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Forecasting inflation with an uncertain output gap*

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4 May 2006

Abstract

The output gap (measuring the deviation of output from its potential) is a crucial concept in the monetary policy framework, indicating demand pressure that generates inflation. The output gap is also an important variable in itself, as a measure of economic fluctuations. However, its definition and estimation raise a number of theoretical and empirical questions. This paper evaluates a series of univariate and multivariate methods for extracting the output gap, and compares their value added in predicting inflation. The multivariate measures of the output gap have by far the best predictive power. This is in particular interesting, as they use information from data that are not revised in real time. We therefore compare the predictive power of alternative indicators that are less revised in real time, such as the unemployment rate and other business cycle indicators. Some of the alternative indicators do as well, or better, than the multivariate output gaps in predicting inflation. As uncertainties are particularly pronounced at the end of the calculation periods, assessment of pressures in the economy based on the uncertain output gap could benefit from being supplemented with alternative indicators that are less revised in real time.

Keywords: Output gap, real time indicators, forecasting, Phillips curve

JEL-codes: C32, E31, E32, E37

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1 Introduction

The output gap - measuring the deviation of output from its potential - is a crucial concept in the monetary policy framework, indicating demand pressure that generates inflation. Because the output gap will have an effect on inflation, an optimal inflation-targeting policy implies a monetary policy response to the output gap. Such a policy response will help stabilize inflation as well as output, as pointed out by Svensson (1997, 2000) and Rotemberg and Woodford (1997). Many central banks that have announced inflation-targeting policies, therefore attempts at stabilizing both inflation and the output gap.

The output gap is also an important variable in itself, as a measure of economic fluctuations. Over time, economic resources are utilized efficiently when economic growth is stable and the output gap remains close to zero (or output close to potential). At this level, employment growth and unemployment will also be stable.

Despite the output gap's central role in monetary policy making, its definition and estimation raise a number of theoretical and empirical questions. Ever since Nelson and Plosser (1982) failed to reject the hypothesis of a unit root in macroeconomic time series, the long run trend in output can no longer be treated as deterministic. Given the uncertainties associated with the estimation of a stochastic trend, measuring potential output (and the output gap) with any degree of accuracy has proved to be difficult.

The uncertainties surrounding the measurement of potential output and the output gap has also direct and strong implications on optimal monetary policy, as pointed out by Rudebusch (2002), Smets (2002) and Ehrmann and Smets (2003). In particular, they show that the optimal weight to place on output stabilisation for the monetary policymaker declines when the output gap is poorly measured. In addition, there is also added uncertainty from the fact that real-time data on output are preliminary and subjected to substantial revisions as time goes by, as emphasized by Orphanides (2001) for U.S. data. The mismeasurement of the output gap in real time represents a major problem for the implementation of policy strategies that rely on information about the current output gap, as pointed out by Orphanides and van Norden (2002) and Orphanides (2003).

A key aspect in all of these investigations is the recognition that policymakers may be uncertain as to the true data-generating processes describing the output gap and the extent of the mismeasurement problem that the authorities face. As a result, standard applications of certainty equivalence based on the classical linear-quadratic-Gaussian control problem do not apply.[1] Hence, simple monetary policy rules based on the output gap may not be robust to output gap uncertainty.

[1] See Svensson and Woodford (2003) for a recent exposition of certainty equivalence in the absence of any model uncertainty.

There have been a variety of suggestions in the literature on how to mitigate the problem of output gap mismeasurement for monetary policy decisions, by placing less weight on the "uncertain" output gap, replacing the gap with the change in output, ignoring the gap fully by relying exclusively on past and future inflation rates or aim directly at stabilizing the nominal income growth, see for instance McCallum (1998, 2001), Orphanides et al. (2000), Rudebusch (2002), Leitemo and Lønning (2002) and Spencer (2004) among many others.

Although the mismeasurement of the output gap based on an inappropriate detrending method is a general problem (see for instance Canova, 1998; Bjørnland, 2000), the mismeasurement of the output gap due to data revisions and lack of hindsight may not necessarily be so. In particular, Gruen et al. (2005) find real-time output gap estimates for Australia which are unbiased and highly correlated with final estimates derived with the latest data and the benefit of hindsight. Similar results are also found in Rünstler (2002) for the Euro area and to a certain degree in Bernhardsen et al. (2004) for Norway when they estimate the real-time output gap using multivariate models. Univariate methods, on the other hand, still provide poor information about the output gap in real time.

With these uncertainties in mind, this paper sets out to evaluate a series of methods for extracting the output gap using Norwegian quarterly data. The different methods range from simple univariate detrending methods to more elaborate multivariate models. Given the uncertainties of real time estimates, in particular for the univariate detrending methods, we argue that as a minimum criteria the output gaps should display a high degree of coherence with other indicators of economic activity that are not (or less) revised in real time. However, as optimal monetary policy is essentially about forecasting inflation, (see Svensson and Woodford, 2005), the usefulness of the output gap for monetary policy is ultimately addressed in terms of its value added in forecasting inflation. We will use the New Keynesian Phillips curve, which relates inflation to real activity, as the maintained theory of inflation. As Gerlach and Svensson (2003), we will attribute greater importance to the output gap if it is a good predictor of future inflation.

To sum up, the methods will be evaluated by comparing the output gaps in terms of (i) statistical properties, (ii) coherence with other (real time) estimates of the business cycle and (iii) value added when forecasting inflation. Finally, we compare the inflation forecasts with forecasts where alternative indicators replace the output gap.

The results illustrate that there is a high degree of correlation between the different output gaps. However, with regard to the usefulness in predicting inflation, the multivariate methods seem to outperform the univariate methods. The multivariate methods also display the highest correlation with other indicators of economic activity that are not (or less) revised in real time, making them more reliable with regard to assessing the current economic situation. Interestingly though, some of the alternative indicators do as well, or in some cases even better, than the multivariate methods in predicting inflation. Hence, assessment of pressures in the economy based on the uncertain output gap could benefit from being supplemented with alternative indicators.

The paper is organized as follows. In Section 2, the different methods are put forward and applied to the Norwegian data. Section 3 evaluates the alternative output gaps in terms of statistical properties and coherence with alternative measures of the business cycle less subject to data revisions. The different output gaps (as well as the alternative measures of the business cycle) are finally evaluated in Section 4 by their value added in predicting inflation, using Phillips curve type inflation equations. Section 5 presents our conclusions.

2 Methods for estimating the output gap

An obvious question when a time series is characterised with a unit root, is how one can distinguish the permanent (trend) component from the transitory (cyclical) component in the data. In particular, the issue of detrending becomes non-trivial when the trend can no longer be treated as deterministic. However, Beveridge and Nelson (1981) have shown that any non-stationary process can in fact be decomposed into a permanent and a transitory component, with plausible statistical properties. The issue to consider, however, is what kind of structural relationship and driving forces one should assume for the different components, as different assumptions may produce different values in the trend-cycle decomposition.

Furthermore, historical estimates of the output gap might also change when data are revised and new information emerges. The problem of data revisions applies to both actual and potential output, implying uncertainty concerning both components. In the present analysis we will refer to the output gap as

$$(1) \qquad ygap_t = y_t - y^*_t$$

The variables are expressed in logarithms, with the output gap, $ygap_t$, being the percentage deviation between actual output (y_t) and potential output (y^*_t). A number of univariate and multivariate methods for estimating the output gap have been developed. Below we review and apply some of these methods to seasonally-adjusted figures from the quarterly national accounts in Norway for the period 1978Q1 to 2004Q2. In spite of seasonal adjustment, variations in the quarterly figures result in substantial, random disturbances in the output gaps. Although the calculations are based on quarterly data, in the figures presenting the various output gap we have aggregated the quarterly figures to annual figures.

