

The accuracy of a forecast targeting central bank*

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Abstract

This paper evaluates inflation forecasts made by Norges Bank which is a leading forecast targeting central bank. It is reasonable to expect that Norges Bank regularly produces inflation forecasts that outperform other forecasts, both 'naive' forecasts, and forecasts from econometric models that are specified and maintained outside the central bank. It is surprising that we find that the superiority of the bank's forecast cannot be asserted, when compared with genuine *ex-ante* real time forecasts from an outsider model. The 1-step Monetary Policy Report forecasts are preferable to the 1-step forecasts from the outside model, but for the policy relevant horizons (4 to 9 quarters ahead), the forecasts from the outsider model are preferred with a wider margin. An explanation in terms of too high speed of adjustment to the equilibrium inflation rate is supported by the evidence. Norges Bank's forecasts are convincingly better than 'naive' forecasts over the second half of the sample, but not over the whole sample, which includes a change in the mean of inflation.

Keywords: *Inflation forecasts, Monetary policy, Forecast comparison, Forecast targeting central bank, Econometric models.*

JEL classification: *C32, C53, E37, E44, E47, E52, E58, E65.*

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1 Introduction

Over the past two decades, several countries have adopted inflation targeting as a framework for monetary policy and the central banks' inflation forecasts have become the target for interest rate setting, see i.e., Svensson (1997). It would be favourable for forecast targeting if it could be asserted that the central bank's forecasting model is a good approximation to the true inflation process in the economy and that inflation is stationary and without intermittent regime shifts. Under these assumptions, there would be very few inflation forecast failures.

A forecast failure occurs when inflation outcomes are outside the forecast uncertainty intervals. Failures are not rare in economic forecasting, see Hendry (2001), and inflation forecasting is no exception, Nymoen (2005). The assumptions about model correctness and of stationary inflation may therefore have low relevance for practical forecast targeting.

Although inflation forecasting central banks must face up to the possibility of forecast failure, an occasional failure is not necessarily destructive to an inflation targeting regime. Woodford (2007) argues that if inflation is under-predicted for several periods, the forecast targeting bank can nevertheless "error correct" without loss of credibility by setting an interest rate which is forecasted to generate too low inflation for a period ahead. As a result, over an extended policy horizon, and with no new breaks in that period, the inflation rate may come out on target. Realistically however, breaks can occur at short intervals and can create repeated forecast failures which may wear down the belief in the inflation forecasts, and they may complicate policy decisions (see e.g, section 3 below).

In Norway, the central bank's inflation forecast has been the operational target of monetary policy since March 2001, and Norges Bank is regarded as a leading practitioner. For example, Woodford (2007) argues that the forecast targeting done by Norges Bank may be an example to be followed by the *US Federal Reserve*.¹ On the other hand, reviewers of Norwegian monetary policy have emphasized the need to evaluate the bank's forecasts and to work towards a clearer understanding of why relatively large inflation errors still occur, see Bjørnland et al. (2004, Ch 4.1 - 4.2) and Juel et al. (2008, Ch 4). The premise is of course that the policy decisions (interest rate setting) depends on the quality of the forecasts. The recognition of the importance of forecast accuracy is also shown by Norges Banks own annual evaluation of their forecasts, and by the priority given to data assembly and to the development of new forecasting methods.²

In this paper, we first review the main hindrances for accuracy in inflation forecasting, see section 2. Existing discussions focus mainly on data measurement problems and the real time aspects of forecasting, e.g., Orphanides (2003), Svensson and Woodford (2005). Experience and research show that there are other sources

¹"A forecast-targeting procedure similar to that of the Norges Bank could plausibly be introduced as a framework intended to ensure that policy conforms to the mandates of the Federal Reserve Act and to make this conformity more evident to Congress and to the public." Woodford (2007, p 22-23).

²Norges Bank's own evaluations are found in the the first Monetary Policy Report each year.

Norges Bank's *Annual Report 2008* (Ch 1) contains a comprehensive account of forecasting methods used. Model developments are summarized in *Annual Report 2007* , see <http://www.norges-bank.no>.

of forecast failure that can be equally important though. First, even for a correctly specified model, the occurrence of intermittent structural breaks in the economy will generate forecast failures see e.g., Clements and Hendry (1999, 2008). Second, in practice, model specification plays a large role in forecast targeting, see e.g., Bårdsen et al. (2003) and Akram and Nymoen (2009).

In particular, structural breaks in the means of economic theoretical equilibrium relationships are damaging for macroeconomic forecasts. Section 3, shows, by a simple example, that the policy consequences of such a break depend on the dynamics of the transmission mechanism and the degree of gradualism in the central bank's interest rate setting.

In section 4 we review some important developments in inflation forecasting in Norges Bank, and we present Monetary Policy Reports (MPRs) forecasts from the period 2002q1-2009q4.³ This provides the backdrop for the main contribution of the paper, which is a comparison of the MPR inflation forecasts with alternative real-time *ex ante inflation* forecasts. In section 5, we present briefly the alternative forecast which are, first, real time forecasts from an outside Norges Bank econometric model and, second, univariate inflation forecasts.

The comparison with the forecasts from the outside econometric model is relevant because that model contains knowledge about the inflation process that Norges Bank may have lost when they changed modelling policy, on the advice of the independent expert group called Norges Bank Watch 2002, Svensson et al. (2002). Whether this change had any cost in terms of forecasting ability is however an empirical question, which we attempt to answer below. The relevance of the univariate forecast stems from the insight that simple forecasting methods may succeed exactly when econometric forecasting models fail. Therefore they can function as robust forecasting devices, see e.g., Clements and Hendry (2008). The results of the comparison are presented in section 5.3, while section 6 contains our conclusion.

2 Why is accurate inflation forecasting difficult?

The theory of economic forecasting builds on the conceptual difference between the forecasting model and the true data generation process (DGP for short). In textbook expositions, it is assumed that the forecasting model corresponds to the DGP, except for an unknown disturbance term. The parameters of the model/DGP can be assumed to be unknown since parameter estimation does not represent any principal difficulty for forecasting. This is because, with suitable assumptions about the distribution of the disturbances, conventional statistical measures of uncertainty, like prediction intervals or forecasts "fans", are valid and can be used to illustrate the realistic uncertainty of the inflation forecasts. This, it seems, was also one premise for choosing the inflation forecast as the target for practical monetary policy, in order to be able to monitor policy performance when lags in the transmission mechanism are a reality, see Svensson (1997) and Clarida et al. (1999).

The problem with the textbook assumption is that it does not match up with the realities of macroeconomic forecasting. Specifically, if the assumption about

³As a matter of fact, the name of the publication changed from *Inflation Report* to *Monetary Policy Report* in 2007. For simplicity, we refer to all reports as MPRs, despite the anachronism.

model correctness really was relevant, forecast failures would be rare, which they are not. The weakest point in the theory is the (often implicit) assumptions about parameter constancy and stationarity. In practical forecasting we cannot expect the parameters to remain constant over the forecasting period—structural breaks are likely to occur when we forecast a changing economy.

As discussed by Clements and Hendry (1999), a frequent source of forecast failure is a regime shift in the forecast period, i.e., *after* the preparation of the forecasts. Since there is no way of anticipating them, it is unavoidable that *post* forecast breaks damage forecasts from time to time. The task is then to be able to detect the nature of the regime shift as quickly as possible, in order to avoid repeated unnecessary forecast failure even after the break has become part of the information set of the (next) updated forecast. Failing to pick up a *before* forecast structural break may be due to low statistical power of tests of parameter instability. There are also practical circumstances that complicate and delay the detection of regime shifts. For example, there is usually uncertainty about the quality of the provisional data for the period that initialize the forecasts, making it difficult to assess the significance of a structural change. Hence both *post* and *pre* forecast structural breaks are realistic aspects of real life forecasting situations of the type faced by inflation targeters. In particular, one should seek forecasting models and tools which help cultivate an adaptive forecasting process. The literature on forecasting and model evaluation provide several guidelines, see e.g., Bates and Granger (1969), Hendry (2001) and Granger (1999).

