\texttt{GAP}_{\texttt{RT-FM-FOR}}$ reduces the total errors of the real time gaps to about 43 percent of that of the standard gap. The error is further reduced by $\texttt{GAP}_{\texttt{RT-FM-NOW-AR}}$ to about 25 percent of the standard gap. In the calculation of this gap, the factor model only contributes with its nowcast. This indicates that there are important dynamics in the real time GDP series that are not captured by the factor model.[17] We would expect this problem to be smaller for a larger and more heterogenous data set. The results also illustrates that the most important contribution from the factor model is to provide reliable starting conditions rather than reducing the data revision problem.

[17]We have tried to include lagged values of GDP growth in the OLS regression. However, it did not improve the results.

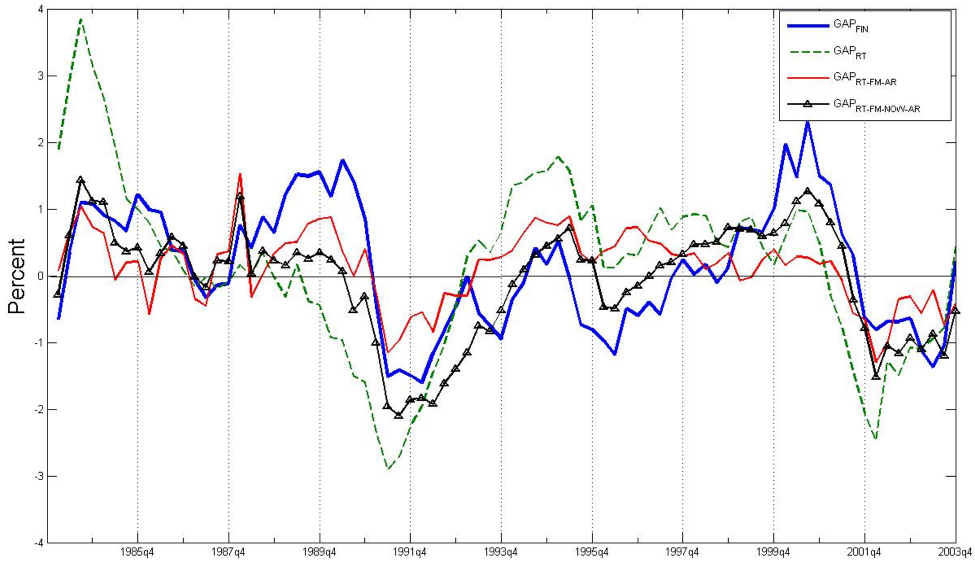

Figure 4: *The real time output gap calculated by the standard approach,* GAP_{RT}*; the real time gap when including nowcast from a factor model and then augmented with 28 forecasts from an AR(1),* $GAP_{RT\text{-}FM\text{-}NOW\text{-}AR}$*; the real time gap when using factor model data including nowcast and then augmented with 28 forecasts from an AR(1),* $GAP_{RT\text{-}FM\text{-}AR}$*; and the ex-post benchmark,* GAP_{FIN}*. Output gaps produced with the HP-filter on data corresponding to vintages from 1984q1 through 2003q4.*

Finally, the small difference between the true real time performance and the quasi real time performance indicates that the data revision problem is small also when forecasts are included in the sample for the factor approach.

5 Economic implications

The economic significance of the different output gaps, can be roughly illustrated by studying the magnitude of the interest rates implied by a simple Taylor rule. Taylor rules are simple monetary policy rules that prescribe how a central bank should adjust its interest rate policy in a systematic manner. The usefulness of Taylor rules for the analysis of historical policy and for econometric evaluation of specific alternative strategies that a central bank can use as the basis for its interest decisions, have been studied in Orphanides (2002) and Orphanides (2003).

Orphanides (2001) illustrates that there is a severe informational problem associated with the implementation and interpretation of such simple monetary policy rules. Real time policy recommendations differ considerably from those obtained with ex post revised data. Further, the studies above illustrates that monetary policy reactions are best captured by a forward looking policy rule, where central banks reacts to forecasts of inflation and output gaps.[18] However, since this is just an illustrative example, we choose to stick to the simple rule first proposed by Taylor (1993). We let the recommended level for the federal funds rate, f_t, in quarter t be given by the following simple rule

$$f_t = a_0 + a_\pi \pi_t + a_y y_t \tag{3}$$

where $a_0 = 1$ and $a_\pi = 1.5$ and $a_y = 0.5$.[19]

Our goal of this simple exercise, is to investigate how different are the implied interest rates from such a simple rule using different measures of the real time output gap. This will give an indication of the importance of the improvements in the measures of the real time gaps.