2.1 Univariate methods

Univariate methods use information in the time series itself (here, mainland GDP) to estimate the output gap. Three examples will be reviewed here.

Hodrick-Prescott filter (HP)

The Hodrick-Prescott filter extracts the value of potential output ${y^*}_t$ that minimises the difference between actual output and potential output while imposing constraints on the extent to which growth in potential output can vary, see Kydland and Prescott (1990) for detailed discussion. The following expression is minimised:

$$(2) \qquad Min\{y_t^*\}_{t=1}^T \left\{ \sum_{t=1}^{T} (y_t - y_t^*)^2 + \lambda \sum_{t=2}^{T-1} \left[(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*) \right]^2 \right\}$$

The first term in the equation is the square of the difference between actual output and potential output. The second term is the square of the change in potential output growth. λ is a parameter with values between zero and infinity that determines the extent of permissible variations in potential growth. λ is determined outside the model. In the borderline case where λ is infinite, there will be minimal variation in potential growth. The result is a linear trend with a constant growth rate. At the other extreme, λ = 0, and the difference between actual and potential output is as small as possible. These two variables will then be identical and the output gap will be zero.

In the calculations, we have considered two different values of λ; 1600 and 40 000.[2] Overall the two output gaps display a similar pattern, although there are periods where they clearly diverge, i.e. the first half of the 1990s and the end of the sample (see appendix A). However, in our comparison of methods later on in this article, we follow international practice and use an output gap based on λ = 1600 (see Kydland and Prescott 1990).

Band-pass filter (BP)

Another common approach to extract business cycle information from a time series is band pass filtering. In this framework, a time series is viewed as a weighted sum of underlying series with different cyclical patterns or frequencies. Since the cycles of different frequencies are uncorrelated in the long run, the variance of a given time series is simply given as the sum of its variances over all frequencies. The function decomposing the total variance by frequency is commonly referred to as the spectrum or spectral density.[3] The basic idea behind band pass filtering is to extract information regarding the frequencies of interest. For the purpose of measuring the cyclical component of GDP, this would typically be the business cycle frequencies. Hence, given a view on the cycle lengths defining a business cycle, one can construct a band pass filter that excludes all other frequencies. Burns and Mitchell (1946) defined the business cycles as fluctuations lasting from 6 to 32 quarters. This has been a standard reference in later studies. Fluctuations with a higher frequency are normally seen as irregular or seasonal, whereas fluctuations with a lower frequency are attributed to movements in the trend or potential GDP.

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[2] Statistics Norway uses λ =40000 in its analyses of the Norwegian economy

[3] See e.g. Hamilton (1994) for an introduction.

An optimal filter would pass through all frequencies in the specified frequency range with probability 1, leaving out all other frequencies. Although such an optimal filter can be derived, it is of little use in practical work since it requires an infinite number of data points. Hence, all the band pass filters proposed in the literature are approximations to the optimal filter. In this study, we use the Band pass filter developed by Baxter and King (1999). Their filter takes the form of a 25-quarter moving average:

$$(3) \qquad ygap_t = \sum_{i=-12}^{12} \alpha_i y_{t-i} ,$$

where the weights, α_i, can be derived from the inverse Fourier transform of the frequency response function. An obvious problem with the filter given in (3), is that we loose 12 quarters of observations for the output gap estimates at the start and end of the sample.[4] Here, we follow Stock and Watson (1998) and extend the output series with forecasts from an AR(4) model. Alternatively we could have used the one sided filter proposed by Christiano and Fitzgerald (1999).

Univariate unobserved component-methods (UC)

The unobserved component-method is based on the premise that an observable variable is composed of two or more components that are not observable. The basic idea is that the unobservable variables can be identified by assuming that they affect the variable that can be observed. In addition, we must specify the underlying processes that are behind the unobservable variables over time. Both the unobservable variables and the observable variable are modelled and estimated as a "maximum likelihood" system using the Kalman filter.

Among the simplest UC models are the local linear trend models. The following equations provide an example of these models:

$$(1') \qquad y_t = y_t^* + ygap_t$$

$$(4) \qquad y_t^* - y_{t-1}^* = \delta_{t-1} + \eta_t$$

$$(5) \qquad \delta_t = \delta_{t-1} + v_t$$

$$(6) \qquad ygap_t = \rho_1 ygap_{t-1} + \rho_2 ygap_{t-2} + \varepsilon_t$$

This specification is taken from Harvey (1985) and Clark (1987). We start with equation (1'), which states that GDP (y) can be decomposed into the unobserved variables potential GDP (y^*) and the output gap ($ygap$). Equations (4) and (5) determine how potential GDP grows. We assume that potential output follows a random walk with drift, where η and v are

[4] Baxter and King (1999) show that +/- 20 gives a reasonable approximation for the US business cycle.

random and normally distributed residuals that are independent of each other (white noise). This specification places few constraints on permitted variations in unobservable potential output. Equation (6) implies that the output gap follows an AR(2) process.

2.2 Multivariate methods

Multivariate models explore the relationships between GDP and other observable variables. Three different methods are presented here.

Production function method (PF)[5]

Output can be described by a production function. The production function models the supply side of the economy, where output is determined by available technology and the input factors labour and capital. Potential output may be perceived as the resulting output level if the input factors are neither exposed to strong pressures nor partially unutilised. The difference between actual output and estimated potential output can then be interpreted as the output gap.

The aggregated production function for the economy[6] can be expressed as a Cobb-Douglas production function:

$$(7) \qquad y_t = \alpha_0 + \alpha_1 l_t + (1-\alpha_1)k_t + e_t$$

where y is GDP, l is person-hours, k is capital stock, e is total factor productivity and α_0 is a constant. All variables are measured as natural logarithms. The coefficients α_1 and $(1 - \alpha_1)$ are the factor shares for labour and capital respectively. Total factor productivity is calculated as the residuals from equation (7) using the least-squares method.

The potential levels of person-hours, capital and total factor productivity are then used to estimate potential output, y^*:

$$(8) \qquad y_t^* = \alpha_0 + \tfrac{2}{3} l_t^* + \tfrac{1}{3} k_t^* + e_t^*$$

We have inserted values for the factor income shares, which can be estimated, at 2/3 for person-hours and 1/3 for capital for mainland enterprises, see the Ministry of Finance (1997).

Potential use of person-hours depends on the potential level of the labour force, working hours per employee and equilibrium unemployment[7]. Potential capital stock is assumed to be

[5] This part is based on the description in Frøyland and Nymoen (2000).
[6] We follow the approach described in Frøyland and Nymoen (2000) and estimate a production function for the sectors manufacturing, construction, services and distributive trades. These sectors account for about ¾ of output in mainland Norway.

the same as actual capital stock since it is difficult to determine to what extent capital stock is used in the production process. Equilibrium unemployment and the potential levels of total factor productivity, the labour force and working hours are calculated using the HP filter[8].