Realistically, the preferable model specification to use for a given observable sample is also unknown *a priori*. However, the link between model mis-specification and forecast failure is not always as straight-forward as one would first believe. The complicating factor is again non-stationarity, regime-shifts and structural change. For example, a time series model in terms of the change in the rate of inflation—a random walk —adapts quickly to regime shifts, and is immune to *pre* forecast structural breaks, even though it is blatantly mis-specified over the historical data period, see Clements and Hendry (1999, Ch 5). In terms of forecasting vocabulary, the random walk model has automatic “intercept correction” to *pre* forecast breaks, making it a robust forecasting method. An economic forecasting model is less adaptable. In order to avoid forecast failure after a (big) structural break the model forecasts must be corrected by the user until the change can be “build into” the model structure. As noted above, this can be time-consuming, for example because it may be difficult to understand the nature and consequences of the break on the basis of only a few data observations. Bårdsen and Nymoen (2009) discuss how fast the forecasts from a macroeconomic model can be expected to adapt to breaks and compare them with robust forecasts.

The relevance of breaks, and the practical problems of incorporating the effects of breaks into a model structure, provide a rationale for considering ensemble forecasts, where forecast from different forecasting mechanism and methods are averaged together. Norges Bank now relies less on its monetary policy model, and more on ensemble inflation forecasts, than they used to do. Interestingly this is motivated by the recognition that the true data generating process is unknown, see Gerdrup et al. (2009).

Uncertainty about model specification and pre and post forecasts structural

breaks are probably the main obstacles to a reasonable degree of inflation forecast accuracy. This does not deny that there are addition problems as well. Three sources that have been more in the forefront of the debate than structural breaks are: data revisions, adjustments to model forecasts and the projections of non-modelled variables in the forecasting model. Inflation forecasts and monetary policy decisions are made in “real time”, so if important variables are inaccurately measured in real time, inflation forecasts will suffer by the conditioning on mismeasured initial conditions. As noted above, Woodford (2007) and others argue that the real-time data problem is the main hindrance for accurate inflation forecasting. Progress has been made with methods that can mitigate this problem. Factor models and the use of large data sets to nowcast the output-gap have for example shown promising results, see e.g., Aastveit (2010).

3 Can forecast errors harm policy?

When central banks set interest rates so that the inflation forecast is in accordance with the inflation target, there is a danger that structural breaks in the monetary policy transmission mechanism will also affect interest rate setting. But in which way, and with what potentially harmful consequences, depends both on the operational aspects of inflation targeting and the nature of the transmission mechanism.

In order to simplify as much as possible, we omit all other variables than the policy instrument. Hence, we consider the simple dynamic model:

$$(1) \quad \begin{aligned} \pi_t &= \delta + \alpha\pi_{t-1} + \beta_1 i_t + \beta_2 i_{t-1} + \varepsilon_t, \quad t = 1, 2, 3, \dots, T, \\ -1 < \alpha < 1, \beta_1 + \beta_2 < 0, \end{aligned}$$

where π_t denotes the rate of inflation, and i_t is the interest rate. ε_t is stochastic and normally distributed with a constant variance and zero autocorrelation.

Suppose, for simplicity, that the central bank has chosen a 2-period horizon—for the time being we may think of the period as annual. The forecasts are prepared conditional on period T information, so

$$(2) \quad \hat{\pi}_{T+1|T} = \delta + \alpha\pi_T + \beta_1 i_{T+1|T} + \beta_2 i_{T|T}$$

$$(3) \quad \hat{\pi}_{T+2|T} = \delta(1 + \alpha) + \alpha^2\pi_T + \alpha\beta_1 i_{T+1|T} + \alpha\beta_2 i_{T|T} + \beta_1 i_{T+2|T} + \beta_2 i_{T+1|T}$$

give the first and second year forecasts. There are two degrees of freedom if the bank chooses to attain the target π^* in period 2, and $i_{T+1|T}$ and/or $i_{T|T}$ can therefore be set to (help) attain other priorities.

For simplicity, set $i_{T+1|T}$ and $i_{T|T}$ to some autonomous level, represented by 0.⁴ In this case, the interest rate path becomes

$$(4) \quad \begin{aligned} i_{T|T} &= 0 \\ i_{T+1|T} &= 0 \\ i_{T+2|T} &= \frac{1}{\beta_1} \{-\mu + \alpha^2(\mu - \pi_T) + \pi^*\} \end{aligned}$$

⁴i.e., we interpret i_t as the deviation from mean, hence the interest rate in period T and the planned interest rate in $T + 1$ are both equal to the mean.

where μ denotes the long run mean of inflation. Assuming that the parameters are constant over the forecast period, this path will secure that $\pi_{T+2|T}$ is equal to π^* on average. This is the benign stationary case with no regime shifts in the forecast period. On the other hand, if μ increases to a higher level μ' in period $T + 1$ and $T + 2$, the forecasts $\hat{\pi}_{T+1|T}$ and $\hat{\pi}_{T+2|T}$ will turn out to be too low, and if large enough, the errors will constitute a forecast failure. However, the forecast failure is not too worrying since only the announced future interest rate $i_{T+2|T}$ is affected. With the ‘policy rule’ in (4), a future interest rate is planned to be changed in such a way that the inflation target is reached in the second year. Today’s interest rate $i_{T|T}$ is not affected, and the planned $i_{T+2|T}$ can always be replaced by $i_{T+2|T+1}$ in the next forecast round. Thus, there seems to be negligible damage on today’s policy associated with a poor forecast.

Note that the apparent “policy irrelevance” of forecast failure depends crucially on the transmission mechanism, namely that the transmission of interest rate changes on inflation is sufficiently fast. Formally, unless $\beta_1 < 0$, the interest rate two years ahead cannot be used to bring the forecasted rate of inflation in line with the target. Central banks typically state that they view the transmission as relatively slow: ‘*Monetary policy influences the economy with long and variable lags*’ is a recurrent formulation.⁵ This is probably the main reason for choosing a different operational procedure in practise, namely to move $\hat{\pi}_{T+1|T}$ in the direction of the target by changing the current interest rate, $i_{T|T}$. As a rule, a central bank’s policy will therefore be to change the interest rate gradually. In our simplified model, we can represent gradual instrument adjustment by:

$$i_{T+j-1|T} = \gamma i_{T+j|T}, \quad j = 1, 2, \dots, h, \quad 0 \leq \gamma < 1$$

which gives the interest rate path:

$$(5) \quad \begin{aligned} i_{T|T} &= \frac{\gamma^2}{B} \{-\mu + \alpha^2(\mu - \pi_T) + \pi^*\} \\ i_{T+1|T} &= \frac{\gamma}{B} \{-\mu + \alpha^2(\mu - \pi_T) + \pi^*\} \\ i_{T+2|T} &= \frac{1}{B} \{-\mu + \alpha^2(\mu - \pi_T) + \pi^*\} \end{aligned}$$

where $B < 0$ is a function of α, β_1, β_2 and γ . Clearly, with gradual interest rate adjustment, the event of a new mean inflation rate μ' in period 2 will not only cause a forecast failure, it will also imply that today’s interest rate $i_{T|T}$ ought to have been set differently.

In sum, long lags in the transmission mechanism, and gradualism in interest rate setting imply that inflation forecast failures also means errors in interest rate setting. We have modelled *post* forecast structural breaks, but the same analysis applies to *pre* forecast structural breaks and real-time data measurement problems that are not taken into account by the forecast targeter.