[18] See also Gali, Lopez-Salido, and Valles (2003) and Clarida, Gali, and Gertler (2000).

[19] Note that we do not rely on forecasts of inflation and output gaps. Hence, inflation and output gaps are lagging with one period in the policy rule. The coefficients in the Taylor rule are equal to the ones in Taylor (1993).

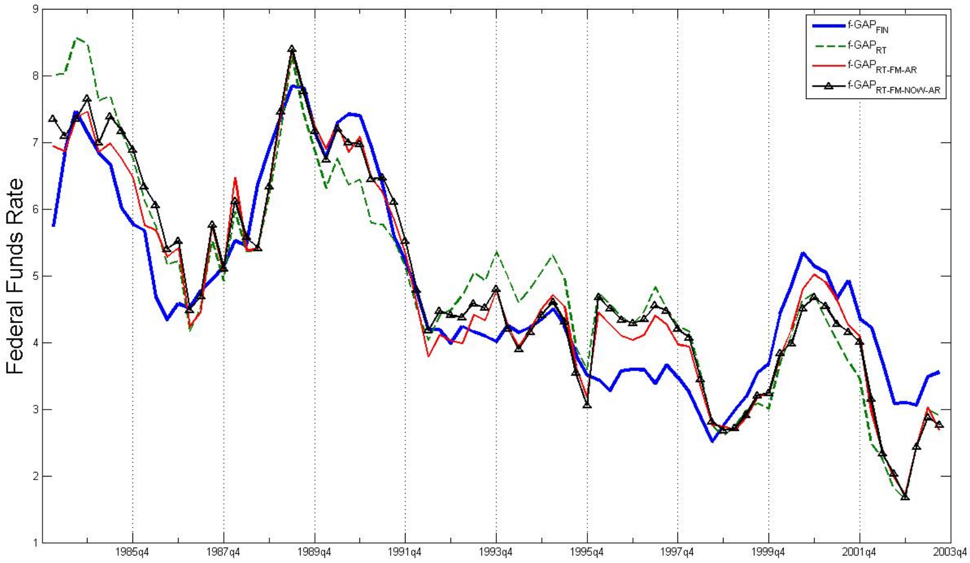

Figure 5: *Implied interest rates from a standard Taylor rule, where real time output gaps are calculated by the standard approach,* $f\text{-}GAP_{RT}$*; the real time gap using the estimated series including the nowcast and augmented with 28 forecasts from an AR(1)* $f\text{-}GAP_{RT\text{-}FM\text{-}AR}$ *; the real time gap when including nowcast from a factor model and then augmented with 28 forecasts from an AR(1),* $f\text{-}GAP_{RT\text{-}FM\text{-}NOW\text{-}AR}$ *and the ex-post benchmark,* $f\text{-}GAP_{FIN}$*. Output gaps produced with the HP-filter on data from 1984q1 through 2003q4.*

Figure 5 shows the implied interest rate from the standard Taylor rule using the different measures of the gap. The correlation between the implied interest rates are high for all the different gaps. In particular, they are all highly correlated with the benchmark interest rate, $\texttt{f-GAP}_{\texttt{FIN}}$. This is not very surprising given that the output gap has a relatively low weight compared to inflation in the Taylor rule. However, the figure illustrates that there are periods where the implied interest rates differ substantially. In particular, in the period from 1992 to 1995 the implied interest rate using the standard real time gap ($\texttt{f-GAP}_{\texttt{RT}}$) performs poorly. The standard gap fails to capture the productivity growth in this period. As a result the implied interest rate is too high in this period. On the other hand, the implied interest rate using one of the factor model gaps ($\texttt{f-GAP}_{\texttt{RT-FM-AR}}$ or $\texttt{f-GAP}_{\texttt{RT-FM-NOW-AR}}$) is close to the benchmark interest rate ($\texttt{f-GAP}_{\texttt{FIN}}$) for the same period. This illustrates that our method has significant economic implications for real time policy decisions.

6 Summary and conclusion

In this paper, we have shown that by using an approximate dynamic factor model we can substantially improve the reliability of real time output gap estimates through two mechanisms.