Multivariate unobserved component-method (MVUC)

The univariate UC model can be expanded by including a number of variables that are assumed to contain information about the output gap. For instance, Scott (2000) extends the univariate model with an equation linking inflation to the output gap and by adding capacity utilisation as an observable. The relationship between the unemployment rate and the output gap through Okun's law[9] are typically explored.

An advantage of the MVUC method over univariate methods is that it uses more information. In addition, the method makes it possible to give some indication of the uncertainty associated with the estimated output gap. In order to make use of this information, however, some assumptions have to be made about the relationship between the different variables. The quality of the estimated output gap will depend on the realism of these assumptions. In the present study, we build on previous literature[10] and propose a model with output, inflation and the unemployment rate as observables. The model is given by the following set of equations:

Observation equations:

$$\Delta y_t = \Delta y_t^* + ygap_t - ygap_{t-1} \tag{9}$$

$$\pi_t = \alpha_{11}\pi_{t-1} + \alpha_{12}\pi_{t-2} + \beta_{11} ygap_{t-1} + \varepsilon_{2,t} \tag{10}$$

$$u_t - u_t^* = \alpha_{21}(u_{t-1} - u_{t-1}^*) + \beta_{21} ygap_{t-1} + \varepsilon_{3,t} \tag{11}$$

State equations:

$$ygap_t = \psi_{11} ygap_{t-1} + \psi_{12} ygap_{t-2} + \upsilon_{1,t} \tag{12}$$

$$\Delta y_t^* = \Delta y_{t-1}^* + \mu_{t-1} + \upsilon_{2,t} \tag{13}$$

$$\mu_t = \mu_{t-1} + \upsilon_{3,t} \tag{14}$$

$$u_t^* = u_{t-1}^* + \gamma_{t-1} + \upsilon_{4,t} \tag{15}$$

$$\gamma_t = \gamma_{t-1} + \upsilon_{5,t} \tag{16}$$

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[7] Equilibrium unemployment can be defined as the level of unemployment that is consistent with stable wage and price developments. Alternative estimates of equilibrium unemployment are discussed in Frøyland and Nymoen (2000).

[8] The values of the parameter λ in the calculations of the potential levels are determined on the basis of what seems reasonable.

[9] This builds on the empirical regularity of the strong correlation between output growth and unemployment growth and unemployment reported by Okun (1962).

[10] For example Apel and Jansson (1999).

where (9) is an identity which simply states that the growth rate of output is equal to the growth in potential output plus the change in the output gap. Equation (10) can be interpreted as a Philips curve, linking inflation, π_t, to the output gap. A version of Okun's law is given in (11), where u_t denotes the unemployment rate and u_t^* refers to the NAIRU, which is assumed to be a latent variable. We assume that the output gap can be represented by an AR(2) process, given in (12). Equation (13) specifies the growth in potential output as a random walk with a stochastic drift, μ_t, given by (14). This is a rather flexible specification that allows for mean shifts in the growth rate of potential output. The process for the NAIRU is determined by equations (15) and (16). Using a more compact matrix notation, the model can be written in state space form as follows:

$$\begin{bmatrix} \Delta y_t \\ \pi_t \\ u_t \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ \alpha_{11} & \alpha_{12} & 0 \\ 0 & 0 & \alpha_{21} \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ \pi_{t-2} \\ u_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & \beta_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & \beta_{21} & 0 & 0 & 1 & -\alpha_{21} & 0 \end{bmatrix} \begin{bmatrix} ygap_t \\ ygap_{t-1} \\ \Delta y_t^* \\ \mu_t \\ u_t^* \\ u_{t-1}^* \\ \gamma_t \end{bmatrix} + \begin{bmatrix} 0 \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix} \tag{17}$$

$$\begin{bmatrix} ygap_t \\ ygap_{t-1} \\ \Delta y_t^* \\ \mu_t \\ u_t^* \\ u_{t-1}^* \\ \gamma_t \end{bmatrix} = \begin{bmatrix} \psi_{11} & \psi_{12} & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} ygap_{t-1} \\ ygap_{t-2} \\ \Delta y_{t-1}^* \\ \mu_{t-1} \\ u_{t-1}^* \\ u_{t-2}^* \\ \gamma_{t-1} \end{bmatrix} + \begin{bmatrix} \upsilon_{1,t} \\ 0 \\ \upsilon_{2,t} \\ \upsilon_{3,t} \\ \upsilon_{4,t} \\ 0 \\ \upsilon_{5,t} \end{bmatrix} \tag{18}$$

where (17) and (18) refers to the observation equation and state equation, respectively. Furthermore, we assume that all the error terms are iid and normally distributed. The model is estimated with Maximum Likelihood using the Kalman filter.

Estimation and empirical results

We use quarterly data for the period 1981q3 to 2004q2 to estimate the model. The output data refers to GDP for mainland Norway, which excludes the oil sector. Unemployment data are taken from the quarterly labour force survey (LFS). The inflation measure is based on the part of CPI which refers to non-tradables, labelled domestic inflation. This is motivated by the fact that total CPI also includes a significant share of import prices, which are less likely to depend on domestic factors. The inflation series was detrended prior to estimation, by using a HP filter with λ equal to 50000, in order to make it stationary.

Table 1 reports the estimation results. As can be seen, all parameters have the expected signs. Furthermore, with the exception of some of the estimated standard deviations of the error terms, all parameters are significantly different from zero at the 5% level.

Table 1 Estimation results for MVUC

Parameter	Estimate	St.dev	z-Statistic
α_{11}	1.269	0.085	14.841
α_{12}	-0.400	0.088	-4.561
α_{21}	0.635	0.093	6.867
β_{11}	0.052	0.026	1.992
β_{21}	-0.159	0.027	-5.922
ψ_{11}	1.146	0.067	17.182
ψ_{12}	-0.195	0.041	-4.802
σ_{ε_2}	0.192	0.019	10.180
σ_{ε_3}	0.025	0.026	0.947
σ_{υ_1}	0.453	0.037	12.351
σ_{υ_2}	0.007	0.012	0.596
σ_{υ_3}	0.000	0.000	0.003
σ_{υ_4}	0.013	0.033	0.393
σ_{υ_5}	0.000	0.000	0.508

Structural vector autoregression (SVAR) model

The SVAR method uses information from a number of variables that have a high degree of correlation with GDP, such as unemployment and domestic inflation, to estimate the output gap. Identification of the SVAR is based on Blanchard and Quah (1989), which showed how a priori restrictions can be imposed on long-term multipliers in a model of endogenous variables in order to identify underlying structural shocks. Blanchard and Quah distinguished primarily between demand and supply shocks. By estimating a model consisting of GDP and unemployment, they assumed that only supply shocks can have a long-term effect on the level of GDP. Demand shocks can have an effect on GDP in the short term, but in the long run the effects of these shocks will eventually die out. Since unemployment is assumed to be stationary, no shocks can (by definition) have a long-term effect on the level of unemployment. The assumption that demand shocks can only have a short term effect on the level of GDP (and unemployment) is fully consistent with a standard aggregated demand and supply model, where the supply curve becomes vertical in the long term.