⁵see, http://www.norges-bank.no/english/monetary_policy/in_norway.html#horizon

4 Norges Bank's inflation forecasts since 2002

On 29 March 2001 Norway formally introduced an inflation targeting monetary policy regime. The operational measure of core inflation has been based on the consumer price index adjusted for the influence of energy prices and indirect taxes (CPI-AET) and the target was set to 2.5 %. CPI-ATE, is published by Statistics Norway together with the headline CPI. Recently, Norges Bank has changed to a new price index called CPI-EX. This price index is not produced by Statistics Norway, but by Norges Bank. CPI-EX allows for permanent, but not temporary effects of energy price changes. Inflation forecasts are published three times a year in the central bank's monetary policy reports. The change in the operational definition of core inflation means that the main forecasts in the monetary policy reports are for the CPI-EX index. However, forecasts for CPI-AET inflation are still included, but only for the first quarters ahead.⁶

The macroeconomic models used by Norges Bank appear to have developed considerably during the decade of inflation targeting. Following the advice in Svensson et al. (2002), Norges Bank developed a New Keynesian model to aid monetary policy documented in Husebø et al. (2004). Following further model development, Norges Bank is now using a dynamic stochastic equilibrium model called NEMO (Norwegian Economic Model), see Brubakk et al. (2006). As discussed in Juel et al. (2008, Ch. 4), NEMO and its predecessor represent the main conceptual reference framework for Norges Bank's forecasting and policy evaluation. More recently, the role of NEMO for the short-term forecasts (defined as 1-5 quarters ahead) has been reduced, as Norges Bank now relies on ensemble forecasts for these horizons, see Gerdrup et al. (2009). The ensemble used for forecasting core inflation contains 167 models, NEMO being one of them.

Other aspects of Norges Bank's forecasts have developed as well. For example, until Monetary Policy Report of 3/05, the inflation forecasts were conditional on an exogenously given interest rate path which implied that the target could be met (credibly) at that interest rate path.⁷ Since MPR 1/06, Norges Bank has published its interest rate forecast together with the inflation forecasts. The interpretation is that the inflation path and the interest rate path are consistent and that the interest rate path "gives" the inflation path.

The horizon for monetary policy is also relevant for understanding Norges Bank's forecasts⁸. Since all end-of-period forecasts are 2.5 %, a short policy horizon will imply forecasts that converge more quickly to the target than will be the case for a longer policy horizon. Initially Norges Bank operated inflation targeting with a 2-year forecast horizon. In the summer of 2004, the policy horizon was changed

⁶Monetary Policy Report 3/09 only contains forecast for 2009q3, 2010q1 and 2010q2.

The CPIEX was introduced in Monetary Policy Report 2/08, see the box on page 54 titled "Underlying inflation". The relevant source on the internet is:

http://www.norges-bank.no/templates/article_____69444.aspx

⁷Alternatively, one can say, as in Juel et al. (2008), that these forecasts were not meant as conditional inflation forecasts for the policy relevant horizon, but this suggests that Norges Bank failed to follow the main principle of inflation targeting, namely that the conditional inflation forecast *is* the target of monetary policy.

⁸See Akram and Nymo (2009) for results on the role of policy horizon for optimal interest rate setting.

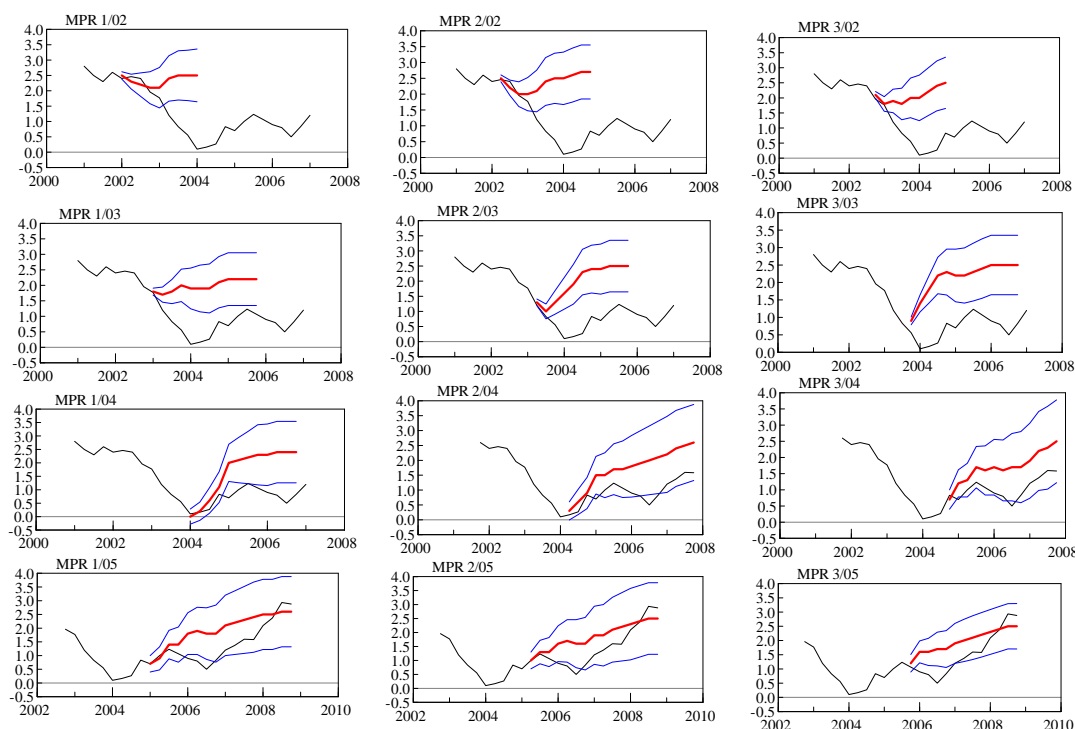


Figure 1: Actual CPI-AET inflation rate and Norges Bank's inflation forecasts (thicker line) and the 90% confidence regions. MPR 1/02 to MPR 3/05.

to 1-3 years.⁹ This caused a change in the following MPR inflation forecasts, which adjusted to 2.5% over 3 years instead of two.

Norges Bank's forecasts are published in fan-charts where the wideness of the bands represents 30%, 60% and 90% probabilities for future inflation rates. The forecasted uncertainty is particularly relevant when assessing forecast performance. Actual inflation rates outside the 90% band represent forecast failures.

Forecasts from 21 Monetary Policy Reports from the years 2002-2008 are shown in figure 1 and 2.¹⁰ In each panel there are graphs for the dynamic inflation forecasts together with the 90% forecast confidence bounds, and also the actual inflation rate.

In figure 1 there are several examples of forecast failure. For example in MPR 2/02, the first four inflation outcomes are covered by the forecast confidence interval, but the continued fall in inflation in 2003 (the second year of the forecast horizon) constitutes a forecast failure. Forecast failure became more evident in the two other forecasting rounds in 2002, and all the three forecasts produced in 2003 predicted significantly higher inflation than the actual outcome. Specifically, the forecast confidence interval of MPR 3/03 did not even cover the actual inflation in the first

⁹http://www.norges-bank.no/english/monetary_policy/in_norway.html#horizon

¹⁰The last Monetary Policy Report in figure 1 is MPR 3/08. The reports from 2009 are omitted because the forecasts there cover only a short horizon, and the prediction intervals are also incomplete or missing. This reflects Norges Bank's change to a new operational definition of inflation, as explained in the main text. The available CPIAET forecasts from MPR1/09, MPR2/09 and MPR3/09 are used in the comparison of mean forecast errors and mean square forecast errors though.

