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FRANCESCO FURLANETTO
KÅRE HAGELUND
FRANK HANSEN
ØRJAN ROBSTAD

NORGES BANK

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Norges Bank Output Gap Estimates: Forecasting Properties, Reliability and Cyclical Sensitivity *

Francesco Furlanetto† Kåre Hagelund‡ Frank Hansen§ Ørjan Robstad¶

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Abstract

This paper documents the suite of models used by Norges Bank to estimate the output gap. The models are estimated using data on GDP, unemployment, inflation, wages, investment, house prices and credit. We evaluate the estimated output gap series in terms of its forecasting properties, its reliability and its cyclical sensitivity to various measures of demand and supply shocks. A simple un-weighted average of the models features a better forecasting performance than each individual model. In addition, it helps predicting inflation in pseudo real-time and exhibits limited variations when new data become available. The summary measure of potential output responds strongly and rapidly to permanent shocks and to narrative measures of technology shocks but, although to a more limited extent, also to transitory shocks.

Keywords: Output Gap, Forecasting Inflation, Cyclical Sensitivity, Output Gap Revisions

JEL codes: C38, E17, E32

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†Corresponding author. Norges Bank and BI Norwegian Business School. Address: Bankplassen 2, PB 1179 Sentrum, 0107 Oslo, Norway. E-mail: francesco.furlanetto@norges-bank.no

‡Norges Bank. E-mail: kåre.hagelund@norges-bank.no.

§Norges Bank. E-mail: frank.hansen@norges-bank.no.

¶Norges Bank. E-mail: orjan.robstad@norges-bank.no.

1 Introduction

The output gap, defined as the difference between actual output and its potential level, is a key variable for central banks, in particular for those operating in a flexible inflation targeting regime, such as the Central Bank of Norway (Norges Bank henceforth). In fact, having an accurate measure of the state of the business cycle is crucial to appropriately evaluate trade-offs between different objectives and to fulfill the central bank's mandate. Norges Bank bases its assessment of the output gap on a broad set of indicators and models that are revised and expanded over time. The objective of this paper is to document the suite of models used as a key input to produce output gap estimates at Norges Bank. In particular, we evaluate its forecasting performance and its reliability when new data become available. In addition, we also provide a novel analysis on the cyclical sensitivity of the output gap to various measures of supply and demand shocks identified with different methods, along the lines of Coibion et al. (2018).

The output gap is not observable and its measurement is obviously challenging. Traditionally, simple univariate statistical filters, such as the Hodrick-Prescott (HP) filter, have been prominent. With sufficient information about the future, these simple methods provide a good measure of capacity utilisation. Unfortunately, as emphasized in the seminal paper by Orphanides and van Norden (2002), they are less reliable in real time as they are often subject to substantial revisions. This is primarily because trend extraction becomes problematic at the end of a given sample period (see Hamilton (2018) for a comprehensive discussion of the HP filter and Canova (2020) for a broader discussion on the properties of several filters and their ability to recover the output gap generated by structural macroeconomic models). Despite these well-known issues, according to Coibion et al. (2018) simple univariate statistical filters still seem to play a central role in the production of output gap estimates at several policy institutions.

In order to estimate the output gap, Norges Bank uses multivariate models which, in addition to GDP data, use data on other variables such as unemployment, wages, inflation, investment, credit growth and house price growth. Over time, a suite of multivariate models composed of unobserved component (UC) models and structural vector-autoregressive (SVAR) models has been developed. A simple un-weighted average of the estimates obtained from the different models included in the suite tracks well the official Norges Bank's output gap series, which is a judgemental measure representing the institutional view on capacity utilization in the Norwegian economy. Norges Bank's approach builds on Fleischman and Roberts (2011), Basistha and Startz (2008) and Jarocinski and Lenza (2018), among others, who find that using multivariate models is key to obtaining more precise and reliable estimates of the output gap for the US and the euro area. The use of data on inflation in combination with GDP follows Kuttner (1994), who initiated the literature on the output gap and Phillips curve estimation in unobserved component models. Clark (1989), Apel and Jansson (1999) and Sinclair (2009) model the relationship between the output gap and unemployment according to Okun's law. The use of data on investment follows Domenech and Gomez (2006), who emphasise the importance of the investment share in the economy as a key variable for identifying cyclical developments. Furthermore, Borio et al. (2017) argue that it is important to take into account data on financial variables when assessing potential output, a point also stressed by Furlanetto et al. (2020) in the context of an estimated macroeconomic model with financial frictions and by Berger et al. (2020) in a Bayesian Vector Autoregression.

We show that the model suite delivers estimates of the output gap that perform relatively well in terms of forecasting and reliability when new data become available. Notably, a simple un-weighted average of the nine output gap estimates features better forecasting properties than the individual models. In addition, such a summary measure of the output gap provides useful information for forecasting purposes. First, a model using the pseudo real-time estimate of the output gap performs better at forecasting inflation than a univariate AR-model in a direct forecasting exercise as in Orphanides and van Norden (2005). Second, when we compare the forecasting performance of bivariate models including the output gap estimate with simple univariate models for inflation, the bivariate models obtain on average a better performance. Significant gains are found, in particular at long horizons. Furthermore, we document that the summary measure of the output gap exhibits limited variation when new data become available, in particular when compared to an estimate obtained with a simple univariate HP filter. Therefore, we confirm that previous results in Fleischman and Roberts (2011), showing that using data on other variables (and on unemployment in particular) is useful to obtain reliable estimates of the output gap for the US, also hold for Norway.

We evaluate the summary measure of the output gap also along a third, and more novel, dimension, which is its cyclical sensitivity to various measures of economic shocks. Coibion et al. (2018) show that estimates of potential output from the Federal Reserve Board, the International Monetary Fund (IMF) and the Organization for Economic Cooperation and Development (OECD) for various countries over-respond to shocks that have no long-run effects on the economy and under-respond to shocks that do have a long-run impact. More specifically, real-time estimates of potential output respond to transitory shocks obtained from a Blanchard-Quah decomposition and to various narrative measures of monetary and fiscal shocks. In contrast, real-time potential output estimates adjust only gradually to permanent shocks obtained from Blanchard-Quah decompositions and from narrative measures of supply shocks. Coibion et al. (2018) rationalize these results by showing that impulse responses of estimates of potential GDP from all organizations are nearly indistinguishable from the responses of a one-sided HP filter applied to real-time GDP data. We document that this is not the case for the summary measure of potential output obtained from Norges Bank's suite of models. In fact, the summary measure responds as much as actual GDP (and substantially more than an HP-filtered GDP series) to shocks with permanent effects obtained from a Blanchard-Quah decomposition and to shocks to a cyclically adjusted measure of Total Factor Productivity (TFP) for Norway. Moreover, the summary measure of potential output responds less than actual output but more than an HP-filtered GDP series to shocks with transitory effects obtained from a Blanchard-Quah decomposition and to monetary policy shocks derived using high frequency identification. All in all, our analysis shows that the summary measure of potential output responds rapidly and significantly to supply shocks but also to demand shocks, although to a more limited extent.