Faust and Leeper (1997) have criticized the use of long run restrictions to identify structural shocks, and show that unless the economy satisfies some types of strong restrictions, the long run restrictions will be unreliable. For the long run restrictions to give reliable results, they argue that the aggregation of shocks in small models should be checked for consistency using alternative models. As pointed out by the same authors, the Blanchard and Quah (BQ) model could be solved for the growth rate of prices rather than for the unemployment rate.[11]

In our analysis here, we try to accommodate some of this criticism by expanding the bivariate BQ model to also include domestic inflation. With three variables, we can identify three different shocks: two demand shocks and one supply shock. We assume as in Blanchard and Quah (1989) that neither of the demand shocks can have a long-term effect on unemployment, but allow one of them; a real demand (or preference) shock to have a potential long-lasting effect on GDP (see Gali and Rabanal (2004) for further interpretation). This has been done to investigate the possibility that one of the demand shocks can have a more persistent effect on output than the other, although without changing the unemployment rate permanently as a result.[12]

The aggregate supply shock is allowed to have a long-term effect on GDP, unemployment and prices. Since the unemployment rate has increased in the course of our estimation period and is perceived to be nonstationary, it is reasonable to assume that the real (supply) shock

[11] Strictly speaking, Faust and Leeper's (1997) critique refers to a bivariate model using only one long run restriction like that of BQ, where the problem stems from the fact that the underlying model has more sources of shocks (with sufficiently different dynamic effects on the variables considered) than does the estimated model.

[12] It may also be that real demand shocks like government consumption/investment can change potential output, due to changes in capital accumulation. This effect may, however, be expected to be small, since capital accumulation is slow, and with little consequences for long run unemployment.

can affect equilibrium unemployment over time. Inflation is perceived to be stationary, so none of the shocks can by definition affect inflation permanently.

If we let z be a vector with the three stationary variables (Δu_t,Δy_t,Δp_t)' where Δ denotes quarterly changes, u_t is unemployment rate, y_t is GDP and p_t is domestic prices, the moving average representation of the VAR model can be written as

$$(19) \quad z_t = A(L)e_t$$

where e_t is a vector of reduced form serially uncorrelated residuals with covariance matrix Ω. Assume that the orthogonal structural disturbances ε_t can be written as linear combinations of the innovations e_t, i.e. e_t=$B_0\varepsilon_t$. A (restricted) form of the moving average containing the vector of original structural disturbances can then be found as

$$(20) \quad z_t = B(L)\varepsilon_t$$

where $A(L)B_0$=$B(L)$. The ε_t's are normalized so they all have unit variance. If B_0 is identified, one can derive the MA representation in (20). By systematizing the three uncorrelated structural shocks as: $\varepsilon_t = (\varepsilon_t^{AS}, \varepsilon_t^{RD}, \varepsilon_t^{ND})'$, where ε_t^{AS} is an aggregate supply shock, ε_t^{RD} is a real demand shock and ε_t^{ND} is the remaining demand (i.e. nominal demand) shocks, the matrix of long run multipliers can written as

$$(21) \quad \begin{bmatrix} \Delta u \\ \Delta y \\ \Delta p \end{bmatrix}_t = \begin{bmatrix} B_{11}(1) & B_{12}(1) & B_{13}(1) \\ B_{21}(1) & B_{22}(1) & B_{23}(1) \\ B_{31}(1) & B_{32}(1) & B_{33}(1) \end{bmatrix} \begin{bmatrix} \varepsilon^{AS} \\ \varepsilon^{RD} \\ \varepsilon^{ND} \end{bmatrix}_t$$

where $B(1) = \sum_{j=0}^{\infty} B_j$ indicate the long run matrix of B(L). Hence, the restrictions that neither of the demand shocks can affect the unemployment rate permanently is found as; $B_{12}(1)$=$B_{13}(1)$=0. Furthermore, the restriction that nominal demand shocks can not affect GDP permanently is simply found as; $B_{23}(1)$=0. In the long run, (19) and (20) implies

$$(22) \quad A(1)\Omega A(1)' = B(1)B(1)'$$

As B(1) will be lower triangular, expression (22) implies that B(1) will be the unique lower triangular Cholesky factor of $A(1)\Omega A(1)'$.

Based on the above identification, GDP can now potentially be split into two different components; A component determined by shocks that have a permanent effect on the supply side of all the variables in the economy, and a component determined by shocks that affect demand in the short term. The first component will represent potential GDP and will consist of the accumulated supply shocks, while the latter can be interpreted as the output gap and will consist of the accumulated aggregate demand shocks. For the third shock, the real demand shock that can potentially affect output in the long run, we assume that it contributes to the output gap the first two years (business cycle frequencies), whereas any effect above that will contribute to developments in potential output. However, as the impulse responses in appendix B show, the impact on GDP will eventually die out, although at a slower pace than for the nominal demand shocks.[13]

Estimation and empirical results

We use quarterly data for the period 1981q1 to 2004q2 to estimate the model. However, some initial values are lost due to the aggregation of shocks, so that the output gap will be available from 1982q4. The data used for GDP, unemployment and domestic inflation are the same that were used for the MVUC method, and they are all seasonally adjusted. However, to be consistent with the flexible specification of output growth using the MVUC method, the irregular component will be removed from GDP prior to analysis.

Based on a set of information criteria, the VAR model is estimated with 5 lags. With 5 lags, the model satisfies a series of goodness-of-fit properties. In appendix B, the impulse responses for GDP, prices and unemployment for the three structural shocks are displayed. The effects are as expected; Nominal demand shocks increase output at first, but as the long run restriction eventually bites, the effects gradually fades away towards zero. During this period, unemployment falls temporarily whereas prices increase gradually and permanently. Real demand shocks increase output at first, but the effect thereafter slowly fades out. Following the same shock, unemployment first increases, but then gradually falls and becomes negative until the effect eventually dies out. Prices increase also gradually, but the effects are much smaller than those of the aggregate nominal demand shocks. Finally, aggregate supply shocks increase output and reduce unemployment permanently, whereas prices fall persistently as expected. Hence, the shocks with estimated effects seem consistent with theory predictions.

3 Comparison of methods

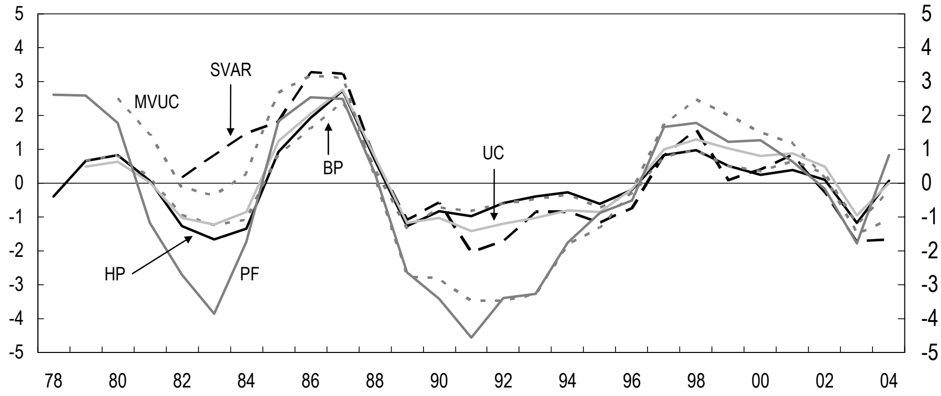
For an overall picture of the differences between the methods, all the output gaps are shown in Chart 1.[14] The different output gaps describe the main economic fluctuations in Norway as they are commonly referred to, with two downturns in the 1980s, an upturn from the mid-1990s and a downturn over the past couple of years. The PF method differs from the other methods in estimating a considerably more negative output gap during the downturn in the

[13] Assuming instead that real demand shocks can have a long run effect on the unemployment rate will not change the results.