First, through the factor model we are able to handle a jagged edge in the data and incorporate new information from non-synchronized variables as they become available. This produce superior nowcasts and improves the starting conditions for the filter extracting deviations from trend in the GDP series. However as the forecasting properties of the factor model deteriorates rather quickly with a longer time horizon, we combine our approach with the augmentation method of Mise, Kim, and Newbold (2005)), where a simple autoregressive model is used to produce forecasts. Our approach reduce the forecasting error for the output gap to one quarter of that of the standard method.

Second, our proposed method for computing the real time output gap is very robust relative to data revisions. We have shown that with our approach, errors due to data revisions are only eight percent of errors when using the standard approach. To the extent that revisions are due to new idiosyncratic information or measurement errors, the factor model will allocate such information to an idiosyncratic component while our gap estimate is based on the forecastable, common component of the data.

However, our results confirm that it is the end-of-sample problem rather than the revision errors that are the main driver of the unreliability in real time gap measures. Even though our approach successfully reduce the uncertainty, there are still substantial uncertainty left in the real time gap measure.

Our results may be intertwined with the filtering method's ability to separate changes in trend from changes in deviation from trend. Research in progress focus on how our approach fares with alternative detrending methods to the HP filter, as well as alternative methods to estimate an output gap directly through the factor model.

References

Aastveit, K. A. and T. G. Trovik (2008): "Nowcasting Norwegian GDP: The role of asset prices in a small open economy," Working Paper 2007/09, Norges Bank.

Angelini, E., G. Camba-Mendez, D. Giannone, L. Reichlin, and G. Rnstler (2008): "Short-Term Forecasts of Euro Area GDP Growth," Technical Report.

Bai, J. and S. Ng (2002): "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 70(1):191–221.

——— (2007): "Determining the Number of Primitive Shocks in Factor Models," *Journal of Business & Economic Statistics*, 25:52–60.

Banerjee, A., M. Marcellino, and I. Masten (2008): "Forecasting Macroeconomic Variables Using Diffusion Indexes in Short Samples with Structural Change," CEPR Discussion Papers 6706, C.E.P.R. Discussion Papers.

Bernanke, B. S. and J. Boivin (2003): "Monetary policy in a data-rich environment," *Journal of Monetary Economics*, 50(3):525–546.

Bernhardsen, T., O. Eitrheim, A. S. Jore, and O. Roisland (2005): "Real-time data for Norway: Challenges for monetary policy," *The North American Journal of Economics and Finance*, 16(3):333–349.

Canova, F. (1998): "Detrending and business cycle facts," *Journal of Monetary Economics*, 41(3):475–512.

Cayen, J.-P. and S. van Norden (2005): "The reliability of Canadian output-gap estimates," *The North American Journal of Economics and Finance*, 16(3):373–393.

Chamberlain, G. and M. Rothschild (1983): "Arbitrage, Factor Structure, and Mean-Variance Analysis on Large Asset Markets," *Econometrica*, 51(5):1281–304.

Clarida, R., J. Gali, and M. Gertler (2000): "Monetary Policy Rules And Macroeconomic Stability: Evidence And Some Theory," *The Quarterly Journal of Economics*, 115(1):147–180.

Croushore, D. and T. Stark (2001): "A Real-Time Data Set for Macroeconomists," *Journal of Econometrics*, 105(1):111–130.

——— (2003): "A Real-Time Data Set for Macroeconomists: Does the Data Vintage Matter?," *The Review of Economics and Statistics*, 85(3):605–617.

Doz, C., D. Giannone, and L. Reichlin (2007): "A Two-Step Estimator for Large Approximate Dynamic Factor Models Based on Kalman Filtering," Technical Report 6043, C.E.P.R. Discussion Papers.

Forni, M., D. Giannone, M. Lippi, and L. Reichlin (2005): "Opening the Black Box: Structural Factor Models with Large Cross-sections," Manuscript, Universite Libre de Bruxelles.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2000): "The Generalized Dynamic-Factor Model: Identification And Estimation," *The Review of Economics and Statistics*, 82(4):540–554.

Gali, J., J. D. Lopez-Salido, and J. Valles (2003): "Technology shocks and monetary policy: assessing the Fed's performance," *Journal of Monetary Economics*, 50(4):723–743.

GARRATT, A., K. LEE, E. MISE, AND K. SHIELDS (2008): "Real Time Representation of the Output Gap," *The Review of Economics and Statistics*, 90(4):792–804.

