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Real-time Data for Norway: Challenges for Monetary Policy

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Abstract:

National accounts data are always revised. Not only recent data, but also figures dating many years back can be revised substantially. This means that there is a danger that an important part of the central bank's information set is flawed for a long period of time. In this paper we present a data base consisting of various vintages of real-time data from 1993Q1 to 2003Q4. We describe the nature of the data revisions, the causes of the revisions, and investigate whether the revisions are true martingale differences, or whether they can be forecasted. In the spirit of Orphanides and van Norden (2002), we analyze how data revisions and model uncertainty affect the reliability of output gap estimates. We also compare Taylor type interest rate rules based on real-time data versus final data and assess the consequences for monetary policy if policy was conducted using this type of interest rate rules. Finally, we analyze the implications of output gap uncertainty for monetary policy using a small New Keynesian macroeconomic model.

Keywords: Monetary policy, output gap, real-time data, interest rate rules

JEL-Classification: C53, E37, E52

Non Technical Summary

In this paper we discuss consequences of lack of accuracy in the available real-time information for the process of conducting monetary policy.

A central bank processes huge amounts of information when it assesses the state of the economy as part of the monetary policy making process. Data uncertainty may disturb this assessment, and as data subsequently get revised this complicates the evaluation of the conduct of monetary policy. Some variables, such as the level of production in a particular period, may contain serious measurement errors and could be substantially revised over time. Thus, final data - available with a lag of 2-3 years - will typically deviate from real-time data. Hence, final data may - in retrospect - tend to point in the direction of some other path for the policy rate than the one the central bank chose on the basis of current real-time information. This is not to say, of course, that the central bank decisions were based on bad judgment at the time decisions were taken. Nevertheless, it is the final data - and not real-time data - that determines what would have been the appropriate monetary policy in the past.

The problem with lack of accuracy in real-time information is particularly evident for measures of production and growth, as they are crucial input variables for monetary policy decisions and normally revised - sometimes substantially - over time. A basic summary measure of the state of the real economy is the output gap, measured as the difference between production and potential production. As a theoretical concept the output gap is a key variable for monetary policy. Moreover, in addition to the real-time data problems, there are also important methodological problems in finding reliable estimates of it.

While the literature on real-time data and monetary policy has so far been dominated by analysis on US data, typically following up on the seminal work by Dean Croushore and Tom Stark at the Federal Reserve Bank of Philadelphia, this paper provides evidence based on a quarterly real-time database for Norway, which consists of vintages of data from 1993Q1 to 2003Q4.

We compare results for a class of univariate output gap models which have been considered in the literature and output gaps estimated using a Cobb Douglas production function. The different output gap estimates obtained from final data are compared with those from real-time data, and we decompose the total revision into the sum of data revisions and revisions due to other sources. In general, we find that other revisions are relatively more important than the data revisions for most models. The reliability of the various output gap models is poor. Total revisions are large and persistent, and the correlations between real time and final estimates are generally low. None of the models considered stands out as an obvious choice for estimating output gaps in real time.

Included is also an analysis of whether final growth rate data can be predicted on the basis of real time information. The results indicate that future revisions to output growth for the Norwegian mainland economy are unpredictable.

When we assess the implications for Taylor type interest rates the results clearly indicate that the inaccuracy of real time information may be a substantial challenge to monetary policy as final data in retrospect may give other paths for the policy rate compared to those suggested by real time data.

Finally, analyzing the consequences for monetary policy within a small New Keynesian macroeconomic model, the main welfare costs associated with failing to capture movements in potential output arise because monetary policy does not respond quickly enough to changes in the true output gap, thereby letting inflation move too far away from the target and closing the output gap too slowly. Furthermore, output gap mismeasurements reduce the optimal coefficients in generalized Taylor rules considerably compared to the full information case

Nicht technische Zusammenfassung

Im vorliegenden Beitrag wird untersucht, wie sich ein Mangel an Genauigkeit der verfügbaren Echtzeitinformationen auf die Durchführung der Geldpolitik auswirkt.

Bei der Beurteilung des Zustands einer Volkswirtschaft im Rahmen des geldpolitischen Entscheidungsprozesses verarbeitet eine Zentralbank große Informationsmengen. Datenunsicherheit kann zu einer Verzerrung dieser Einschätzung führen, und da die

Daten im Nachhinein korrigiert werden, erschwert dies die Beurteilung der Geldpolitik. Einige Variablen, beispielsweise das Produktionsniveau in einem bestimmten Zeitraum, können schwerwiegende Messfehler enthalten und im Zeitverlauf stark revidiert werden. Aus diesem Grunde weichen die endgültigen Daten, die mit einer Verzögerung von zwei bis drei Jahren vorliegen, in der Regel von den Echtzeitdaten ab. Daher können die endgültigen Daten – rückblickend – tendenziell einen anderen Pfad für den Leitzins nahe legen als den von der Zentralbank auf Basis der aktuellen Echtzeitinformationen gewählten. Dies bedeutet natürlich nicht, dass die Entscheidungen der Zentralbank zum Zeitpunkt der Entscheidungsfindung auf falschen Einschätzungen beruhten. Dennoch sind es die endgültigen Daten, nicht die Echtzeitdaten, die Aufschluss darüber geben, welche Geldpolitik in der Vergangenheit angemessen gewesen wäre.