[14] See appendix A for a detailed graph of all the individual output gaps.

early 1980s.[15] Both the MVUC and PF method also estimate a more severe downturn at the beginning of the 1990s than the other methods. From around 1995 to 2003, the output gaps correspond fairly closely, particularly from 2001. Note that for two of the univariate methods, the HP and BP filters, the estimate for the output gap is particularly uncertain towards the end of the sample.

Chart 1 Output gap, all methods. Percentage of potential GDP.



Tables 2 to 5 contain statistical summaries of the different methods for the (common) period 1982 to 2004. Table 2 first compares some key properties of the output gap. One reasonable criterion is that the average value of the output gap should over time be close to zero. The PF method differs from the other methods, with an average value for the output gap of -0.7. The PF and MVUC methods also display the highest standard deviation (2.17 and 2.11 respectively). However, we have no objective criteria other than indicating that the output gaps should not be "too wide" or "too narrow".

Table 2 Statistical summary for the output gap, 1982 to 2004

Method	HP	BP	UC	PF	MVUC	SVAR
Average	-0.05	-0.06	0.03	-0.70	-0.17	0.10
Standard deviation	1.07	0.96	1.18	2.17	2.11	1.46
Lowest value	-1.7	-1.4	-1.4	-4.6	-3.5	-2.1
Highest value	2.7	2.4	2.8	2.5	3.2	3.3

Table 3 shows the correlation coefficients between the different methods. As expected from looking at the charts, the correlation between the alternative output gaps is generally high, particularly between the univariate methods. The correlation coefficients are lowest between the PF and either the SVAR, BP or HP method.

[15] The HP filter was used to calculate potential employment and potential total factor productivity for the PF method. Alternative values for the smoothing parameter λ affect developments in these variables. However, allowing for a reasonable range of variation for λ, potential output is not affected to any substantial extent.

Table 3 Correlation between output gaps calculated by different methods, 1982 to 2004

Method	HP	BP	UC	PF	MVUC	SVAR
HP	1	0.99	0.95	0.67	0.80	0.71
BP		1	0.96	0.66	0.80	0.72
UC			1	0.77	0.92	0.78
PF				1	0.83	0.66
MVUC					1	0.77
SVAR						1

Table 4 Concordance in business cycles, 1982 to 2004

Method	HP	BP	UC	PF	MVUC	SVAR
HP	1	0.95	0.91	0.86	0.82	0.74
BP		1	0.89	0.89	0.84	0.78
UC			1	0.89	0.86	0.78
PF				1	0.86	0.80
MVUC					1	0.83
SVAR						1

Table 4 shows a measure of concordance in business cycles, i.e. the proportion of time that the cycles of two series spend in the same phase, see McDermott and Scott (2000). This is of particular interest in analyses where the focus is on the sign of the gap and not necessarily its magnitude. Table 4 confirms the impression from the charts and Table 3 that the alternative methods provide close descriptions of cyclical developments.

Table 5 Turning points

Method Period	HP	BP	UC	PF	MVUC	SVAR
Upturn mid-1980s	1987q2	1987q2	1987q2	1987q3	1987q2	1987q1
Downturn early 1990s	1989q3	1989q3	1990q4	1991q3	1991q4	1991q4
Upturn late 1990s	1997q4	1997q4	1997q4	1997q1	1997q4	1998q4
Downturn early 2000s	2003q1	2003q1	2003q1	2003q2	2003q2	2003q1

It is also interesting to investigate whether the different methods yield the same conclusion as to when an upturn or a downturn begins. Table 5 shows the quarter and year pinpointed by the different methods as the turning point in the business cycle. A turning point may be defined as the quarter the output gap reaches its highest (or lowest) value within a period generally regarded as an upturn (or downturn).

The different methods are in relative agreement in indicating that the upturn in the mid-1980s peaked in the first part of 1987.[16] This is in line with the general perception of the business cycle (see for example Bjørnland (2000) and Johansen and Eika (2000)). However, the methods pinpoint different dates for the trough in the early 1990s. The HP and BP methods date the turning point as early as 1989q3, while the MVUC and SVAR method indicates 1991q4. Most methods find that the upturn ended in 1997q4, while the PF method finds the endpoint to be three quarters earlier and the SVAR method one year later. However, all methods concur in that the subsequent downturn troughed in the first half of 2003.

Alternative indicators in real time

Most indicators of economic activity like GDP and its components are revised over time, sometimes substantially. Given the uncertainties of real time estimates, in particular for the univariate detrending methods, we argue that as a minimum criteria the output gaps should display a high degree of correlation with indicators of economic activity that are not revised in real time, or at least, subject to only minor revisions.

The Industrial Confidence Index (ICI) published by Statistics Norway is such a variable. While this indicator is not revised, except for revisions due to changes in seasonal factors, it only covers manufacturing industry. Nevertheless, it may be a good indicator of business cycle conditions.

The unemployment rate is an alternative indicator of economic activity. However, although not affected by revisions[17], the unemployment rate is usually lagging GDP in the business cycle (see Bjørnland, 2000), thereby indicating different turning points. This emphasizes that the markets for goods and services pick up earlier than the labour market. Furthermore, as the unemployment rate has increased over time, we need to measure the unemployment rate as a deviation from trend, i.e. the unemployment gap (UGAP). This involves the issue of de-trending again. However, as the unemployment rate only changes gradually and very smoothly, it turns out that the different methods provide very similar pattern for the unemployment gap. For simplicity, the UGAP is therefore calculated by smoothing the unemployment rate (taken from the labour force survey (LFS)) by a Hodrick Prescott filter with λ=40000. The series is identical to the unemployment gap used in the PF method.

An index of financial variables (FVI) is another potential indicator of economic activity constructed from financial variables.[18] The FVI is a composite index of the main share index from Oslo Stock Exchange (OSEBX), 5 year interest rates, an exchange rate index, house

[16] We have not included the trough in the early 1980s since calculations of the output gap using the SVAR method starts in 1982.

[17] From time to time, the calculation method has changed. This has not altered the general development in the series.

[18] The index is preliminary, based on work in progress in Norges Bank.

prices and the credit indicator (C2). The individual indices in the FVI are not revised, but some of the series have to be de-trended (using the Hodrick Prescott filter).

In tables 6 and 7 we show correlations and concordance between the output gaps and ICI, FVI and UGAP, respectively, for the period 1988-2004. We have chosen to start in 1988 here and in the subsequent analysis, as this is the first observation available for ICI and FVI.

Table 6 Correlation between output gaps and different indicators, 1988 to 2004

Method	ICI	FVI	UGAP
HP	0.28	0.53	0.65
BP	0.27	0.55	0.65
UC	0.29	0.72	0.77
PF	0.37	0.75	0.69
MVUC	0.39	0.77	0.75
SVAR	0.23	0.70	0.71

Table 7 Concordance between output gaps and different indicators, 1988 to 2004

Method	ICI	FVI	UGAP
HP	0.56	0.76	0.82
BP	0.56	0.79	0.82
UC	0.55	0.82	0.88
PF	0.55	0.86	0.86
MVUC	0.58	0.85	0.94
SVAR	0.55	0.86	0.86

Correlations between ICI and the output gaps are low. This is probably due to the nature of this indicator, which reflects only one sector of the economy. The fluctuations in the ICI are much larger and more irregular than fluctuations in output gaps. Concordance is less affected by irregular fluctuations from one quarter to the next; hence concordances between ICI and the output gaps in table 7 indicate a closer relationship than the correlations do.