Our paper integrates and extends previous analysis on Norwegian data by Bernhardsen et al. (2005) and Bjørnland et al. (2008) and contributes to a recent literature whose aim is to document and evaluate the performance of output gap estimates produced routinely at central banks. Two prominent examples are Edge and Rudd (2016) and Champagne et al. (2018) for the Board of Governors of the Federal Reserve and the Bank of Canada respectively. Edge and Rudd (2016) show that the real-time issues emphasized by Orphanides and van Norden (2002) become less severe when using a longer sample period. In particular, they find that revisions have become smaller since the mid 1990s and that there is no deterioration in forecast performance when inflation projections are conditioned on real time rather than on final estimates of the output gap. Champagne et al. (2018) present a similar analysis for Canada, but also include the Great Recession in their sample, arguably a period in which the measurement of potential output was particularly challenging. They also find that the staff gap estimates are subject to smaller revisions. In addition, they show that models that condition on the real-time estimates of the output gap perform slightly worse than those conditioned on the final estimate (although none of the models using output gap estimates outperform simple univariate models). It is important to stress that both Edge and Rudd (2016) and Champagne et al. (2018) evaluate the revision and forecasting properties of the *official estimates* of the output gap produced at the Fed and Bank of Canada, respectively. In contrast, Norges Bank, by choice, rarely revises historical estimates of the output gap further back than the current business cycle. This is because the purpose of the Norges Bank's official output gap estimate is also to reflect the view of the economy that was the basis for the monetary policy decisions at the time. Therefore, we focus our attention on *model-based* estimates that constitute a key input (combined with judgement and insights obtained from other models of the labor market) in the production of the official estimate, at least in recent years. Our distinctive contribution consists in investigating the cyclical sensitivity of these estimates. As far as we know, no other central bank has proposed an evaluation along this dimension.

The rest of the paper is structured as follows. Section 2 presents the different models included in the suite. Section 3 evaluates the output gap estimates derived from the different models in the suite and a simple summary measure. Finally, Section 4 concludes.

2 The Suite of Models

To estimate the output gap, Norges Bank relies on a suite of models composed by several unobserved component models and two structural vector autoregressions. The different models are described in the following sections.

2.1 Unobserved Component (UC) Models

Unobserved component (UC) models are a key component of the suite. A UC model posits that GDP (y_t) can be decomposed into an output gap ($\hat{y}_t$) and potential GDP ($\bar{y}_t$)

which are both unobservable:

$$y_t = \hat{y}_t + \bar{y}_t \tag{1}$$

In addition, the model specifies how the unobserved variables evolve over time:

$$\hat{y}_t = \lambda_y \hat{y}_{t-1} + \epsilon_t \tag{2}$$

$$\Delta \bar{y}_t = G_t + \eta_t \tag{3}$$

The output gap (equation (2)) depends on the output gap in the previous period and on a shock (ϵ_t) that is phased out over time. The change in potential GDP (equation (3)) depends on potential growth (G_t) and on a shock to the level of potential GDP (η_t). Potential growth is also allowed to vary over time:

$$G_t = C_G + \lambda_G (G_{t-1} - C_G) + \psi_t \tag{4}$$

In equation (4), ψ_t represents a shock to potential growth whose persistence is governed by the parameter λ_G while C_G is a constant. When λ_G is set equal to 1, the process follows a random walk. The traditional HP filter measure of the output gap can be derived as special case of the model above when λ_G is equal to 1 and the relative variances of ϵ_t and ψ_t are restricted appropriately. However, as discussed in the Introduction, a more recent literature has shown that developments in variables other than GDP are important to obtain reliable estimates of the output gap. Therefore, seven multivariate UC models are included in the suite of models. In all models we use data on GDP for mainland Norway (thus excluding petroleum and ocean transport activities, as is standard in macroeconomic analysis for Norway). The models can be described as follows:

1. UC 1 uses annual data on GDP for mainland Norway, real wage growth as reported by Statistics Norway (Wages/CPI adjusted for taxes and energy) and registered unemployment (Norwegian Labour and Welfare Administration, NAV)) and is estimated over the period 1990-2019.

2. UC 2 uses annual data on GDP for mainland Norway, real wage growth and unemployment (Labour Force Survey, LFS) and is estimated over the period 1990-2019.

3. UC 3 uses annual data on GDP for mainland Norway, real wage growth, registered unemployment (NAV) and business investment as a percentage of GDP for mainland Norway and is estimated over the period 1990-2019.

4. UC 4 uses quarterly data on GDP for mainland Norway and change in domestic inflation and is estimated over the period 1990:Q1 - 2019:Q2.

5. UC 5 uses quarterly data on GDP for mainland Norway, registered unemployment (NAV) and domestic inflation and is estimated over the period 1990:Q1 - 2019:Q2.

6. UC 6 uses quarterly data on GDP for mainland Norway and four-quarter growth in total domestic credit and is estimated over the period 1990:Q1 - 2019:Q2.

7. UC 7 uses quarterly data on GDP for mainland Norway and four-quarter growth in house prices and is estimated over the period 1990:Q1 - 2019:Q2.

The models differ in terms of estimation frequency,[1] data series, estimation period and modeling of potential growth. All models are estimated using Bayesian methods as in (Planas et al. (2008)) and are described more in detail in the Appendix.

For illustrative purposes, we focus now on UC 1. A Phillips curve for real wages and a relationship between unemployment and the output gap are specified (Okun's law):

$$\hat{W}_t = \lambda_W \hat{W}_{t-1} + \gamma \hat{y}_t + \upsilon_t \tag{5}$$

$$\hat{u}_t = \lambda_u \hat{u}_{t-1} + \beta \hat{y}_t + \omega_t \tag{6}$$

Both the wage gap ($\hat{W}_t$) and the unemployment gap ($\hat{u}_t$) are related to the output gap ($\hat{y}_t$).[2]

Figure 1: Estimated output gap in percent from unobserved component model UC 1 and from a univariate model.

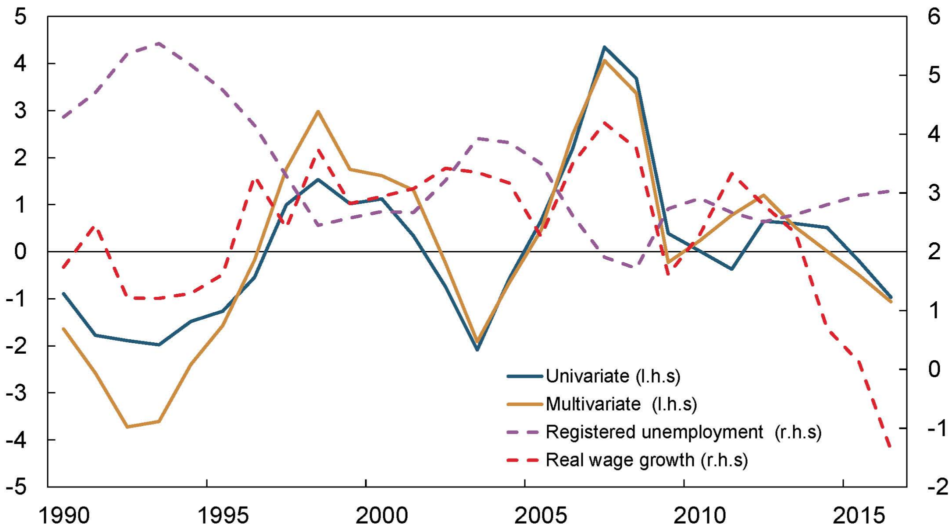


Figure 1 presents the output gap estimate obtained from model UC 1 (cf. yellow solid line). The blue solid line refers to an estimate of the output gap based on a univariate version of the model (i.e. when only the equations (1) to (4) are used). The dashed lines plot the evolution of unemployment and real wage growth over the sample period. At the beginning of the 1990s, unemployment was high and real wage growth was low. When these data are taken into account in the estimation, the output gap is shown to be more negative at the beginning of the 1990s compared with an estimate that relies only on

[1]Since the official quarterly series for wages is extremely noisy, the first three models in the suite are estimated using annual data. In a centralized wage negotiation system in which wages are changed once per year in a synchronized way as in Norway, the relevant wage measure is annual. The estimates from these models are converted into quarterly data using the Denton algorithm (Denton (1971)). Missing data within a year are extrapolated using simple AR forecasts.