GIANNONE, D., L. REICHLIN, AND L. SALA (2004): "Monetary Policy in Real Time," *NBER Macroeconomic Annual*, pages 161–200.

GIANNONE, D., L. REICHLIN, AND D. SMALL (2008): "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, 55(4):665–676.

HODRICK, R. J. AND E. C. PRESCOTT (1997): "Postwar U.S. Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking*, 29(1):1–16.

MISE, E., T.-H. KIM, AND P. NEWBOLD (2005): "On Suboptimality of the Hodrick-Prescott filter at time series endpoints," *Journal of Macroeconomics*, 27:53–67.

ORPHANIDES, A. (2001): "Monetary Policy Rules Based on Real-Time Data," *American Economic Review*, 91(4):964–985.

——— (2002): "Monetary-Policy Rules and the Great Inflation," *American Economic Review*, 92(2):115–120.

——— (2003): "Historical monetary policy analysis and the Taylor rule," *Journal of Monetary Economics*, 50(5):983–1022.

ORPHANIDES, A. AND S. VAN NORDEN (2002): "The Unreliability of Output-Gap Estimates in Real Time," *The Review of Economics and Statistics*, 84(4):569–583.

STARK, T. AND D. CROUSHORE (2002): "Forecasting with a real-time data set for macroeconomists," *Journal of Macroeconomics*, 24(4):507–531.

Stock, J. H. and M. W. Watson (1989): "New Indexes of Coincident and Leading Economic Indicators," *NBER Macroeconomic Annual*, pages 351–393.

——— (2002a): "Forecasting Using Principal Components From a Large Number of Predictors," *Journal of the American Statistical Association*, 97:1167–1179.

——— (2002b): "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business & Economic Statistics*, 20(2):147–62.

——— (2005): "Implications of Dynamic Factor Models for VAR Analysis," NBER Working Papers 11467, National Bureau of Economic Research, Inc.

——— (2008): "Forecasting in Dynamic Factor Models Subject to Structural Instability," in Castle, J. and N. Shephard, editors, *The Methodology and Practice of Econometrics, A Festschrift in Honour of Professor David F. Hendry*. Oxford University Press, Oxford.

Taylor, J. B. (1993): "Discretion versus policy rules in practice," *Carnegie-Rochester Conference Series on Public Policy*, 39:195–214.

Watson, M. W. (2007): "How accurate are real-time estimates of output trends and gaps?," *Economic Quarterly*, (Spr):143–161.

A Appendix

A.1 Description of data set

We apply the following transformations to the raw data in order to induce stationarity: 1 = No transformation, 2 = First differences, 5 = First differences in logs. Below is a complete description of the data set.

#	category	description	mnemonic	transformation
1	GDP	REAL GNP/GDP (SA)	ROUTPUT	1
2	Money	M1 MONEY STOCK (NSA)	M1	5
3	Money	M2 MONEY STOCK (NSA)	M2	5
4	Real Variables	CIVILIAN UNEMPLOYMENT RATE (SA)	RUC	2
5	Real Variables	CAPACITY UTILIZATION, TOTAL	CUT	2
6	Real Variables	CAPACITY UTILIZATION, MANUFACTURING	CUM	2
7	Real Variables	EMPLOYEES ON NONAGRICULTRAL PAYROLLS	EMPLOY	2
8	Real Variables	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING	IPM	5
9	Real Variables	INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX	IPT	5
10	Real Variables	INDEX OF AGGRETATE WEEKLY HOURS, TOTOAL	H	5
11	Real Variables	INDEX OF AGGRETATE WEEKLY HOURS, SERVICE SECTOR	HS	5
12	Real Variables	INDEX OF AGGRETATE WEEKLY HOURS, GOODS SECTOR	HG	5
13	Financials	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)	FSPCOM	5
14	Financials	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)	FSPIN	5
15	Financials	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)	FSDXP	2
16	Financials	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)	FSPXE	5
17	Interest rates	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)	FYFF	2
18	Interest rates	Cmmercial Paper Rate (AC)	CP90	2
19	Interest rates	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)	FYGM3	2
20	Interest rates	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)	FYGM6	2
21	Interest rates	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)	FYGT1	2
22	Interest rates	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)	FYGT5	2
23	Interest rates	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)	FYGT10	2
24	Interest rates	BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)	FYAAAC	2
25	Interest rates	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)	FYBAAC	2
26	Interest rates	cp90-fyff	scp90	1
27	Interest rates	fygm3-fyff	sfygm3	1
28	Interest rates	fygm6-fyff	sFYGM6	1
29	Interest rates	fygt1-fyff	sFYGT1	1
30	Interest rates	fygt5-fyff	sFYGT5	1
31	Interest rates	fygt10-fyff	sFYGT10	1
32	Interest rates	fyaaac-fyff	sFYAAAC	1
33	Interest rates	fybaac-fyff	sFYBAAC	1
34	Currency	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)	EXRUS	5
35	Currency	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)	EXRSW	5
36	Currency	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)	EXRJAN	5
37	Currency	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)	EXRUK	5
38	Currency	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)	EXRCAN	5
39	Prices	PRODUCER PRICE INDEX: FINISHED GOODS (82=100,SA)	PWFSA	5
40	Prices	PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (82=100,SA)	PWFCSA	5