With regard to the UGAP and the FVI, correlations and concordances with the output gaps are higher. The correlation and concordance measures are lowest for the two univariate methods; HP and BP, and highest for MVUC. However, the fact that all the multivariate methods do rather well when compared with alternative indicators of economic activity, indicates the usefulness of adding additional variables when identifying the output gap.

4 Forecasting inflation

So far, we have compared some properties of the different output gaps. We now proceed to test to what extent they contribute to forecast inflation developments. More formally, this involves estimating a forecasting equation for inflation that includes the output gap as an explanatory variable, and then determine if the output gap contains additional information compared to a simple autoregressive (AR) model. We have used a simple Phillips curve relationship between domestic inflation and the output gap (see Orphanides and van Norden, 2004).

$$(23) \qquad \pi^h_{t+h} = \alpha + \sum_{j=1}^{n} \beta_j \pi^1_{t-j} + \sum_{j=1}^{m} \lambda_j ygap_{t-j} + \varepsilon_{t+h},$$

where π^h_{t+h} is domestic inflation over h quarters ending in quarter $t+h$. α, β and λ are coefficients and ε is a white noise residual. Inflation h quarters ahead is expressed as a linear function of past inflation and output gaps[19]. In the estimations, n = 8 and m = 4. In the autoregressive model, λ_j = 0, for j 0 1,..,8. We have estimated one model for each output gap, for the period 1989Q1 to 2004Q1 (4-step forecast) and the period 1989Q1 to 2003Q1 (8-step forecast). Only significant lags are included in the final model used for making forecasts.[20]

Chart 2 RMSFE. 4-step forecasts 1989Q1 – 2004Q1

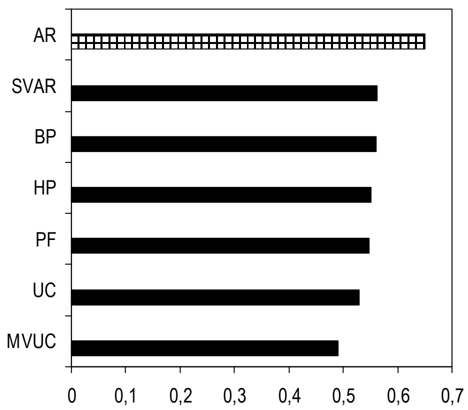


Chart 3 RMSFE. 8-step forecasts 1989Q1 – 2003Q1

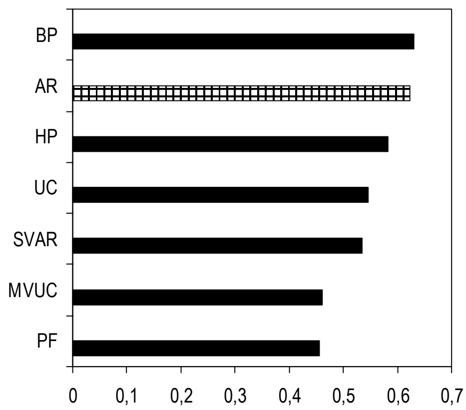


Chart 2 and 3 graph the 4-step and 8-step root mean square forecast error (RMSFE) for the different output gaps respectively[21] In the final part of this section we will present tests for statistical significance of these forecasts, using the Diebold and Mariano (1995) test statistics. Chart 2 emphasises that the MVUC provides the lowest RMSFE with regard to predicting inflation at the 4 quarter horizon, followed closely by UC and PF. However, the differences between the alternative gaps are not large, and all do clearly better than the benchmark AR model.

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[19] Since the output gap in period t is not known until period (t+1), only past values of the output gap is included.
[20] Estimation results can be obtained by the authors on request.
[21] See table C.1. in Appendix C for more detailed estimation and prediction results for the different output gaps.

At the 8 quarter horizon, the information-content in the different output gaps with regard to predicting inflation is more varied. Of the different output gaps, the three multivariate methods exhibit the smallest forecast errors. PF is the best followed closely by MVUC and then SVAR. This is interesting, as the multivariate methods use information from other variables when calculating the gap, which may also prove to be useful when forecasting. The differences between the gaps have however widened, and now the BP filter actually do worse than the benchmark AR model, implying that there is no gain from adding the BP gap to the inflation forecasting equation in (23). UC is, however, almost as good as SVAR.

Finally, we compare the RMSFE for the different output gaps with the RMSFEs from a forecasting equation where the output gaps are replaced by a series of other indicators. In addition to the three above mentioned variables, whose real-time properties are better than the output gaps', we also consider some alternative variables that, although revised in real time, may be equally useful as the output gap in predicting inflation. Chart 4 and 5 graph the RMSFEs resulting from adding these alternative indicators to the analyses at the 4-quarter and the 8-quarter horizon respectively. The full set of alternative variables[22] used are:

UGAP	Unemployment gap. LFS unemployment ratio filtered by the HP-filter (λ=40000)
Δ_1U	LFS unemployment, quarterly change
Δ_4U	LFS unemployment, change from same quarter previous year
FVI	Index of financial variables
ICI	Industrial Confidence Index
NGAP	Employment gap, Mainland Norway. Employment filtered by the Hodrick Prescott filter (λ=40000)
Δ_1N	Employment Mainland Norway, quarterly growth
Δ_4N	Employment Mainland Norway, growth from same quarter previous year
Δ_1GDP	GDP Mainland Norway, quarterly growth,
Δ_4GDP	GDP Mainland Norway, growth from same quarter previous year
W-share	Wage cost share in private services Mainland Norway
Δ_4W-share	Wage cost share in private services Mainland Norway, quarterly change
Δ_4W-cost	Wage cost, growth from same quarter previous year
LPE	Unit Labour costs

[22] Sources: Statistics Norway and own calculations

From Chart 4, it is evident that all the output gaps do relatively well compared to the alternative indicators at the 4-quarters horizon (being centred low in Chart 4). Hence, the information content in these gaps with regard to forecasting inflation is at least as good as in other, plausible candidates. Interestingly though, the best indicator for predicting inflation at the 4 quarter horizon is the FVI, followed closely by the employment gap and the ICI.

At the 8-quarters horizon, however, the output gaps are more spread out, indicating that the information content is more varied. Clearly, only the multivariate methods can compete with these alternative indicators in predicting inflation. Of the univariate methods the BP method does worse than all other indicators. Of the alternative indicators, the employment gap does the best in predicting inflation, followed by the FVI and the unemployment gap. Note however, that the ICI is no longer among the best indicators, implying that it is not as useful as the multivariate output gaps in predicting inflation at the longer horizons.