[2]A time-varying trend for real wages and unemployment are estimated, following the same specification used for GDP (see equation (3)). The full model specification is described in the Appendix.

GDP data. The multivariate model also indicates higher capacity utilisation at the end of the 1990s, while the estimation of the output gap in the period preceding the financial crisis is approximately the same. In the years following the financial crisis, the multivariate model indicates somewhat higher capacity utilisation, both as a result of higher real wage growth and lower unemployment. In the wake of the fall in oil prices in 2014, the model indicates somewhat lower capacity utilisation compared with the univariate model, primarily due to a sharp fall in real wage growth.

2.2 Structural VAR Models

The model suite also includes structural VAR models. We estimate the following system:

$$y_t = \mu_0 + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \tag{7}$$

where y_t is a vector of endogenous variables, μ_0 is a vector of constant terms and u_t is a vector of reduced form residuals. A_l for $l \in [1, p]$ are matrices of coefficients on lagged variables while p refers to the number of lags for the endogenous variables included in the system.

The use of VAR models to estimate the output gap has been advocated recently by Coibion et al. (2018). Two VAR models have been part of the model suite since the beginning of its development. The first model (SVAR 1) builds on Blanchard and Quah (1989) and uses data on GDP growth for mainland Norway and unemployment (NAV). The second model (SVAR 2) follows Cerra and Saxena (2000) and also includes data on domestic inflation. In Blanchard and Quah (1989), it is assumed that GDP growth is driven by two types of shocks: demand shocks and (permanent) supply shocks. Demand shocks are identified as shocks that do not affect GDP in the long term. Potential output is thereafter defined as GDP in the absence of the identified demand shocks. Cerra and Saxena (2000) identify in addition a temporary supply shock that does not have long-term effects on domestic inflation or GDP. As in Blanchard and Quah (1989), potential output is given by the counterfactual level of GDP driven only by permanent supply shocks. Both models are described in more detail in the Appendix.

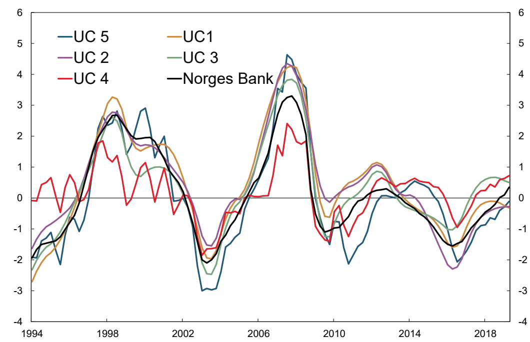
2.3 Output Gap Estimates from the Different Models

Figure 2 shows output gap estimates from the different models together with Norges Bank's assessments of the output gap (black solid line) as presented in Monetary Policy Report 3/19. It is important to stress that the solid black line represents the official Norges Bank view on the state of resource utilization. In contrast to, e.g. the US and Canada, there is no separate staff assessment of the output gap. The Norges Bank output gap series has been published since 2003, well before the development of the suite of models that started around 2012 and reached the state reported here only around 2017. Therefore, the suite of models captures the institutional view over the first part of the sample, while it influences the institutional view in the second part of the sample.

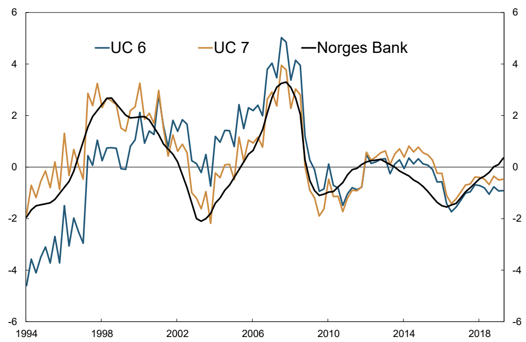
Notably, the official Norges Bank series is rarely revised further back than the current business cycle.

Panel (a) shows the estimates based on the first five unobserved component models. Norges Bank's official measure of the output gap is closely in line with the estimates from the different models. However, in retrospect, some of the models indicate that capacity utilisation in the pre-Great Recession period was somewhat higher than in Norges Bank's assessment. In the period following the financial crisis, the different models provide a somewhat different view on the path of the output gap. In particular, the model using LFS unemployment data (UC 2) identifies a sharp drop in capacity utilization in 2014. In this period LFS unemployment increased substantially more than registered unemployment in response to the large decline in the oil price. This episode highlights the benefits of including alternative labor market indicators into the suite.

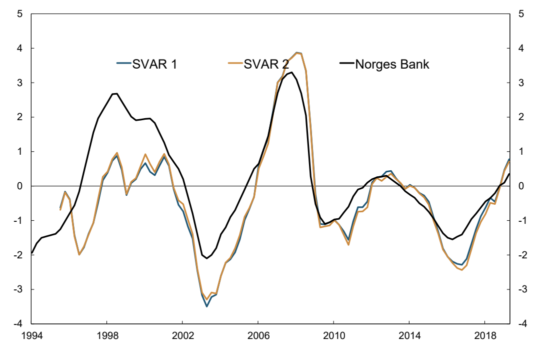
Figure 2: *Output gap estimates from the different models and summary measures. 1994Q1 - 2019Q2*



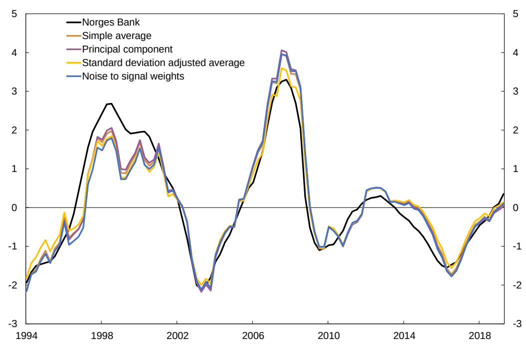
(a) UC models



(b) Financial UC models



(c) SVAR models



(d) Summary measures

The output gap estimates from UC models using financial variables as observables (panel (b)) show somewhat different paths. The model using data on credit growth indicates that the output gap was substantially lower in the mid-1990s. This is because credit growth was low in this period compared with its historical average, thus driving GDP below its potential level. In the 2000s, credit growth accelerated. This may indicate that financial imbalances were building up and that output was well above its potential level. In fact, UC 6 indicates that the output gap was substantially higher during the downturn in 2003-2004 and in the period preceding the financial crisis. In the period following the financial crisis, the model is more closely in line with Norges Bank's assessments, although financial factors sustain a positive output gap until 2015. The model that includes data on house price inflation (UC 7) does not present the same picture as the gap based on credit growth, most likely because house price fluctuations correlate to a greater extent with GDP fluctuations. A partial exception is identified around 2014, when the housing sector was booming in the context of a stagnating economy.