#	category	description	mnemonic	transformation
41	Prices	PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS(82=100,SA)	PWIMSA	5
42	Prices	PRODUCER PRICE INDEX:CRUDE MATERIALS (82=100,SA)	PWCMSA	5
43	Prices	INDEX OF SENSITIVE MATERIALS PRICES (1990=100)(BCI-99A)	PSM99Q	5
44	Prices	NAPM COMMODITY PRICES INDEX (PERCENT)	PMCP	1
45	Prices	CPI-U: ALL ITEMS (82-84=100,SA)	PUNEW	5
46	Prices	CPI-U: APPAREL & UPKEEP (82-84=100,SA)	PU83	5
47	Prices	CPI-U: TRANSPORTATION (82-84=100,SA)	PU84	5
48	Prices	CPI-U: MEDICAL CARE (82-84=100,SA)	PU85	5
49	Prices	CPI-U: COMMODITIES (82-84=100,SA)	PUC	5
50	Prices	CPI-U: DURABLES (82-84=100,SA)	PUCD	5
51	Prices	CPI-U: SERVICES (82-84=100,SA)	PUS	5
52	Prices	CPI-U: ALL ITEMS LESS FOOD (82-84=100,SA)	PUXF	5
53	Prices	CPI-U: ALL ITEMS LESS SHELTER (82-84=100,SA)	PUXHS	5
54	Prices	CPI-U: ALL ITEMS LESS MIDICAL CARE (82-84=100,SA)	PUXM	5
55	Survey	U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)	HHSNTN	2

A.2 Tables

q/r	2	4	6	8	10
2	0.81	0.84	0.71	0.81	0.91
3	-	0.83	0.83	0.89	0.96
4	-	0.81	0.86	0.91	0.91
5	-	-	0.82	0.90	0.93

Table A-1: *Robustness of choice of number of factors. Performance of factor model approach relative to standard approach. Ratios of Mean Squared Errors relative to* $\mathtt{GAP}_{\mathtt{FIN}}$*, i.e.* $\frac{mean((\mathtt{GAP}_{\mathtt{RT\text{-}FM}} - \mathtt{GAP}_{\mathtt{FT}})^2)}{mean((\mathtt{GAP}_{\mathtt{RT}} - \mathtt{GAP}_{\mathtt{FT}})^2)}$

Measure	Last vintage	1 year after	2 year after	3 year after
True real time performance	0.71	0.63	0.73	0.77
Data revision performance	0.08	0.40	0.29	0.36
Quasi real time performance	0.68	0.46	0.56	0.72

Table A-2: *Relative Mean Squared Error between output gaps and their relevant benchmarks, i.e.* $\frac{mean((GAP_{RT\text{-}FM} - GAP_{QRT\text{-}FM})^2)}{mean((GAP_{RT} - GAP_{QRT})^2)}$*. We consider four different benchmark gaps. The gap calculated with the last vintage of data, with vintage 1 year after first release, 2 years after first release and 3 years after first release. Gaps are computed with the Hodrick-Prescott filter (HP). A value below 1 indicates better performance of the gap to the left in the numerator of the formula. Time subscripts are suppressed. Based on vintages from 1984q1 to 2007q3, spanning time series from 1970m1 to 2003m10.*

Measure	2003q4	2002q4	2001q4	2000q4
True real time performance	0.71	0.73	0.67	0.56
Data revision performance	0.08	0.09	0.09	0.09
Quasi real time performance	0.68	0.71	0.69	0.61