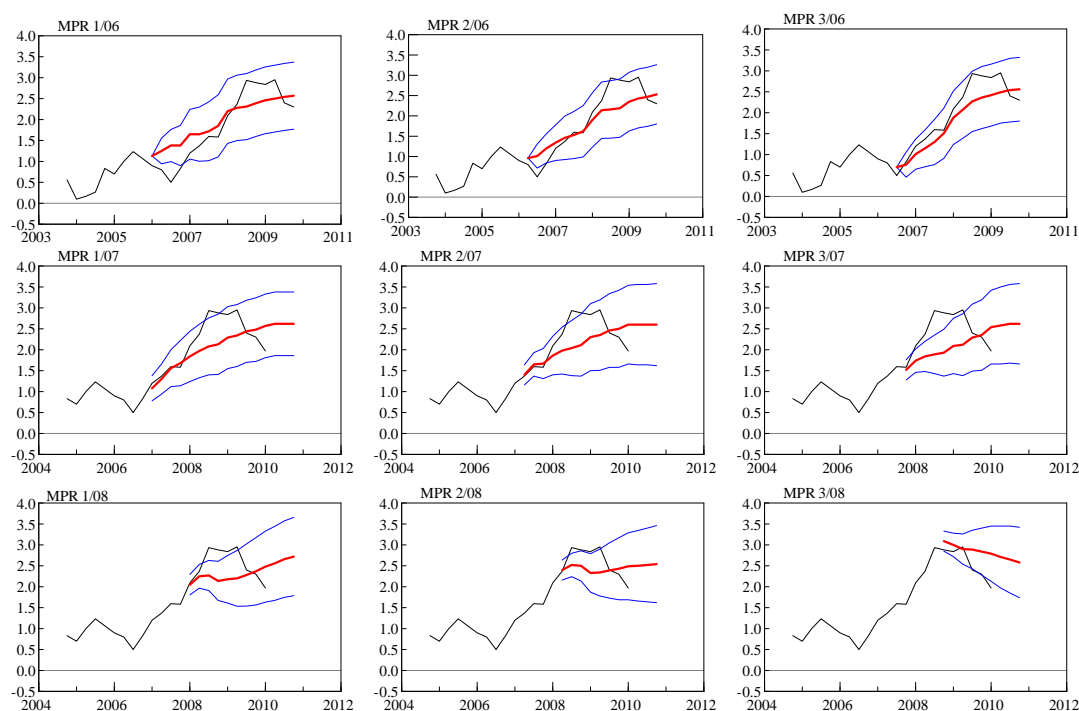


Figure 2: Actual CPI-AET inflation rate and Norges Bank's inflation forecasts (thicker line) and the 90% confidence regions. MPR 1/06 to MPR 3/08.

forecast period.

The seventh panel shows that the forecasted zero rate of inflation for 2004(1) in MPR 1/04 turned out to be very accurate. The change from the MPR 3/04 forecast is evident, and can be seen as an adaptation to a lower inflation level. That process continued in MPR 2/04, where the effect of the lengthening of the forecasting and policy horizon mentioned above is clearly visible. Although also the MPR 2/04 forecasts are too high, only one of them represents (formally) a forecast failure. The last four panels in figure 1 show many of the same features. The 1-step, and sometimes also the 2-step forecasts are accurate, but otherwise the forecasted inflation rate is too high. The MPR 1/05-3/05 forecasts for the end-of-horizon are accurate though, as actual inflation was a little higher than 2.5 %.

Norges Bank's inflation forecasts from 2006, 2007 and 2008 are shown in figure 2. Compared to the first group of forecasts, these graphs shows a more balanced picture with positive and negative forecast errors. The uncertainty bands also seem to be better calibrated to the real uncertainty facing the inflation forecaster.¹¹

¹¹The "zero" uncertainties for some of the 1-step forecasts from MPR 1/06, MPR 2/0 and 1/03 are reproduced here as they appear in the data. It is not clear that the intention was to communicate "no uncertainty". We see that in the later reports the practice of reporting uncertainty also the 1-step forecasts is taken up again.

5 Relative forecast accuracy

As shown above, the MPR forecast errors bear the marks of slow adaptation to a reduction of the inflation rate that became manifest during 2003. After 2004 there are fewer very large forecast errors. The first period with large forecast errors was analysed in Nymoen (2005), where it was shown how an econometric inflation model produced better forecasts. The explanation offered was that explanatory factors like imported inflation and labour market pressure were better represented in the econometric model than in the monetary policy model used by Norges Bank. These econometric inflation forecasts were however *ex post*, since the econometric model was designed late in the year 2003, after the biggest forecast failures had occurred. In the period 2004-2009 we have however published forecasts from the same model and these forecasts are directly comparable to the Monetary Policy Report forecasts from the same period.

Below, we compare the MPR forecasts with the forecast from the outsider econometric model which is presented briefly in section 5.1. The second group of contesting forecasts use univariate time series models, which are introduced in section 5.2. Section 5.3 shows the comparison.

5.1 An outside Norges Bank econometric model

Real time forecasts from the macroeconometric model in Nymoen (2005) have been published on the internet since June 2004 and have been dubbed *Automatized Inflation Forecasts* (AIFs).¹² The AIF forecasting model consists of an econometric “inflation function” for Norway and equations for each of the explanatory variables. It is a closed system, and after estimation of the model’s parameters, dynamic inflation forecasts are easy to produce (hence “Automatized”).

In more detail, AIF consists of an equation for the rate of inflation (CPI-ATE), and 8 equations which are needed to forecast the following variables: the rate of unemployment, productivity growth, the logarithms of the nominal and the real exchange rates, foreign inflation, domestic and foreign interest rates and the logarithm of the oil price. The model is presented in the appendix A.

Like any forecasting model, the AIF forecasting model has evolved over time. Model evolution is necessary for having a reasonably well adapted econometric forecasting system, but there is still no guarantee that the model is not outpaced by the sequence of structural breaks, see e.g., Eitrheim et al. (2002). Despite the revisions, the current version of the AIF model has the same ability as before to outperform Norges Bank’s forecasts *ex post*, as figure 3 shows. The graph shows AIF *ex post* forecasts for the period 2002q4-2006q4, together with the MPR 3/03 forecasts.

In section 5.3 we investigate whether this result emerges also after 2003. For that purpose we compare forecasts from all MPRs in the period 2004-2009 to genuine real time forecasts from the AIF forecasting model that have been published on the internet during the period 2004-2009. In particular we test whether the MPR forecasts from that period are (still) characterized by too rapid return to the inflation

¹²The url for the AIF project is http://folk.uio.no/rnymoen/forecast_air_index.html.