The two structural VAR models (panel (c)) deliver similar estimates and are closely in line with Norges Bank's official assessment of the output gap in the second part of the sample. They indicate a substantially lower output gap at the end of the 1990s and a more negative gap during the downturn in 2003-2004 if compared with UC models and the assessment of Norges Bank.

Panel (d) presents four ways to weight together the different estimates of the output gap: a simple un-weighted average, the average with weights adjusted for the standard deviation of each individual model, the average with weights based on the noise-to-signal ratio (presented in Table 4) and a principal component.[3] Overall, these simple combinations of different models are closely in line with Norges Bank's official output gap assessment over time.

All in all, labor market variables are widely used and are important drivers of the output gaps in the model suite. In practice, models relying on unemployment data have proven to be reliable, in particular when new information arrives. This is confirmed by recent evidence for the US that was not available when the suite was implemented. In fact, Barbarino et al. (2020) document that models relating the unemployment rate to the output gap produce stable real-time output gap estimates since labor market data alleviate the end-point problem of statistical models. In addition, Morley and Wong (2020) estimate the output gap with a Bayesian VAR comprising a large dataset of 138 variables and find that the unemployment rate is the single most important variable that contributes to the cycle. The extensive use of data on wage inflation builds on Phillips (1958) who specified his original analysis in terms of wage inflation and unemployment. In a small open economy like Norway where the exchange rate and import prices in general play a major role in explaining variation in consumer price inflation, the wage Phillips curve provides a clearer signal on the state of capacity utilization in the economy. Finally, a strong focus on the labor market is also justified under the mandate assigned to Norges Bank stating that the central bank should i) target a rate of inflation close to 2 percent

[3] A normalization by the standard deviation of each individual output gap series is performed in order to avoid that models with large variance or amplitude mechanically have a large impact on the summary measure of the output gap. This adjustment has limited impact since the nine series have similar amplitude. A normalization in terms of the signal-to-noise ratio is performed in order to attach a lower weight to models that are more likely to be revised.

over time, ii) contribute to *high and stable employment* and iii) counteract the build-up of financial imbalances.

3 Evaluation of the Models

Since the output gap is not observable, there is no direct way of evaluating the model estimates. Nevertheless, three criteria have been discussed in the literature:

1. The estimated output gap should have reasonable forecasting properties for inflation.
2. Ex-post revisions should not be too extensive. When new data become available, the output gap estimate should not change substantially.
3. The estimated output gap should respond substantially and rapidly to shocks that have a permanent (or at least a very persistent) effect on GDP and respond mildly or not at all to shocks that have only transitory effects.

It is important to stress here that all models are estimated using the final vintage of data (from 2019:Q2). We therefore ignore the role of data revisions in real-time revisions of output gap estimates.[4] Put differently, we conduct a pseudo real-time analysis that allows us to investigate the role of parameter instability and end-point problems of the statistical filters. Notably, Orphanides and van Norden (2002) show that most real-time revisions of output gap estimates are due to the filtering methods rather than data revisions, a point also emphasized more recently by Barbarino et al. (2020), with a special focus on the role of labor market data for real-time stability.

3.1 Forecasting Properties

One important and challenging dimension to evaluate output gap estimates is the ability to forecast inflation. In fact, Orphanides and van Norden (2005) show that models using real-time estimates of the output gap perform worse at forecasting inflation than models using the final estimates of the gap as well as univariate AR-models of inflation. To evaluate the forecasting properties of our estimates, we follow Orphanides and van Norden (2005) and perform a direct forecasting exercise. We estimate the following equation:

$$\pi_{t+h} = \alpha + \sum_{s=0}^{4} \lambda_s \pi_{t-s} + \sum_{s=0}^{4} \beta_s \hat{y}_{t-s} + \varepsilon_t \tag{8}$$

where π_t is four-quarter growth in domestic CPI inflation and $\hat{y}_t$ represents the pseudo real-time output gap estimate. Equation (8) is a simple Phillips curve, where inflation depends on its own dynamics and on the output gap in previous periods. We estimate a separate regression for each forecast horizon (up to eight quarters ahead). More specifically, we estimate the output gaps and equation (8) recursively and then project inflation

[4] Ideally, it is desirable to take data revisions into account. Unfortunately, a sufficient historical dataset of real-time vintages for all variables included in the suite is not available.

for eight quarters after the estimation is stopped.[5] We also estimate a bivariate VAR model with inflation and the output gap as an alternative to the direct forecasting approach in equation (8). In both cases, we investigate whether the forecasting accuracy improves using pseudo real-time information on a summary measure of the output gap based on the simple un-weighted average of the models belonging to the suite.

Table 1: Inflation forecast evaluation in comparison to an AR(4) model

	Direct forecasting		Bivariate VAR	
Horizon	Average model suite	HP-filter	Average model suite	HP-filter
1	1.02	1.03	1.02	1.03
2	0.95	1.02	0.96	1.05
3	0.95	1.09	0.90	1.07
4	0.94	1.15	0.86	1.08
5	0.88	1.21	0.86	1.09
6	0.90	1.29	0.88	1.12
7	0.98	1.34	0.93	1.15
8	1.09	1.37	0.98	1.19

Forecast error (RMSFE) from equation (8) and a bivariate VAR with pseudo real-time output gap estimates combined with domestic inflation relative to the RMSFE of AR(4). Numbers below one indicate RMSFE that is lower than the AR model. Estimation period is from 1990:Q1 using expanding windows from data vintage 2019:Q2 and pseudo out-of-sample evaluation is 2000:Q2 - 2019:Q2.

In Table 1 we show how the simple summary measure of the output gap helps predicting domestic CPI inflation in pseudo real-time at different horizons when the benchmark for comparison is a simple AR model with four lags, arguably a model that generates forecasts that are hard to improve upon (cf. Champagne et al. (2018)). More specifically, values above (below) 1 mean that the model has a larger (smaller) average forecast error than the AR-model. As an alternative for comparison, we also evaluate the output gap obtained from an HP-filter with λ equal to 40000.[6] In both exercises, the models using pseudo real-time estimates of the output gap perform better than the AR(4) model and largely better than the HP-filter based measure at all horizons with the exception of horizon 1. Therefore, our results are somewhat more rosy than Orphanides and van Norden (2005) and suggest that the output gap helps forecasting inflation, at least to some extent.

In an additional forecasting exercise we replace inflation with the domestic CPI price level to assess the output gaps ability to forecast cumulative inflation over longer horizons. For

[5] First, the output gaps and equation (8) are estimated using data up to 2000:Q1 and then forecasts are produced for 2000:Q2 until 2002:Q1. Thereafter, the estimation period is extended by one quarter at a time up to 2019:Q2. Equation (8) is similar to the Phillips curve used in Edge and Rudd (2016) and Champagne et al. (2018). Since they can rely on real time forecasts for the output gap, these papers can use conditional forecasts to evaluate longer horizons.

[6] A value of λ equal to 40 000 is relatively high compared to the standard value of 1600 for quarterly data. Historically, a lower value would have implied a far too shallow recession after the banking crisis in the late 1980s, in particular when compared with other indicators such as the unemployment rate.

the first four quarters this is almost identical to forecasting annual inflation, but with a slightly different model specification. Results are presented in Table 2. In general, the forecast errors are lower in the level specification for all models, including the AR-model, thus suggesting that the level-specification is preferable for forecasting purposes. In relative terms, the largest improvements are featured by the models including the summary measure of the output gap, in particular at longer horizons. We remark that the better performance with respect to the AR model is statistically significant at horizons three to eight in a Diebold-Mariano test, in many instances at the one percent level. The summary measure of the output gap performs consistently better than the HP-filter based measure also in this exercise, in particular at long horizons.