Table A-3: *Relative Mean Squared Error between output gaps and their relevant benchmarks, i.e.* $\frac{mean((GAP_{RT\text{-}FM} - GAP_{FT})^2)}{mean((GAP_{RT} - GAP_{FT})^2)}$. *We consider four different benchmark gaps. The gap calculated with 2003q4, 2002q4, 2001q4 and 2000q4 as the last observation of data. Gaps are computed with the Hodrick-Prescott filter (HP). A value below 1 indicates better performance of the gap to the left in the numerator of the formula. Time subscripts are suppressed. Based on vintages from 1984q1 to respectively 2007q3, 2006q3, 2005q3 and 2004q3 spanning time series from 1970m1 to respectively 2003m10, 2002m10, 2001m10 and 2000m10.*

A.3 Figures

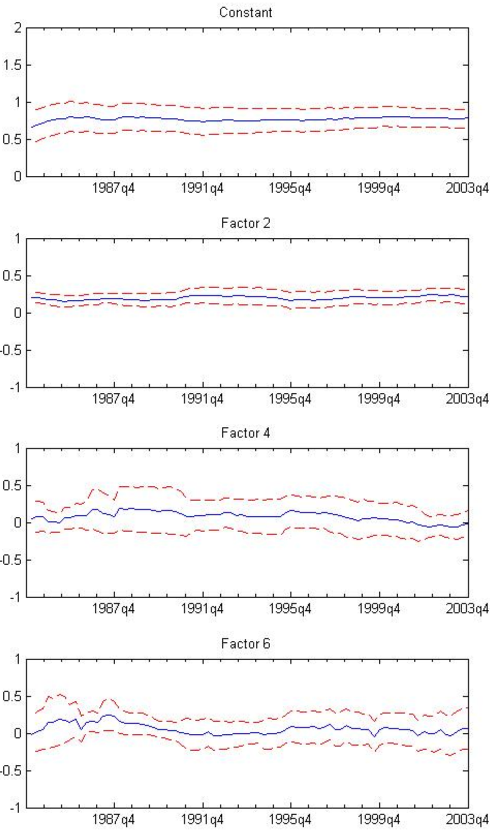

Figure A-1: *Estimates of the coefficients from the regression of GDP growth on the factors using the final data vintage. Recursive estimates with 95 percent confidence interval*

WORKING PAPERS (ANO) FROM NORGES BANK 2005-2008

Working Papers were previously issued as Arbeidsnotater from Norges Bank, see Norges Bank's website http://www.norges-bank.no

2005/1 Q. Farooq Akram
Efficient consumption of revenues from natural resources –
An application to Norwegian petroleum revenues Research Department, 33 p

2005/2 Q. Farooq Akram, Øyvind Eitrheim and Lucio Sarno
Non-linear dynamics in output, real exchange rates and real money balances: Norway, 1830-2003 Research Department, 53 p

2005/3 Carl Andreas Claussen and Øistein Røisland
Collective economic decisions and the discursive dilemma Monetary Policy Department, 21 p

2005/4 Øistein Røisland
Inflation inertia and the optimal hybrid inflation/price level target
Monetary Policy Department, 8 p

2005/5 Ragna Alstadheim
Is the price level in Norway determined by fiscal policy? Research Department, 21 p

2005/6 Tommy Sveen and Lutz Weinke
Is lumpy investment really irrelevant for the business cycle? Research Department, 26 p

2005/7 Bjørn-Roger Wilhelmsen and Andrea Zaghini
Monetary policy predictability in the euro area: An international comparison
Economics Department, 28 p

2005/8 Moshe Kim, Eirik Gaard Kristiansen and Bent Vale
What determines banks' market power? Akerlof versus Herfindahl Research Department, 38 p

2005/9 Q. Farooq Akram, Gunnar Bårdsen and Øyvind Eitrheim
Monetary policy and asset prices: To respond or not? Research Department, 28 p

2005/10 Eirik Gard Kristiansen
Strategic bank monitoring and firms' debt structure Research Department, 35 p

2005/11 Hilde C. Bjørnland
Monetary policy and the illusionary exchange rate puzzle Research Department, 30 p

2005/12 Q. Farooq Akram, Dagfinn Rime and Lucio Sarno
Arbitrage in the foreign exchange market: Turning on the microscope
Research Department, 43 p