Chart 4 RMSFE. 4-step forecasts 1989Q1 – 2004Q1

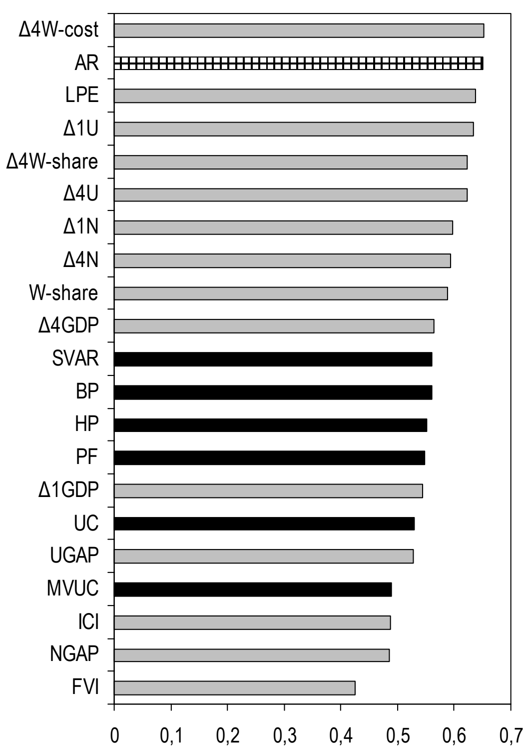
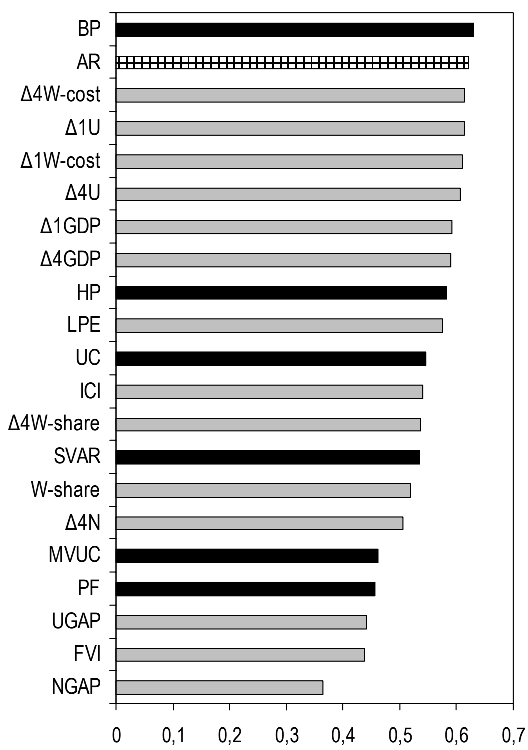


Chart 5 RMSFE. 8-step forecasts 1989Q1 – 2003Q1



Note also that neither the first nor the fourth differences of the unemployment rate do any good in predicting inflation at either the 4- or 8-quarter horizon. On the other hand, the unemployment gap is among the indicators with the best predictive abilities, emphasizing that it is the pressure in the labour market (from potential) and not the changes in the unemployment rate that are most relevant in predicting future inflation.

Statistical significance

We explore the statistical significance of these results using a test proposed by Diebold and Mariano (1995). The test assesses whether the inflation rate predicted by adding each output gap to the Phillips curve relation (23) above, is significantly more accurate than the benchmark autoregressive forecast itself.

Table 9 presents the Diebold-Mariano (DM) test statistic with corresponding p-values for the forecast to be equally accurate. As the benchmark forecast, the AR inflation forecast is used. Failure to reject the null hypothesis implies that the inclusion of the output gap measure does not improve the AR model significantly. Note, however, that the use of Diebold-Mariano statistics may provide non-normal critical values for asymptotic inference if the two models being compared are nested. However, Clark and McCracken (2001) find that the limiting distribution of these statistics is non-pivotal for forecast horizons greater than one period, and is therefore less of a problem here (see also the discussion in Orphanides and van Norden, 2004).

The results using the DM test confirm in many important ways the results from above. At the 4-quarter horizon, all the forecast are significantly better than the AR forecast as measured by the 5 or 10 percent level (UC, PF and MVUC reject the null hypothesis of similar forecast at the 5 percent level). With regard to the 8-quarter horizon, the picture is somewhat more diverse. Now the forecasts by HP or BP are no longer significantly better than the AR forecast. On the other hand, the forecast by UC, PF, MVUC and SVAR are clearly better than the AR, as we can reject the null hypothesis of similar forecast at the 5 percent level.

Table 8 Test of statistical significance of forecasts relative to an AR model for inflation. Diebold-Mariano test[1)]. 1989 to 2004

Method	4-quarter	8-quarter
HP	-1.47 (0.070)	-0.85 (0.198)
BP	-1.36 (0.088)	0.19 (0.573)
UC	-2.00 (0.023)	-1.67 (0.048)
PF	-2.09 (0.018)	-3.06 (0.001)
MVUC	-2.51 (0.006)	-2.88 (0.002)
SVAR	-1.40 (0.080)	-1.81 (0.035)

1) p-values in parenthesis.

Hence, the three multivariate methods and probably also UC, do significantly better than the benchmark AR in predicting inflation. However, when it comes to comparing the overall best indicator at the 4-quarter horizon (FVI) and at the 8-quarter horizon (NGAP) with the output gaps, both provide statistically significant improved forecast of inflation compared to the output gaps (see Table 9). Hence, assessment of pressures in the economy based on the output gap could benefit from being supplemented with alternative indicators such as FVI and the employment gap.

Table 9 Test of statistical significance of forecasts. Diebold-Mariano test[1)]
1989 to 2004

Method	Relative to FVI 4-quarter	Relative to NGAP 8-quarter
HP	2.72 (0.997)	4.66 (1.000)
BP	2.87 (0.997)	4.95 (1.000)
UC	2.80 (0.997)	4.16 (0.999)
PF	2.62 (0.996)	2.45 (0.993)
MVUC	2.05 (0.979)	2.72 (0.997)
SVAR	3.21 (0.999)	4.39 (0.999)

1) p-values in parenthesis.

5 Conclusion

The output gap - measuring the deviation of output from its potential - is a core concept in the monetary policy framework, indicating demand pressure that generates inflation. The output gap is also an important variable in itself, as a measure of economic fluctuations. Over time, economic resources are utilized efficiently when economic growth is stable and the output gap remains close to zero (or output close to potential; i.e. the long run trend). At this level, employment growth and unemployment will also be stable.

Despite its central role in monetary policy making, its definition and estimation raise a number of theoretical and empirical questions. In particular, as there are substantial uncertainties associated with the estimation of the long run trend, measuring potential output (and the output gap) with any degree of accuracy has proved to be difficult. Furthermore, there is also added uncertainty from the fact that real-time data on output are preliminary and subjected to substantial revisions as time goes by. The mismeasurement of the output gap in real time represents a major problem for the implementation of policy strategies that rely on information about the current output gap, as pointed out by Orphanides and van Norden (2002) and Orphanides (2003).

With these uncertainties in mind, we have evaluated a series of methods for extracting the output gap. As optimal monetary policy is essentially about forecasting inflation, (see Svensson and Woodford, 2005), the usefulness of the output gap for monetary policy is addressed in terms of its value added in forecasting inflation. However, given the uncertainties of real time estimates, we argue that as a minimum criteria the output gaps should also display a high degree of correlation with indicators of economic activity that are not much revised in real time. Finally, we also compare the inflation forecasts with forecasts where these alterative indicators replace the output gap.

Our comparison of the methods illustrates that there is a high degree of correlation between the methods as a whole. However, in some periods, some methods diverge from the others both with regard to the magnitude of fluctuations and the dates of the turning points. The PF method in particular differs from the other methods. On the other hand, with regard to the usefulness in predicting inflation, all the three multivariate methods, and MVUC in particular, outperform the univariate methods. The multivariate methods also display the highest correlation with real time estimates such as the unemployment gap, making them also more reliable with regard to assessing the current economic situation.

Interestingly though, some of the alternative indicators like the employment gap and an index of financial variables do as well, or in some cases even better, than the multivariate methods in predicting inflation. As uncertainties are particularly pronounced at the end of the calculation periods, assessment of pressures in the economy based on the uncertain output gap could benefit from being supplemented with alternative indicators such as the (un)employment gap.