Table 2: Price level forecast evaluation in comparison to an AR(4) model

	Direct forecasting		Bivariate VAR	
Horizon	Average model suite	HP-filter	Average model suite	HP-filter
1	0.95	0.98	0.95	0.98
2	0.95	0.95	0.89	0.93
3	0.89	0.91	0.82	0.90
4	0.86	0.87	0.77	0.86
5	0.83	0.85	0.72	0.84
6	0.80	0.86	0.69	0.82
7	0.75	0.85	0.66	0.80
8	0.68	0.85	0.63	0.79

Forecast error (RMSFE) from equation (8), replacing inflation with the price index, and a bivariate VAR with 4 lags, relative to the RMSFE of an AR(4) model. Average model suite is the simple average of the output gap models. The hp-filter is estimated using $\lambda = 40000$. *Estimation period is from 1990:Q1 using expanding windows from data vintage 2019:Q2 and pseudo out-of-sample evaluation is 2000:Q2 - 2019:Q2.*

We now evaluate alternative summary measures of the output gap and the individual models in the exercise based on a bivariate VAR model presented earlier in Tables 1 and 2.[7] In fact, so far we have focused our attention only on a simple un-weighted average of the individual models as summary measure of the output gap. In the last three columns in Table 3 we compare its performance against two alternative measures (both plotted in Figure 2, panel (d)), the first with weights adjusted for the standard deviation of each individual model and the second with weights based on the noise-to-signal ratio. We observe that the three summary measures obtain a very similar forecasting performance, thus justifying our focus on the simple un-weighted average when combining the individual models.

In Table 3 we evaluate also the forecasting performance of bivariate VAR models using output gap estimates from each model belonging to the suite. Two remarks are in order. First, the simple un-weighted average of the models features a better forecasting performance than each individual model. Second, the bivariate VAR models using output gap

[7]Similar results are obtained in the direct forecasting exercise and are available upon request.

estimates from each individual model perform all better than the AR(4) model with one exception. In fact, the model using data on domestic credit growth (UC 6) performs on average worse than the AR(4) model, thus supporting the disconnect between the credit cycle and inflation dynamics, as discussed in Christiano et al. (2010), Borio et al. (2017) and Furlanetto et al. (2019).

Table 3: Price level forecast evaluation: Individual models and weighted estimates

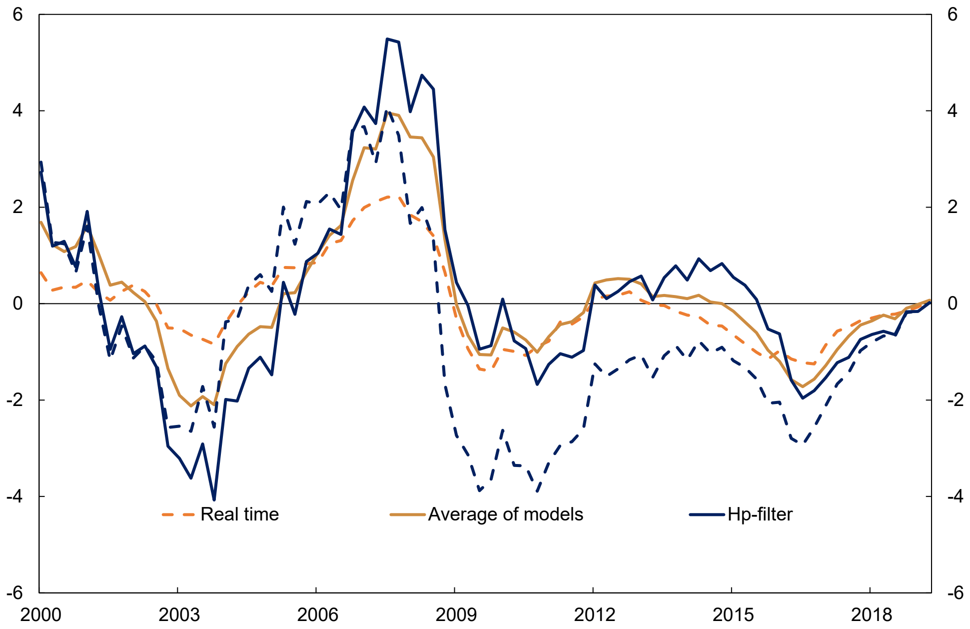
	Individual models									Weighted estimates		
H.	UC1	UC2	UC3	UC4	UC5	UC 6	UC 7	SVAR1	SVAR2	Avg	std adj.	NSR
1	1.02	1.01	1.05	0.98	1.05	1.04	**0.97**	1.03	1.03	0.95	0.95	0.95
2	**0.90**	0.94	0.92	0.93	1.00	1.04	0.93	0.98	0.99	0.89	0.88	0.90
3	**0.84**	0.89	0.86	0.88	0.95	1.01	0.89	0.93	0.94	0.82	0.81	0.83
4	**0.79**	0.84	0.81	0.84	0.90	1.00	0.85	0.88	0.89	0.77	0.74	0.77
5	**0.74**	0.91	0.76	0.79	0.86	1.00	0.82	0.84	0.86	0.72	0.69	0.71
6	**0.70**	0.78	0.73	0.75	0.83	1.00	0.80	0.82	0.84	0.69	0.65	0.68
7	**0.67**	0.76	0.70	0.72	0.80	0.99	0.79	0.81	0.84	0.66	0.62	0.65
8	**0.63**	0.74	0.66	0.68	0.76	0.97	0.78	0.79	0.84	0.63	0.59	0.61

Forecast error (RMSFE) from a bivariate VAR with 4 lags, relative to the RMSFE of an AR(4) model. Avg is a simple un-weighted average of the individual models. std adj. is the average of the individual models adjusted for their relative standard deviation. NSR weights the individual models based on the pseudo real-time noise-to-signal ratio (NSR(SD)) reported in Table 4, where models with small NSR are given higher weight. Estimation period is from 1990:Q1 using expanding windows from data vintage 2019:Q2 and pseudo out-of-sample evaluation is 2000:Q2 - 2019:Q2. Single model with lowest RMSFE at each horizon in bold.

3.2 Pseudo Real-Time Evaluation

The second criterion is that a good estimate of the output gap, as measured in pseudo real time, should not change substantially when new data become available. Figure 3 plots the output gap estimate derived from a simple HP filter and the summary measure obtained from the suite. Solid lines refer to estimates using the entire data set for both models while dashed lines refer to estimates obtained recursively using data up to that point. The difference between the "final" output gap estimate and the pseudo real-time estimate is considerably smaller for the summary measure than for the one based on the HP filter. Not surprisingly, the difference between the two estimates is substantially reduced when the entire data set is used.

Figure 3: Reliability of the summary measure of the output gap and a HP filter measure ($\lambda = 40000$).