2005/13 Geir H. Bjønnes, Steinar Holden, Dagfinn Rime and Haakon O.Aa. Solheim
"Large" vs. "small" players: A closer look at the dynamics of speculative attacks
Research Department, 31 p

2005/14 Julien Garnier and Bjørn-Roger Wilhelmsen
The natural real interest rate and the output gap in the euro area: A joint estimation
Economics Department, 27 p

2005/15 Egil Matsen
Portfolio choice when managers control returns Research Department, 31 p

2005/16 Hilde C. Bjørnland
Monetary policy and exchange rate interactions in a small open economy
Research Department, 28 p

2006/1 Gunnar Bårdsen, Kjersti-Gro Lindquist and Dimitrios P. Tsomocos
Evaluation of macroeconomic models for financial stability analysis
Financial Markets Department, 45 p

2006/2 Hilde C. Bjørnland, Leif Brubakk and Anne Sofie Jore
Forecasting inflation with an uncertain output gap Economics Department, 37 p

2006/3 Ragna Alstadheim and Dale Henderson
Price-level determinacy, lower bounds on the nominal interest rate, and liquidity traps
Research Department, 34 p

2006/4 Tommy Sveen and Lutz Weinke
Firm-specific capital and welfare Research Department, 34 p

2006/5 Jan F. Qvigstad
When does an interest rate path „look good"? Criteria for an appropriate future interest rate path Norges Bank Monetary Policy, 20 p

2006/6 Tommy Sveen and Lutz Weinke
Firm-specific capital, nominal rigidities, and the Taylor principle Research Department, 23 p

2006/7 Q. Farooq Akram and Øyvind Eitrheim
Flexible inflation targeting and financial stability: Is it enough to stabilise inflation and output? Research Department, 29 p

2006/8 Q. Farooq Akram, Gunnar Bårdsen and Kjersti-Gro Lindquist
Pursuing financial stability under an inflation-targeting regime Research Department, 29 p

2006/9 Yuliya Demyanyk, Charlotte Ostergaard and Bent E. Sørensen
U.S. banking deregulation, small businesses, and interstate insurance of personal income
Research Department, 57 p

2006/10 Q. Farooq Akram, Yakov Ben-Haim and Øyvind Eitrheim
Managing uncertainty through robust-satisficing monetary policy Research Department, 33 p

2006/11 Gisle James Natvik:
Government spending and the Taylor pinciple Research Department, 41 p

2006/12 Kjell Bjørn Nordal:
Banks' optimal implementation strategies for a risk sensitive regulatory capital rule: a real options and signalling approach Research Department, 36 p

2006/13 Q. Farooq Akram and Ragnar Nymoen
Model selection for monetary policy analysis – importance of empirical validity
Research Department, 37 p

2007/1 Steinar Holden and Fredrik Wulfsberg
Are real wages rigid downwards? Research Department, 44 p

2007/2 Dagfinn Rime, Lucio Sarno and Elvira Sojli
Exchange rate forecasting, order flow and macroeconomic information
Research Department, 43 p

2007/3 Lorán Chollete, Randi Næs and Johannes A. Skjeltorp
What captures liquidity risk? A comparison of trade and order based liquidity factors
Research Department, 45 p

2007/4 Moshe Kim, Eirik Gaard Kristiansen and Bent Vale
Life-cycle patterns of interest rate markups in small firm finance Research Department, 42 p

2007/5 Francesco Furlanetto and Martin Seneca
Rule-of-thumb consumers, productivity and hours Research Department, 41 p

2007/6 Yakov Ben-Haim, Q. Farooq Akram and Øyvind Eitrheim
Monetary policy under uncertainty: Min-max vs robust-satisficing strategies
Research Department, 28 p

2007/7 Carl Andreas Claussen and Øistein Røisland
Aggregating judgments on dependent variables: an (im)possibility result
Research Department, 17 p

2007/8 Randi Næs, Johannes Skjeltorp og Bernt Arne Ødegaard
Hvilke faktorer driver kursutviklingen på Oslo Børs? Forskningsavdelingen, 68 s

2007/9 Knut Are Astveit and Tørres G. Trovik
Nowcasting Norwegian GDP: The role of asset prices in a small open economy
Research Department, 29 p

2007/10 Hilde C. Bjørnland, Kai Leitemo and Junior Maih
Estimating the natural rates in a simple new Keynesian framework
Economics Department, 33 p