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Appendix A Output gap using all methods.

Chart A.1 Hodrick-Prescott filter (HP). Output gap with λ at different values. Percentage of potential GDP.

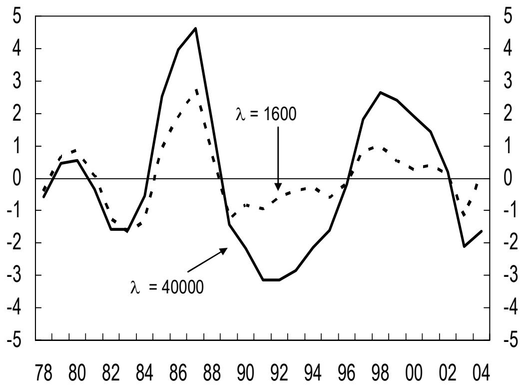


Chart A.2 Band-pass filter (BP). Output gap. Percentage of potential GDP.

Chart A.3 Univariate unobserved component-method (UC). Output gap. Percentage of potential GDP.

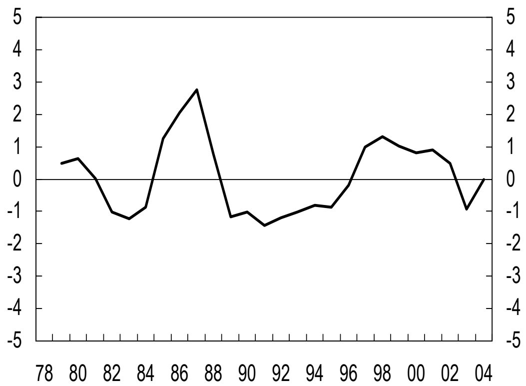
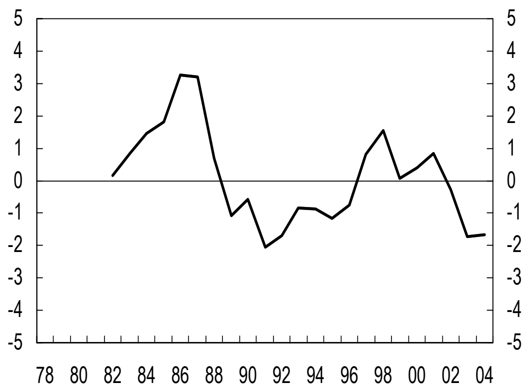


Chart A.4 Production function method (PF). Output gap. Percentage of potential GDP.

Chart A.5 Multivariate "unobserved component"-method (MVUC). Output gap. Percentage of potential GDP.

Chart A.6 Structural vector autoregressive method (SVAR). Output gap. Percentage of potential GDP.



Appendix B Impulse responses using the SVAR method[1]

Figure B.1 Impulse responses for GDP

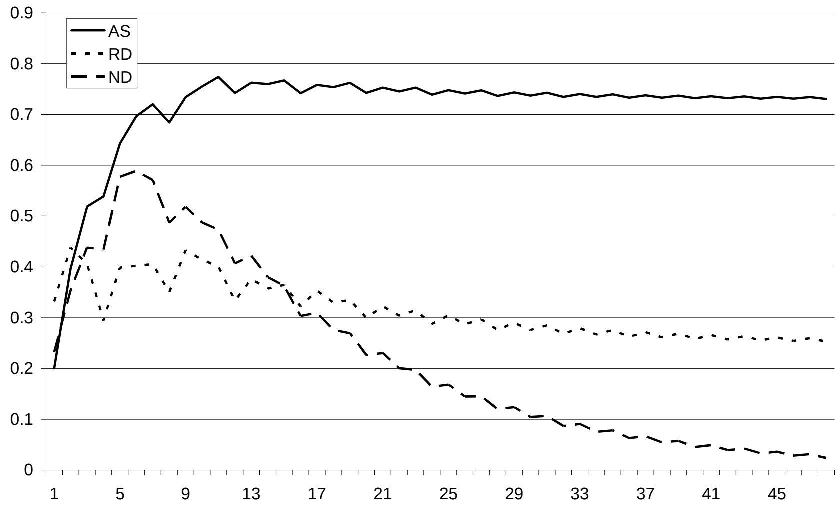


Figure B.2 Impulse responses for prices

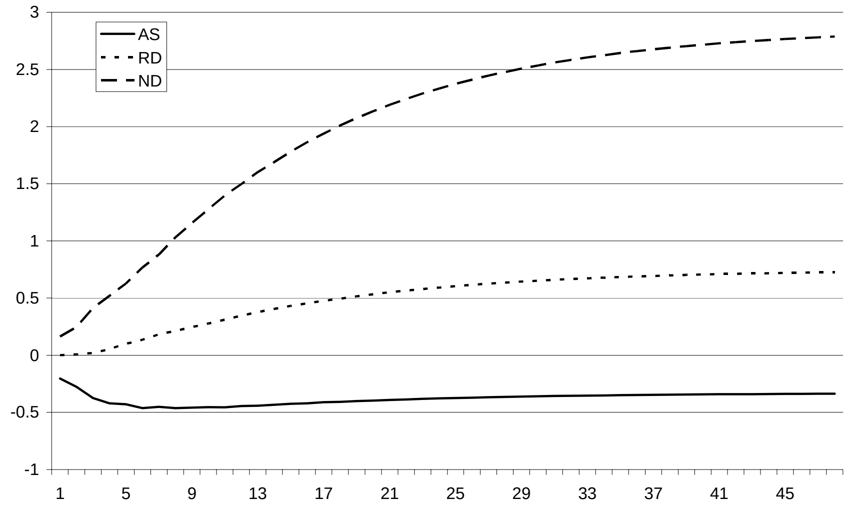
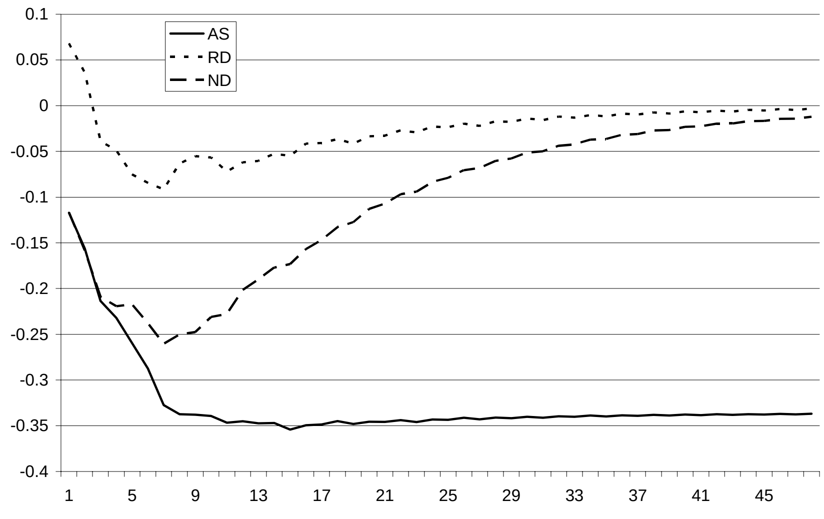


Figure B.3 Impulse responses for unemployment



[1)] (AS) Aggregate supply shock; (RD) Real demand shock; (ND) Nominal demand shock