Following Edge and Rudd (2016) and Champagne et al. (2018), we evaluate in Table 4 the statistical properties of output gap revisions for each model belonging to the suite and for the summary measure. Notwithstanding the important caveat that the role of data revisions is not accounted for by our estimates, the mean revision is rather small for most models and for the summary measure in particular with a value of 0.13 percentage point. Such a value for the mean revision compares favorably with recent estimates for Canada and the US. The standard deviation and the root mean squared revision (RMSR) are slightly lower than 0.7, a value perhaps large in absolute terms but substantially smaller than the corresponding numbers for the HP filter-based measure. The correlation between the final and the pseudo real-time estimates are larger than 0.9 for most models and equal to 0.92 for the summary measure. In addition, the two estimates share the same sign in almost 90 percent of cases for the summary measure. Finally, we report two measures for the noise-to-signal ratio, based on the standard deviation and on the root mean squared error as in Edge and Rudd (2016). Both values are slightly lower than 0.5 for the summary measure of the output gap.

Table 4: Summary statistics of output gap revisions

Model	Mean	std dev	RMSR	Corr.	Sign agree	NSR(SD)	NSR(RMSR)
UC 1	0.08	0.60	0.61	0.94	0.92	0.39	0.40
UC 2	0.50	0.70	0.86	0.90	0.77	0.45	0.55
UC 3	-0.19	0.59	0.62	0.90	0.90	0.42	0.45
UC 4	-0.03	0.48	0.48	0.85	0.82	0.53	0.53
UC 5	0.33	1.59	1.62	0.44	0.66	0.90	0.92
UC 6	0.11	0.59	0.60	0.94	0.87	0.37	0.38
UC 7	0.26	1.22	1.25	0.55	0.70	0.86	0.88
SVAR 1	0.01	0.63	0.63	0.94	0.85	0.37	0.37
SVAR 2	0.13	0.66	0.68	0.94	0.82	0.40	0.40
Average	0.13	0.66	0.67	0.92	0.89	0.47	0.48
HP filter	0.76	1.37	1.57	0.75	0.71	0.70	0.80

This table reports summary statistics of output gap revisions for each model included in the suite. We use data from the GDP vintage from 2019:Q2 and have pseudo real-time estimates from 2000:Q1 - 2019:Q2. The first two columns report the mean revision and the standard deviation. RMSR is the root of the mean squared revision. Corr is the correlation between the final estimate (2019:Q2) and the pseudo real-time estimate. Sign agree indicates how often the sign of the final estimate and the first estimate is the same. Noise-to-signal ratio (NSR) is the standard deviation/RMSR of the revision relative to the final estimate.

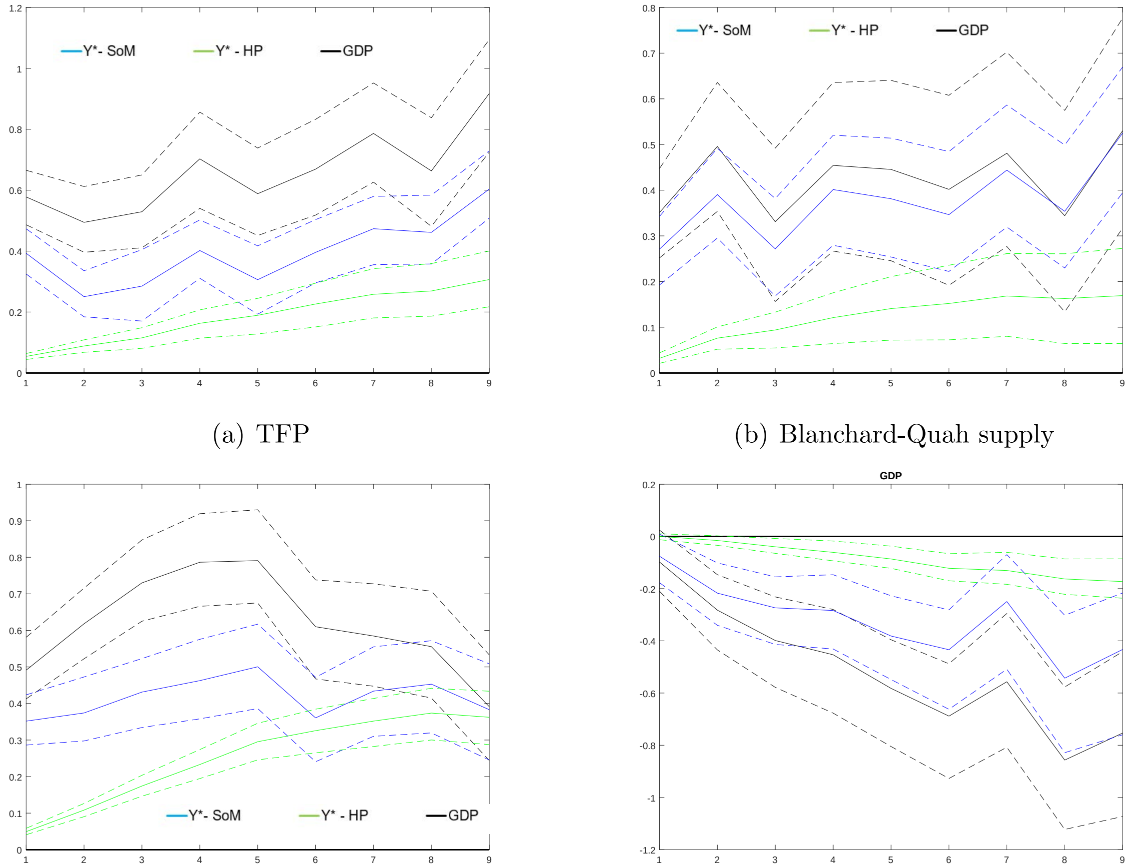
3.3 Cyclical Sensitivity

We now evaluate the summary measure of the output gap along a third dimension, i.e. its cyclical sensitivity to various measures of economic shocks in keeping with the analysis in Coibion et al. (2018).

We first consider a measure of technology shocks proxied by quarterly changes in cyclically adjusted total factor productivity (TFP), following Fernald (2014). The cyclical adjustment, however, is different. Since hours per worker, the indicator used by Fernald (2014), are not closely related to the cycle in Norway, we rely on the Norges Bank's Regional Network measure of capacity utilization for the Norwegian economy over the period 2005-2018. We extend the series backward to 2000 with Statistics Norway's capacity utilization measure for manufacturing.

Figure 4 shows how the summary measure of potential GDP obtained from the model suite and the HP-filter measure respond to an exogenous increase in TFP using local projection methods (cf. Jordà (2005)) as in Coibion et al. (2018). The summary measure of potential output (blue solid line) responds substantially more than the HP-filtered GDP series (green solid line) to an expansionary TFP shock. We conclude that the summary measure of potential output reacts strongly and persistently to technology shocks, although not as much as actual output (solid black line).

Figure 4: *Impulse responses of the summary measure of potential output from the suite of models (SoM) and the HP filter measure* ($\lambda = 40000$)*. 2000:Q1 - 2019:Q2*



(a) TFP

(b) Blanchard-Quah supply

(c) Blanchard-Quah demand

(d) Monetary policy shock

We repeat the same exercise in response to shocks derived from a Blanchard-Quah decomposition. As in Coibion et al. (2018), we interpret shocks with potentially permanent effects as supply shocks and shocks with transitory effects as demand shocks.[8] The summary measure of potential output responds strongly to the permanent shock, as much as actual GDP. This confirms that the Norges Bank's summary measure of potential output behaves differently than the estimates of potential output provided by Federal Reserve Board, IMF and OECD reviewed by Coibion et al. (2018).