2007/11 Randi Næs and Bernt Arne Ødegaard
Liquidity and asset pricing: Evidence on the role of investor holding period
Research Department, 31 p

2007/12 Ida Wolden Bache
Assessing estimates of the exchange rate pass-through Research Department, 60 p

2007/13 Q. Farooq Akram
What horizon for targeting inflation? Research Department, 45 p

2007/14 Q. Farooq Akram, Yakov Ben-Haim and Øyvind Eitrheim
Robust-satisficing monetary policy under parameter uncertainty Research Depatrment, 33 p

2007/15 Ida Wolden Bache and Bjørn E. Naug
Estimating New Keynesian import price models Research Department, 40 p

2008/1 Anne Sofie Jore, James Mitchell and Shaun P. Vahey
Combining forecast densities from VARs with uncertain instabilities
Economics Department, 26 p

2008/2 Henrik Andersen
Failure prediction of Norwegian banks: A logit approach Financial Markets Department, 49 p

2008/3 Lorán Chollete, Randi Næs and Johannes A. Skjeltorp
The risk components of liquidity Research Department, 28 p

2008/4 Hilde C. Bjørnland and Kai Leitemo
Identifying the interdependence between US monetary policy and the stock market
Economics Department, 28 p

2008/5 Christian Kascha and Karel Mertens
Business cycle analysis and VARMA models Research Department, 40 p

2008/6 Alan S. Blinder
On the design of Monetary policy committees Norges Bank Monetary Policy, 22 p

2008/7 Francesco Furlanetto
Does monetary policy react to asset prices? Some international evidence
Research Department, 44 p

2008/8 Christian Huurman, Francesco Ravazzolo and Chen Zhou
The power of weather. Some empirical evidence on predicting day-ahead power prices through weather forecasts Research Department, 28 p

2008/9 Randi Næs, Johannes A. Skjeltorp and Bernt Arne Ødegaard
Liquidity at the Oslo Stock Exchange Research Department, 49 p

2008/10 Francesco Furlanetto and Martin Seneca
Fiscal shocks and real rigidities Research Department, 41 p

2008/11 Randi Næs, Johannes A. Skjeltorp and Bernt Arne Ødegaard
Liquidity and the business cycle Research Department, 45 p

2008/12 Q. Farooq Akram
Commodity prices, interest rates and the dollar Research Department, 33 p

2008/13 Henrik Andersen, Sigbjørn Atle Berg and Eilev S. Jansen
The dynamics of operating income in the Norwegian banking sector
Financial Markets Department, 27 p

2008/14 Lars Fredrik Øksendal
Monetary policy under the gold standard – examining the case of Norway, 1893-1914
Norges Bank's bicentenary project, 103 p

2008/15 Hilde C. Bjørnland and Jørn I. Halvorsen
How does monetary policy respond to exchange rate movements? New international evidence
Research Department, 45 p

2008/16 Hilde C. Bjørnland
Oil price shocks and stock market booms in an oil exporting country
Research Department, 37 p

2008/17 Özer Karagedikli, Troy Matheson, Christie Smith and Shaun Vahey
RBCs and DSGEs: The computational approach to business cycle theory and evidence
Research Department, 36 p

2008/18 Ida Wolden Bache and Kai Leitemo
The price puzzle: Mixing the temporary and permanent monetary policy shocks
Monetary Policy Department, 12 p

2008/19 Q. Farooq Akram, Dagfinn Rime and Lucio Sarno
Does the law of one price hold in international financial markets? Research Department, 43 p

2008/20 Amund Holmsen, Jan F. Qvigstad, Øistein Røisland and Kristin Solberg-Johansen
Communicating monetary policy intentions: The case of Norges Bank
Monetary Policy Department, 33 p

2008/21 Pelin Ilbas
Revealing the preferences of the US Federal Reserve Research Department, 52 p

2008/22 Christian Kascha and Francesco Ravazzolo
Combining inflation density forecasts Research Department, 39 p

2008/23 Knut Are Aastveit and Tørres G. Trovik
Estimating the output gap in real time: A factor model approach Research Department, 42 p

Knut Are Aastveit and Tørres Trovik: Estimating the output gap in real time: A factor model approach Working Paper 2008/23

KEYWORDS:
Output gap
Real time analysis
Monetary policy
Forecasting
Factor model