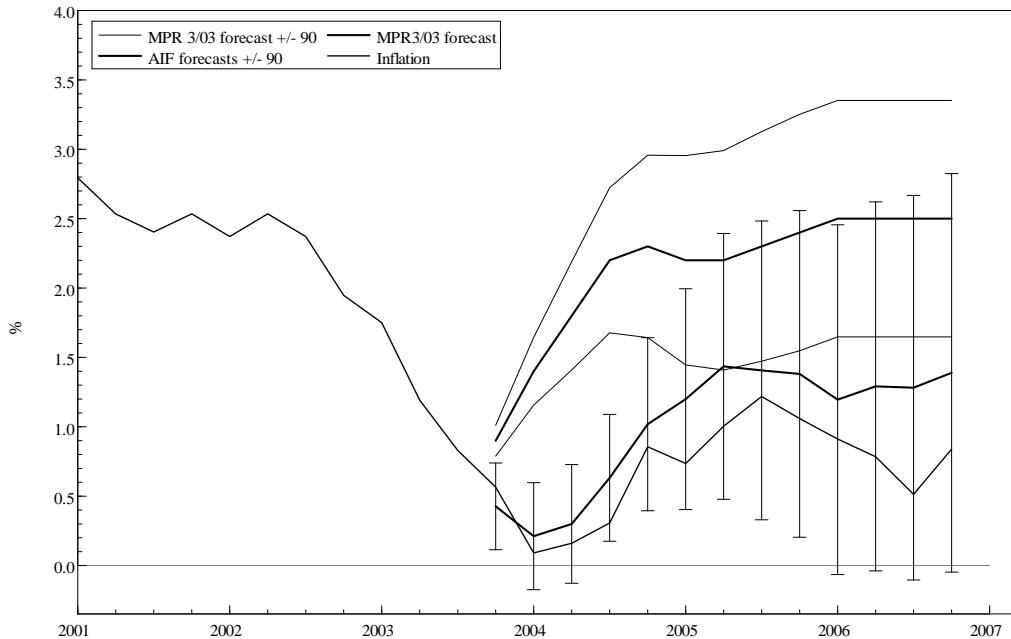


Figure 3: Ex post AIF forecasts for 2003q4 - 2006q4, with 90% confidence regions shown as bars, and with MPR 3/03 forecasts also shown for comparison. The sample period for the estimation of the parameters of the AIF model ends in 2003q2. MPR 3/03 is also conditional on the information in 2003q3.

target of 2.5%, in which case the MPR forecast errors might have tendency to become unnecessary large over a 4-12 quarter forecasting horizon.

5.2 Univariate forecasts

In addition to the AIF forecasts, we also compare the MPR forecasts with three simple univariate forecasting methods. The first is a random walk model of inflation (M1 below) where a unit root is imposed, so that the full value of the previous inflation rate is retained in the forecast. This ensures a form of error-correction in the forecasts, so that the random walk model (M1) may succeed exactly in the situations where econometric forecasting models fail, see e.g. Clements and Hendry (1999, Ch. 5). One particularly relevant case is when there is a structural break in the mean of inflation. As this break moves from being a *post-forecast* break to becoming a *pre-forecast* break, the M1 forecast will adapt quickly to the new mean of inflation.

It follows that differenced data model M1 can have smaller and less systematic errors than the forecasts resulting from an econometric model of the type represented by AIF and from Norges Bank's macroeconomic model NEMO which by design is a high powered equilibrium model.

As noted above, the 2001-2009 period contains one marked drop in mean inflation, which occurred in 2003. After 2004, inflation again has a positive drift, and M1 will then have a tendency to miss the evolution of inflation by one period. However, two other models, which are almost as easy to use as M1, may be better suited to

compete with economic forecasts in that period, They are the random walk with drift, M2 below, and an autoregressive model, M3.

M2 adds an estimated intercept to the random walk model, so it may forecast a trend. In M3 an autoregressive coefficient for the lagged inflation rate is also estimated, so the unit root of M1 is no longer imposed. M3 may forecast well when the inflation rate is relatively stationary.

The M1-M3 forecasts are updated each quarter. The M1 forecasts only update the initial value. For M2 and M3, we use a rolling 40 quarter sample for the estimation of the parameters. For example: the M2 and M3 forecasts for 2004q1-2006q1 use data from 1994q1 to 2003q4 for estimation, while the 2007q1-2009q4 forecasts use a sample from 1997q1 to 1996q4.

To summarise, we will assess the forecasts of the following univariate methods:

- M1: The rate of inflation in period t is equal to the inflation rate in period $t - 1$.
- M2: As M1, but with an estimated intercept added.
- M3: As M2, but an autoregressive coefficient is estimated (instead of being restricted to one, as in M1 and M2).

The CPI-AET based inflation data are never revised, and it is therefore relevant to compare the M1-M3 forecasts with the MPR forecasts for the whole period of inflation targeting. All four sets of forecasts are, for our practical purpose, real time forecasts.

5.3 Forecast comparison

As mentioned above, we compare the MPR inflation forecasts with real time forecasts from the AIF macroeconomic model and forecast from the three robust methods M1-M3. We start with the period from 2004 until 2009 since the first AIF forecast were published on the internet in June 2004.¹³

Panel a) of figure 4 shows the mean forecast errors, MFE, for the MPR and the AIF forecasts from one to twelve quarters ahead. The length of the forecast horizon is along the horizontal axis. Hence, the start of the graph marked MPR in panel a) gives the MFE for *Forecast horizon 1* as the average of all 1-step ahead forecast errors in the Monetary Policy Reports from 1/04 to 3/09. Then follows the average of all 2-step ahead forecast errors, for the same sequence of MPR forecasts, and so on, until *Forecast horizon 12* which marks the end of the graph. The graph marked AIF in panel a) has a similar interpretation: it shows the average forecast errors from all published AIFs, as a function of the forecast horizon. The last observation of inflation used in the underlying calculations is from the first quarter of 2010.

A negative MFE means that the inflation forecasts were on average higher than the actual inflation rates in the period. For example, a horizon of four quarters the AIF forecasts were on average 0.2 percentage points too high. The biases are

¹³The AIF project have been discussed by Norges Bank Watch (2008), see Juel et al. (2008), who conclude that it represents a relevant alternative to the MPR forecasting method.

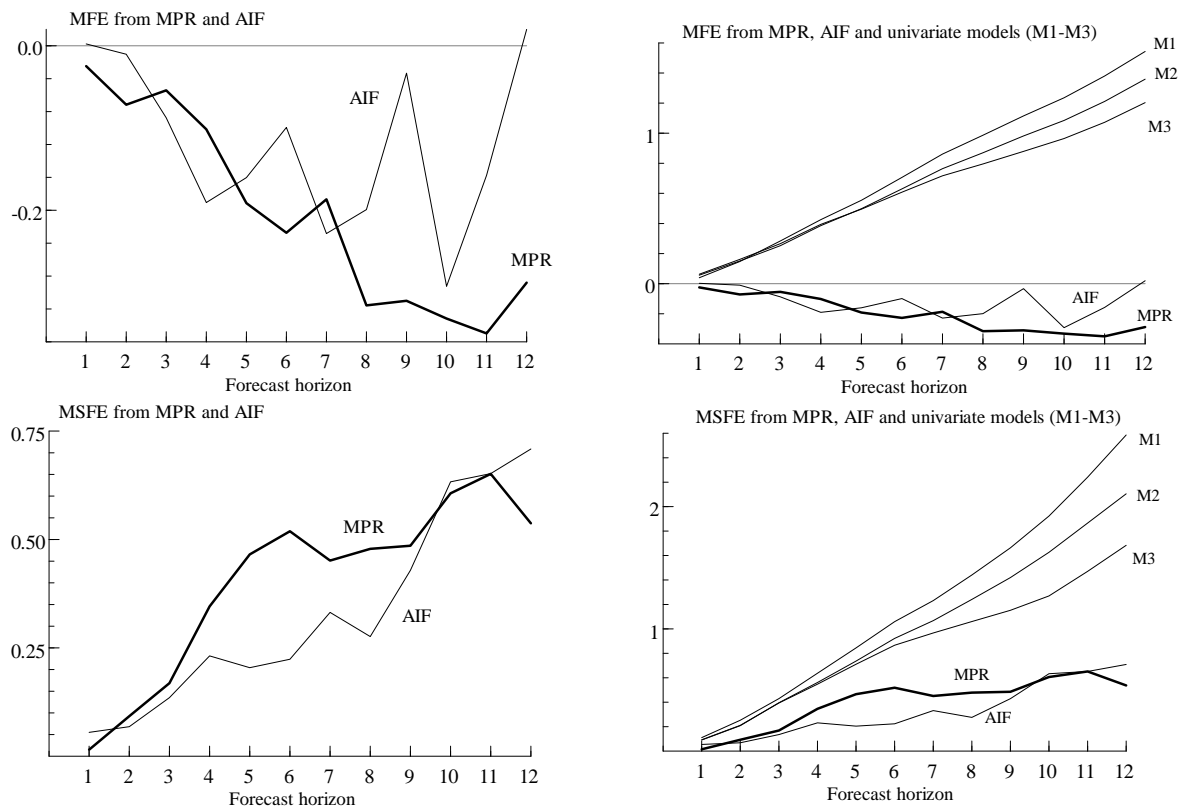


Figure 4: Mean forecast errors (MFE) and mean square forecast errors (MSFE) for core inflation (annual rate of change in CPI-ATE) for MPR (Norges Bank) and AIF (outside econometric model) forecasts. The MPR and AIF forecasts were published in the period 2002-2009. Panel a. and c. show the MFE and MSFE for forecast horizons 1-12 for MPR and AIF. Panel b. and d. also show the MFEs and MSFEs for the random walk (M1), the random walk with drift (M2) and the autoregressive model (M3).