The summary measure of potential output also responds to some extent to demand shocks obtained from the Blanchard-Quah decomposition. It reacts more than the measure of potential output based on the HP filter in the short run (see panel (c) in Figure 4). Note that such a response to demand shocks is common in Dynamic Stochastic General Equilibrium models where potential output is defined as the counterfactual level of output in the absence of sticky prices and sticky wages. In this kind of model, potential output responds to demand shocks like government spending shocks, investment specific shocks

[8]For an extension of the Blanchard-Quah decomposition allowing for demand shocks with potentially permanent effects, see Furlanetto et al. (2020).

or discount factor shocks.

As Blanchard (2018) notes, even monetary policy shocks have an effect on potential output if one assumes in the counterfactual that nominal rigidities are removed only from the date of the shock on, thus taking history as given up to the date of the shock. We consider the effects of monetary policy shocks on potential output by using a series of shocks derived by Brubakk et al. (2019) using high frequency financial data around monetary policy meetings. In panel (d) in Figure 4 we present impulse responses to a contractionary monetary policy shock. As in the case of demand shocks, the summary measure of potential output reacts more than the HP filter-based measure and less than actual output. Somewhat intriguingly, monetary policy shocks seem to have persistent effects on both actual output, in line with recent evidence using local projection methods presented in Jordà et al. (2020).

All in all, we conclude that the summary measure of potential output responds to shocks substantially more than a measure based on the HP filter, in particular when it comes to shocks with potentially permanent effects but to some extent also to demand shocks.

4 Conclusion

We documented the suite of models currently used to estimate the output gap at Norges Bank. The models are estimated using data on GDP, unemployment, inflation, wages, investment, credit and house prices. A simple un-weighted average of the models outperforms individual models and helps predicting domestic CPI when compared with a simple AR model. In addition the summary measure of the output gap shows relatively little variation when new information arrives, unlike simple trend estimates based only on GDP data. Notably, it responds strongly and rapidly to permanent shocks and to narrative measures of technology shocks but also, although to a more limited extent, in response to transitory shocks and to monetary policy shocks.

The suite of models has been expanded and refined over time and we find it encouraging to document that its performance has proved satisfactory, even in a dimension like the cyclical sensitivity that has so far been untested for measures of output gaps produced by other central banks. Nonetheless, it is fair to say that the suite could (and should) be extended in several dimensions to account for recent developments in the literature. This includes the use of models featuring stochastic volatility (Mertens (2020) and Clark and Ravazzolo (2015)), dynamic factor models (Aastveit and Trovik (2014) and Jarocinski and Lenza (2018)), large Bayesian Vector Autoregressions (Morley and Wong (2020)) and the use of alternative benchmarks for comparison (Kamber et al. (2018)). The application of some of these techniques to the case of Norway is in our agenda for future research.

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5 Appendix

5.1 UC models 1 and 2: GDP mainland Norway, unemployment (NAV or LFS) and real wage growth

Definition of GDP:

$$y_t = \hat{y}_t + \bar{y}_t \tag{9}$$

Process for the output gap:

$$\hat{y}_t = \lambda_y \hat{y}_{t-1} + \epsilon_t \tag{10}$$

Process for the growth in potential GDP:

$$\Delta \bar{y}_t = G_t + \eta_t \tag{11}$$

Process for potential growth:

$$G_t = C_G + \lambda_G (G_{t-1} - C_G) + \psi_t \tag{12}$$

Process for the real wage gap:

$$\hat{W}_t = \lambda_W \hat{W}_{t-1} + \gamma \hat{y}_t + \upsilon_t \tag{13}$$

Process for the trend in real wages:

$$\Delta \bar{W}_t = C_W + \lambda_{\bar{W}} (\Delta \bar{W}_{t-1} - C_W) + \mu_t \tag{14}$$

Process for the unemployment gap:

$$\hat{u}_t = \lambda_u \hat{u}_{t-1} + \beta \hat{y}_t + \omega_t \tag{15}$$

Process for the change in unemployment trend (NAIRU):

$$\Delta \bar{u}_t = \lambda_{\bar{u}} \Delta \bar{u}_{t-1} + \upsilon_t \tag{16}$$

Table 5: UC 1. Estimated and calibrated parameters. Annual data. Estimation period: 1990-2019

Parameter	Prior	Prior distribution	Posterior mode
λ_y	0.7(0.2)	Gamma	0.79(0.12)
λ_G	0.9(0.2)	Gamma	0.77(0.14)
λ_W	0.75(0.25)	Gamma	0.89(0.12)
$\lambda_{\bar{W}}$	0.6(0.2)	Gamma	0.61(0.14)
λ_u	0.5(0.2)	Gamma	0.43(0.07)
$\lambda_{\bar{u}}$	0.9(0.1)	Gamma	0.87(0.09)
γ	0.29	Calibrated	
β	-0.29	Calibrated	
σ_ϵ	2(10)	Inverse Gamma	1.20(0.18)
σ_η	2(10)	Inverse Gamma	0.71(0.18)
σ_ψ	1(10)	Inverse Gamma	0.32(0.15)
σ_υ	0.5(10)	Inverse Gamma	0.17(0.10)
σ_μ	2(10)	Inverse Gamma	0.72(0.11)
σ_ω	0.4(10)	Inverse Gamma	0.09(0.03)
σ_v	0.2(10)	Inverse Gamma	0.06(0.03)

Standard deviation in parantheses.

Table 6: UC 2. Estimated and calibrated parameters. Annual data. Estimation period: 1990-2019

Parameter	Prior	Prior distribution	Posterior
λ_y	0.7(0.2)	Gamma	0.78(0.12)
λ_G	0.9(0.2)	Gamma	0.77(0.13)
λ_W	0.75(0.25)	Gamma	0.91(0.13)
$\lambda_{\bar{W}}$	0.6(0.2)	Gamma	0.59(0.17)
λ_u	0.5(0.2)	Gamma	0.49(0.07)
$\lambda_{\bar{u}}$	0.9(0.1)	Gamma	0.86(0.10)
γ	0.29	Calibrated	
β	-0.29	Calibrated	
σ_ϵ	2(10)	Inverse Gamma	1.12(0.25)
σ_η	2(10)	Inverse Gamma	0.77(0.29)
σ_ψ	1(10)	Inverse Gamma	0.32(0.16)
σ_υ	0.5(10)	Inverse Gamma	0.17(0.12)
σ_μ	2(10)	Inverse Gamma	0.75(0.12)
σ_ω	0.4(10)	Inverse Gamma	0.23(0.06)
σ_v	0.2(10)	Inverse Gamma	0.05(0.02)

Standard deviation in parentheses.

5.2 UC model 3: GDP mainland Norway, unemployment (NAV), real wage growth and investment share

In addition to equations (9 to 16), the investment share (business investment as share of GDP for mainland Norway) is related to the output gap, following Domenech and Gomez (2006):

$$x_t = \lambda_x x_{t-1} + (1 - \lambda_x)\bar{x}_t + \gamma_x \hat{y}_t + e_t \tag{17}$$

$$\Delta \bar{x}_t = z_t \tag{18}$$

where x_t is the investment share and $\bar{x}_t$ is the trend component of the investment share. e_t is a shock to the investment share, while z_t represents a shock to the level of potential investment.