small to begin with, for the short forecasting horizons. There is a tendency that the size of the bias grows with the length of the forecasting horizon, in particular this is true for the MPR forecasts. The biases of the AIF forecasts are smaller than Norges Bank's forecast bias for horizons 1 and 2 while MPRs have smaller bias for horizons 3, 4 and 7. For the other horizons, the AIF average forecast errors are smaller than the MPR average errors.

Panel b) also shows average forecast errors, but we have here included the MFEs for the three univariate methods. M1-M3. As noted, M1 is a random walk model for the rate of inflation, M2 is a random walk with drift, and M3 is an autoregressive model for inflation. The 1-step ahead forecasts of M1-M3 have small and positive biases. The biases increase with the length of the forecast horizon—and much faster than for the two 'discipline' forecasting methods MPR and AIF. It is interesting to note that, because of the sign difference, an ensemble forecast made up MPR, AIF and M1-M2 could have had a near zero mean squared forecast error.

Panel c) shows the mean squared forecast errors, MSFE for MPR forecasts and AIF forecasts, as a function of the forecast horizon. Given a symmetric loss

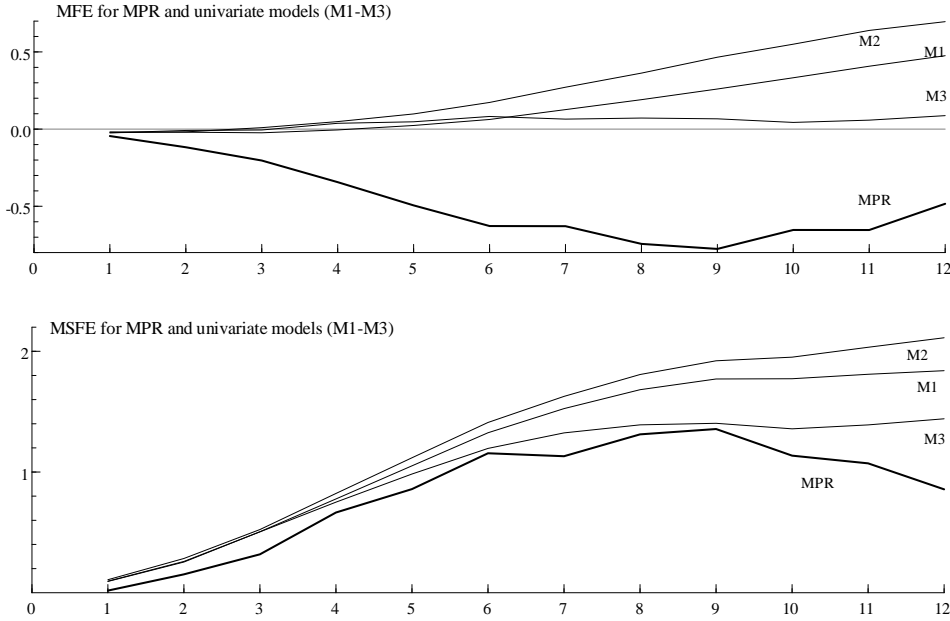


Figure 5: Mean forecast errors (MFE) and mean square forecast errors (MSFE) for core inflation (annual rate of change in CPI-ATE) for MPR (Norges Bank) and the three univariate models: random walk (M1), random walk with drift (M2) and autoregressive model (M3). The MPR forecasts were published in the period 2002-2009. Panel a. shows the MFEs for forecast horizons 1-12, and panel b) shows the MSFEs.

function, which is relevant for inflation targeting, the forecast with the lowest MSFE may be regarded as the preferred forecast. The MPRs from 2004 to 2009 have 1-step inflation forecasts with a lower MSFE than the 1-step AIFs from the same period. However, already for the 2-step forecasts, the roles are reversed. Importantly, for MSFEs for the 4-to-8-step forecasts are much larger for MPR than for the AIF. This is a surprising result which supports the hypothesis formulated above, about the speed of adjustment in inflation being overestimated in the MPR forecasting model. It is even more noteworthy since it is found for a sample where almost all the MPR forecasts were produced after the extension of the policy horizon in 2004, which resulted in slower speed of adjustment in the MPR forecast, as we have seen.

The last panel (d) in figure 4 shows the MSFE graphs for the three univariate forecast M1-M3 for comparison. All three are clearly inferior to both the MPR forecast and the AIF forecasts. The M3 forecasts, from the autoregressive inflation model, is the best of the three. Hence the robust feature of M1 is not enough to make it perform nearly as well as the discipline models MPR and AIF over this forecast sample. The conclusion might have been different if 2003 had been included, but that would be another forecast contest.

In figure 5 we compare the forecast accuracy of the Monetary Policy Report forecasts for the longer period 2002-2010, with forecasts from the three univariate models. This means that the year 2003, which was difficult to forecast, is now part of the sample. The graphs shows that both the average forecast errors and the MSFEs

for the central bank forecasts are much larger in magnitude when 2003 is included in the evaluation period. In contrast, the average forecast errors of the univariate forecasts are smaller than in the assessment that omitted 2003, confirming that they are relatively robust to changes in the mean of the forecasted variable. In particular M3 has a low bias, for all forecast horizon.

The second panel of figure 5, with the MSFEs, shows that there is less absolute improvement for M1-M3 compared to figure 4, panel d). However, because the MPR forecasts are poorer than on the sample that omits 2003, the relative accuracy of the univariate forecast are much closer to MPR than in the comparison we saw in figure 4.

6 Conclusions

Norges Bank is a leading forecast targeting central bank, and it is reasonable to expect that Norges Bank produces inflation forecasts that regularly outperform both ‘naive’ forecasts and forecasts from econometric models that are specified and maintained outside the central bank. When it comes to forecasting inflation, the forecast targeting central bank may be expected to know the most and to be best.

It is surprising therefore that the superiority of the Monetary Policy Report inflation forecasts cannot be asserted. This is the conclusion when MPR forecasts over the period 2004-2009 are compared with genuine *ex ante* real time forecasts from an outsider model called AIF. The 1-step MPR forecasts are preferable to the 1-step forecasts from AIF, but for the policy relevant horizons (4 to 9 quarters ahead), the evidence goes in favour of the of the outsider model. Because there are fewer AIF forecast to average over, there will be more uncertainty about the forecast accuracy of AIF than about the MPR forecasts. That said, the situation has been more or less stable since the comparisons started in 2005, which indicate that there are structural elements in MPR forecasting system that makes it difficult for Norges Bank’s forecasters to win a contest like this one—which on the face of it should be an easy victory.

Based on the properties of the AIF model, one can hypothesize that the tendency of the MPR forecasts to adjust too quickly to the target will damage the forecast accuracy of the MPR. This hypothesis is supported by the evidence. The opposite hypothesis, that the AIF forecasts will suffer because it is not well adapted to forecast targeting regime that has been in operation since 2001, is not supported by the evidence presented above.

Following the earlier difficulties with forecasting inflation in 2003, Norges Bank has moved in the direction of ensemble forecast, and thereby Norges Bank place less weight than intended on the quantitative theoretical macro model NEMO. Also our results confirm that there can be potential gains from forecast averaging. Even very inaccurate forecasts, like those from a random walk, would have positive weights, since they correct a bias in the two discipline forecasts. Finally we note that, in this case study, econometric systems compete successfully with the ‘naive’ univariate forecasting methods. This conclusion has one important caveat though: When the sample is extended to include the year 2003, when inflation suddenly dropped, the mean forecast errors of one of the univariate models are much smaller than the average error of the central bank forecast. This outcome is ‘as predicted’ once we

recognize that univariate forecasts are quite robust to sudden changes in the mean of inflation.

A The AIF forecasting model

Our approach is to represent the effects of the labour market, the market for foreign exchange and the price setting in domestic product markets in a compact econometric model of Norwegian. We build on earlier modelling projects like the one documented in Bårdsen et al. (2003). The model can also be seen as a condensed version of the incomplete competition model of wage and price dynamics, see Bårdsen and Nymoen (2003).

Since the purpose the model is to forecast the annual rate of inflation we have modelled the fourth difference of the natural logarithm of CPI-AET. It is denoted Δp_t in this appendix. As mentioned in the main text, the specification of the “inflation function” has evolved over time (even within the short period of this project). That said, the rate of unemployment (U_t), the logarithm of the real exchange rate (rex_t), foreign inflation $\Delta_4 p_{*t}$ and interest rates, domestic (i_t) and foreign (i_{*t}), have consistently made up the set of explanatory variables. In this appendix we document the current version of the model

A.1 The inflation equation

The inflation equation, used in the AIF forecasts published in February 2009,¹⁴ is reported in equation (6).

$$\begin{aligned}
 (6) \quad \Delta_4 p_t = & \underset{(0.05)}{0.717} \Delta_4 p_{t-1} - \underset{(0.07)}{0.251} \Delta_4 p_{t-3} + \underset{(0.05)}{0.250} \Delta_4 p_{t-4} \\
 & + \underset{(0.0015)}{0.017} + \underset{(0.07)}{0.971} D_{p,t} \\
 & - \underset{(0.003)}{0.0019} U_{t-2} - \underset{(0.004)}{0.0016} U_{t-4} \\
 & - \underset{(0.018)}{0.073} (i_{t-4} - i_{*t-4}) - \underset{(0.024)}{0.115} \Delta i_{t-4} + \underset{(0.024)}{0.223} \Delta i_{*,t-4} \\
 & + \underset{(0.020)}{0.110} \Delta_4 p_{*t-2} + \underset{(0.004)}{0.032} rex_{t-4} \\
 & T = 1983(1) - 2009(4) = 108 \qquad \qquad \qquad OLS \\
 & \hat{\sigma} = 0.19\% \\
 F_{AR1-5}(5, 91) = & 1.0125[0.42] \qquad \chi^2_{normality}(2) = 0.10836[0.95] \\
 F_{ARCH\ 1-4}(4, 100) = & 0.79160[0.53] \qquad F_{x_ix_j}(22, 85) = 0.56915[0.93] \\
 F_{x^2}(20, 44) = & F(76, 31) = 0.61974[0.95] \qquad F_{RESET}(2, 94) = 2.1603[0.12]
 \end{aligned}$$

On the right hand side of equation (6) we first have the three autoregressive terms $\Delta_4 p_{t-1}$, $\Delta_4 p_{t-3}$ and $\Delta_4 p_{t-4}$. Conventional standard errors are in brackets below each coefficient, showing that they are statistically significant different from

¹⁴See http://folk.uio.no/rnymoen/forecast_air_index.html.

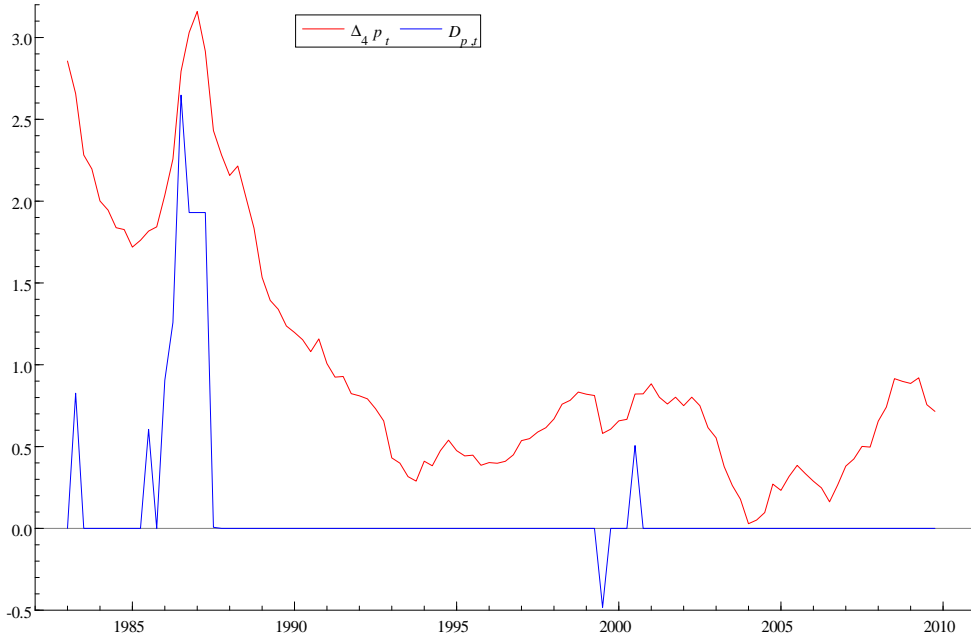


Figure 6: $\Delta_4 p_t$ and the composite structural break dummy $D_{p,t}$. (The dummy has been rescaled to match the range of $\Delta_4 p_t$).

zero. The huge positive coefficient for $\Delta_4 p_{t-1}$ is not surprising. Since we model the annual rate of inflation it represents inflation persistence. The third and the fourth lags of inflation are also significant, but the almost identically sized coefficients have opposite signs, showing that these autoregressive terms capture more high-frequency dynamics than the first lag.

The second line of (6) shows the deterministic part of the equation, consisting of an intercept and a composite dummy $D_{p,t}$. The dummy represents the estimated inflation effects of currency devaluations that occurred during the 1980's, but also the cost-push effect of the reduction in the length of the working week in January 1987, see Nymoen (1989). The dummies were obtained by the utility for automatic detection of breaks in *PcGive 13*, see Doornik and Hendry (2009a). Figure 6 shows $D_{p,t}$ together with $\Delta_4 p_t$. As expected, the structural break dummies are mainly located in the 1980s. There is however a drop in inflation in 1999(3) which is detected as a break, and a corresponding positive dummy coefficient a year later in 2000q3. There are no detected breaks at the time of the formal introduction of inflation targeting in March 2001 or to events later in the sample period (notably the 'financial crisis').

The remaining part of equation (6) contains the economic explanatory variables. First the rate of unemployment (U_t) enter with its second and fourth lag. This effect may reflect both that price setters adjust their mark-up with the business cycle (U_t is highly correlated with changes in GDP in Norway), but also indirect effects working through wage setting. Specifically, existing research has established an effect from unemployment on wages, both in a Phillips curve framework and in wage equations that can be rationalized from bargaining theory, see Bårdsen et al. (2005, Chapter 3-6) for an overview. The numerically and statistically significant

effects in equation (6) are therefore consistent with several existing studies.