Table 7: UC 3. Estimated and calibrated parameters. Annual data. Estimation period: 1990-2019

Parameter	Prior	Prior distribution	Posterior
λ_y	0.7(0.2)	Gamma	0.73(0.11)
λ_G	0.9(0.2)	Gamma	0.77(0.12)
λ_W	0.75(0.25)	Gamma	0.87(0.14)
$\lambda_{\bar{W}}$	0.6(0.2)	Gamma	0.67(0.19)
λ_u	0.5(0.2)	Gamma	0.49(0.06)
$\lambda_{\bar{u}}$	0.9(0.1)	Gamma	0.85(0.09)
λ_x	0.7(0.2)	Gamma	0.42(0.07)
γ	0.29	Calibrated	
β	-0.29	Calibrated	
γ_x	0.5	Calibrated	
σ_ϵ	2(10)	Inverse Gamma	1.18(0.16)
σ_η	2(10)	Inverse Gamma	0.64(0.17)
σ_ψ	1(10)	Inverse Gamma	0.43(0.27)
σ_υ	0.5(10)	Inverse Gamma	0.17(0.09)
σ_μ	2(10)	Inverse Gamma	0.77(0.13)
σ_ω	0.4(10)	Inverse Gamma	0.10(0.04)
σ_v	0.2(10)	Inverse Gamma	0.06(0.03)
σ_e	1(10)	Inverse Gamma	0.34(0.12)
σ_z	1(10)	Inverse Gamma	0.49(0.30)

Standard deviation in parentheses.

5.3 UC model 4: GDP mainland Norway and change in domestic inflation

Definition of GDP:

$$y_t = \hat{y}_t + \bar{y}_t \tag{19}$$

Process for the output gap:

$$\hat{y}_t = \lambda_y \hat{y}_{t-1} + \epsilon_t \tag{20}$$

Process for the change in potential GDP:

$$\Delta \bar{y}_t = \Delta \bar{y}_{t-1} + \eta_t \tag{21}$$

Process for the change in domestic inflation:

$$\Delta \pi_t = \gamma \hat{y}_t + \upsilon_t + \delta \upsilon_{t-1} \tag{22}$$

$$\upsilon_t = \eta_t \tag{23}$$

The model above is based on Kuttner (1994) (see also Hjelm and Jonsson (2010)) and relates the output gap ($\hat{y}$) to the change in domestic inflation ($\Delta \pi_t = \pi_t - \pi_{t-1}$). Modelling inflation in first differences implies that potential GDP corresponds to the level of GDP consistent with constant inflation.

Table 8: UC 4. Estimated and calibrated parameters. Quarterly data. Estimation period: 1990Q1-2019Q2

Parameter	Prior	Prior distribution	Posterior
λ_y	0.9(0.2)	Gamma	0.90(0.07)
γ	0.1[0,1]	Uniform	0.03(0.01)
δ	0.3(0.2)	Gamma	0.12(0.06)
σ_ϵ	0.7(10)	Inverse Gamma	0.47(0.09)
σ_η	0.1(10)	Inverse Gamma	0.12(0.06)
σ_υ	0.2(10)	Inverse Gamma	0.06(0.01)

Standard deviation in parentheses.

5.4 UC model 5: GDP mainland Norway, domestic inflation and unemployment (NAV)

Definition of GDP:

$$y_t = \hat{y}_t + \bar{y}_t \tag{24}$$

Process for the output gap:

$$\hat{y}_t = \hat{y}_{t-1} + \beta \hat{u}_t + \epsilon_t \tag{25}$$

Process for the growth in potential GDP:

$$\Delta \bar{y}_t = \Delta \bar{y}_{t-1} + \eta_t \tag{26}$$

Process for the unemployment gap:

$$\hat{u}_t = \lambda_u \hat{u}_{t-1} + \omega_t \tag{27}$$

Prcess for the trend in unemployment (NAIRU):

$$\Delta \bar{u}_t = \Delta \bar{u}_{t-1} + \upsilon_t \tag{28}$$

Process for domestic inflation:

$$\pi_t = \lambda_\pi \pi_{t-1} + \gamma \hat{u}_{t-2} + \upsilon_t \tag{29}$$

Table 9: UC 5. Estimated and calibrated parameters. Quarterly data. Estimation period: 1990Q1-2019Q2

Parameter	Prior	Prior distribution	Posterior
λ_y	0.8(0.1)	Gamma	0.9(0.06)
β	-3.45	Calibrated	
λ_u	0.9(0.2)	Gamma	0.9(0.04)
γ	-0.4[-1,0]	Uniform	0.49(0.22)
λ_π	0.5(0.2)	Gamma	0.39(0.12)
σ_ϵ	0.7(10)	Inverse Gamma	0.41(0.04)
σ_η	0.1(10)	Inverse Gamma	0.04(0.04)
σ_ω	0.2(10)	Inverse Gamma	0.1(0.01)
σ_v	0.1(10)	Inverse Gamma	0.07(0.01)
σ_υ	0.2(10)	Inverse Gamma	0.21(0.02)

Standard deviation in parentheses.

5.5 UC models 6 and 7: GDP mainland Norway and growth in credit or in house prices

Definition of GDP:

$$y_t = \hat{y}_t + \bar{y}_t \tag{30}$$

Process for the output gap:

$$\hat{y}_t = \lambda_y \hat{y}_{t-1} + \gamma x_t + \epsilon_t \tag{31}$$

Process for the change in potential GDP:

$$\Delta \bar{y}_t = \Delta \bar{y}_{t-1} + \eta_t \tag{32}$$

Process for the financial variable (x):

$$x_t = x_{t-1} + \upsilon_t \tag{33}$$

where x represents four-quarter growth in total credit (i.e. the sum of credit to households and firms) in UC 6 and house prices in deviation from their historical average in UC 7. In both models, the output gap's standard deviation (ϵ) is set equal to the standard deviation of change in the output gap estimated using an HP filter with λ equal to 1600, i.e. $\sigma_\epsilon = std(\Delta \bar{y}_t^{HP})$ where $\bar{y}^{HP}$ is the output gap estimated using a simple HP filter. The standard deviation of potential output growth is then scaled up by a factor z to ensure that the relative output gap variation is the same as for a normal HP filter, i.e. $\sigma_\eta = (1/z)\sigma_\epsilon$.

Table 10: UC 6. Estimated and calibrated parameters. Quarterly data. Estimation period: 1990Q1-2019Q2

Parameter	Prior	Prior distribution	Posterior
z	4.44	Calibrated	
λ_y	0.8(0.2)	Gamma	0.71(0.11)
γ	0.1(0.2)	Gamma	0.15(0.06)
σ_υ	1.2(10)	Inverse Gamma	1.17(0.07)

Standard deviation in parentheses.

Table 11: UC 7. Estimated and calibrated parameters. Quarterly data. Estimation period: 1990Q1-2019Q2

Parameter	Prior	Prior distribution	Posterior
z	7.2	Calibrated	
λ_y	0.8(0.2)	Gamma	0.80(0.13)
γ	0.1(0.2)	Gamma	0.05(0.012)
σ_υ	3(10)	Inverse Gamma	3.1(0.18)

Standard deviation in parentheses.

5.6 SVAR 1: Mainland GDP and unemployment (NAV)

The model is based on Blanchard and Quah (1989) and includes two lags of the endogenous variables. A demand shock and a supply shock are identified. The demand shock is identified as a shock that has no long-term effects on GDP.

5.7 SVAR 2: Mainland GDP, unemployment (NAV) and domestic inflation

The model is based on (Cerra and Saxena (2000)) and includes two lags of the endogenous variables. A demand shock, a temporary supply shock and a permanent supply shock are identified. The demand shock is identified as a shock that has no long-term effects on GDP. The temporary supply shock is identified as a shock that has no long-term effects on domestic prices.