We interpret the fourth line in equation (6) as representing the inflationary impulses from the market for foreign exchange: Under quite general assumptions, the difference between the interest rate in the domestic, (i_t) and foreign money markets ($i_{*,t}$) affects the nominal exchange rate, see Bårdsen and Nymoen (2005) for an analysis. In equation (6) the interest rate differential manifests itself quite clearly (at the fourth lag) although we have estimated the two coefficients freely in this case.

In the fifth line of the inflation equation, we first include the direct effects of imported inflation, as measured by $\Delta_4 p_{*,t-2}$ the annual rate of change in foreign consumer prices, in foreign currency. Finally, the fourth lag of the logarithm of the real exchange rate (rex_{t-4}) is highly significant with a positive coefficient. Usually, a real depreciation of the currency, corresponding to a higher rex , will lead to a degree of ‘internal revaluation’ after a period of time, which is a relevant interpretation of the significance of rex_{t-4} in equation (6).

Below the equation we report the sample size (number of quarterly observations) by T , and the residual standard error in percent is denoted by $\hat{\sigma}$. We also report a set of mis-specification tests. As indicated by the notation, the normality test is a Chi-square test, while the others are F-distributed under their respective null hypotheses. They are: $F_{AR\ 1-5}$, autoregressive residual autocorrelation, ARCH heteroscedasticity, $F_{ARCH\ 1-4}$, and heteroscedasticity due to squares, F_{x^2} , and cross products of the regressors $F_{x_i x_j}$. Finally F_{RESET} tests the null hypothesis of no functional form mis-specification, see Doornik and Hendry (2009a).

A.2 Marginal equations

All the stochastic variables in equation (6) are in turn modelled by econometric relationship, so that the AIFs are based on estimation and dynamic simulation of a system: There is one equation for each of the 5 explanatory variables in (6), and in addition the annual rate of change in the price of oil ($\Delta_4 p_{ot}$) is modelled because it is used in the equation for $\Delta_4 p_{*,t}$, and the nominal exchange rate (e_t) is also modelled in order to forecast the real-exchange rate (rex) within the forecasting system.

The equations that make-up the AIF forecasting system together with the inflation equation (6), is given in table 1. In order to highlight the relationships between variables, the equations are given in stylized form, for example without intercepts and dummies for structural breaks. The structural breaks are however found by the same method as explained in connection with the inflation equation.

Equation (6) and table 1 is a system of 11 equations. The 11 endogenous variables are: $\Delta_4 p_t$, $\Delta_4^2 p_t$, $\Delta_4 p_{*,t}$, $\Delta_4 p_{ot}$, Δe_t , $\Delta_4 e_t$, rex_t , i_t , Δi_t , $i_{*,t}$, and U_t .

A.3 Data definitions and sources

The forecasting model employs seasonally unadjusted data. Unless another source is given, all data are taken from the RIMINI database in Norges Bank (The Central Bank of Norway). For each RIMINI-variable, the corresponding name in the RIMINI-database is given by an entry [RIMINI: variable name] at the end of the description. The RIMINI identifier is from Rikmodnotat 405, Norges Bank, Research

Table 1: Marginal and definition equations of the AIF forecasting model. All equations are estimated by OLS. The sample period is 1983(1)-2009(4)

The exchange rate	
$\Delta e_t =$	$\frac{1.1}{(0.3897)} \Delta_4^2 p_t - \frac{0.56}{(0.139)} [i_t - i_{*t}] - \frac{0.220}{(0.04)} rex_{t-1} - \frac{0.002}{(0.0019)} U_{t-1}$
The rate of unemployment	
$U_t =$	$\frac{0.88}{(0.02)} U_{t-1} - \frac{4.62}{(1.04)} [i_{t-3} - \Delta_4 p_{t-3}]$
Foreign inflation	
$\Delta_4 p_{*t} =$	$\frac{1.32}{(0.08)} \Delta_4 p_{*t-1} - \frac{0.33}{(0.08)} \Delta_4 p_{*t-2} + \frac{0.012}{(0.002)} \Delta_4 p_{ot} - \frac{0.013}{(0.002)} \Delta_4 p_{ot-1}$
Foreign interest rate	
$i_{*t} =$	$\frac{0.90}{(0.03)} i_{*t-1} + \frac{0.37}{(0.13)} \Delta_4 p_{*t} - \frac{0.17}{(0.13)} \Delta_4 p_{*t-1} + \frac{0.0013}{(0.007)} \Delta_4 p_{ot}$
Domestic interest rate	
$\Delta i_t =$	$\frac{0.19}{(0.06)} \Delta i_{t-1} - \frac{0.23}{(0.04)} i_{t-1} + \frac{0.75}{(0.20)} \Delta_4 p_t - \frac{0.23}{(0.21)} \Delta_4 p_{t-1}$
	$- \frac{0.003}{(0.001)} U_t + \frac{0.002}{(0.001)} U_{t-1} + \frac{0.15}{(0.09)} i_{*t-1}$
Oil price	
$\Delta_4 p_{ot-1} =$	$\frac{1.13908}{(0.09)} \Delta_4 p_{ot-1} - \frac{0.518669}{(0.09)} \Delta_4 p_{ot-1}$
Definition^a	
$i_t =$	$\Delta i_t + i_{t-1}$
$\Delta_4 e_t =$	$\Delta e_t + \Delta e_{t-1} + \Delta e_{t-2} + \Delta e_{t-3}$
$rex_t =$	$\Delta_4 e_t + \Delta p_{*t} + \Delta p_t + rex_{t-1}$
$\Delta_4^2 p_t =$	$\Delta_4 p_t - \Delta_4 p_{t-1}$
<p>^aWe abstract here from the fact that rex_t is defined in terms of p_{ct} (see data definitions), and that in practice there is an estimated relationship for rex_t, while we use an identity here for simplicity.</p>	

department, 9th December 2002. Each variable's name in the PcGive batch file that generate the AIF forecasts is also given, with transformation indicated when relevant.

The variables used in the forecasting equation for the rate of inflation are defined as follows:

P Consumer price index adjusted for the influence of energy prices and indirect taxes, CPI-ATE. 1991=1. [RIMINI: CPIJAE].{PcGive: $cpijae = \ln(CPIJAE)$ }.

P_C Consumer price index (CPI). 1991=1. [RIMINI: CPI].{PcGive: $p = \ln(CPI)$ }.

P_* Consumer prices abroad in foreign currency. 1991=1. [RIMINI: PCKONK].{PcGive: $pck = \ln(PCKONK)$ }.

P_o Oil price index (USD).[RIMINI: SPOILUSD].{PcGive: $oil = \ln(PCKONK)$ }.

E Trade weighted nominal value of the krone based on import-shares of trading countries. [RIMINI: CPIVAL].{PcGive: $v = \ln(CPIVAL)$ }.

Z Value added per man hour at factor costs in the Norwegian non-tradables sector, fixed baseyear (1991) prices. Mill. NOK. [RIMINI: ZYI].{PcGive: $zyi = \ln(ZYI)$ }.

i Money market interest rate (3 month Euro-krone interest rate). [RIMINI: RS].{PcGive: RSH }.

i_* ECU interest rate. For the period 1967(1)-1986(3): Effective interest rate on foreign bonds, NOK-basket weighted. [RIMINI: R.BKUR] For the period 1986(4)-1996(4): ECU weighted effective rate on foreign bonds. [RIMINI: REC/100].{PcGive: RSW }.

U Labour force survey (AKU) rate of unemployment. [RIMINI: UAKU2].{PcGive: $UAKU2$ }.

REX Real effective exchange rate. $REX = EP_*/P_C$.

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