Besonders deutlich wird das Problem der mangelnden Genauigkeit von Echtzeitinformationen bei den Messgrößen für Produktion und Wachstum, da sie wichtige Variablen für die geldpolitischen Entscheidungen darstellen und allgemein im Laufe der Zeit – mitunter deutlich – revidiert werden. Ein einfaches zusammenfassendes Maß für den Zustand der Realwirtschaft ist die Produktionslücke, die als Differenz zwischen der Produktion und dem Produktionspotenzial gemessen wird. Als theoretische Größe ist die Produktionslücke eine Schlüsselvariable für die Geldpolitik. Allerdings gibt es neben den Schwierigkeiten in Bezug auf die Echtzeitdaten auch erhebliche methodische Probleme, verlässliche Schätzungen dafür zu erhalten.

Während die einschlägige Literatur zu Echtzeitdaten und Geldpolitik bislang von Analysen auf der Grundlage von US-Daten beherrscht wurde, die sich meist auf die Forschungsarbeit von Dean Croushore und Tom Stark von der Federal Reserve Bank of Philadelphia stützten, werden im vorliegenden Beitrag Angaben aus einer vierteljährlich aktualisierten Echtzeitdatenbank für Norwegen verwendet, welche die Datenjahrgänge vom ersten Quartal 1993 bis zum vierten Quartal 2003 enthält.

Wir vergleichen die Ergebnisse eines in der Literatur betrachteten Typs univariater Produktionslücken-Modelle mit den anhand einer Cobb-Douglas-Produktionsfunktion geschätzten Produktionslücken. Dabei werden die verschiedenen, auf endgültigen Daten basierenden Schätzungen der Produktionslücke den auf Echtzeitdaten beruhenden

Schätzungen gegenübergestellt; die gesamte Revision wird in die Summe der Datenrevisionen und der Revisionen aufgrund anderer Faktoren zerlegt. Im Allgemeinen stellt sich bei den meisten Modellen heraus, dass die Revisionen aufgrund anderer Faktoren relativ stärker zu Buche schlagen als die Datenrevisionen. Die Zuverlässigkeit der verschiedenen Produktionslücken-Modelle ist gering. Der Gesamtumfang der Revisionen ist beachtlich und anhaltend, und die Korrelation zwischen Echtzeit- und endgültigen Schätzungen ist generell niedrig. Keines der verwendeten Modelle sticht als nahe liegende Option zur Schätzung der Produktionslücke in Echtzeit hervor.

Wir haben auch analysiert, ob endgültige Daten zur Wachstumsrate auf der Grundlage von Echtzeitinformationen repliziert werden können. Die Ergebnisse deuten darauf hin, dass sich künftige Datenrevisionen bezüglich des Produktionswachstums für die Wirtschaft des norwegischen Festlands nicht vorhersagen lassen.

Wenn wir die Auswirkungen auf die Taylor-Zinssätze untersuchen, so lassen die Resultate eindeutig den Schluss zu, dass die Ungenauigkeit der Echtzeitinformationen die Geldpolitik vor eine beträchtliche Herausforderung stellen kann, da endgültige Daten im Rückblick andere Pfade für den Leitzins nahe legen können als den von Echtzeitdaten abgeleiteten.

Untersucht man schließlich die Folgen für die Geldpolitik innerhalb eines kleinen neukeynesianischen makroökonomischen Modells, so ergibt sich, dass die Wohlfahrtskosten, die aus dem Unvermögen resultieren, Veränderungen des Potenzialwachstums zu erfassen, hauptsächlich darauf zurückzuführen sind, dass die Geldpolitik nicht schnell genug auf Veränderungen der tatsächlichen Produktionslücke reagiert; dies hat zur Folge, dass die Inflation zu weit vom Ziel abweichen kann, und die Produktionslücke sich zu langsam schließt. Zudem führen Fehlmessungen der Produktionslücke im Fall von allgemeinen Taylor-Regeln – verglichen mit einer Situation, in der vollständige Daten vorliegen – zu einer beträchtlichen Verringerung der optimalen Koeffizienten.

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1 Introduction

A central bank processes huge amounts of information when it assesses the state of the economy as part of the monetary policy making process. Data uncertainty may disturb this assessment, and as data subsequently get revised this complicates the evaluation of the conduct of monetary policy. Some variables, such as the level of production in a particular period, may contain serious measurement errors and could be substantially revised over time. Thus, final data - available with a lag of 2-3 years - will typically deviate from real-time data. Hence, final data may - in retrospect - tend to point in the direction of some other path for the policy rate than the one the central bank chose on the basis of current real-time information. This is not to say, of course, that the central bank decisions were based on bad judgment at the time decisions were taken. Nevertheless, it is the final data - and not real-time data - that determines what would have been the appropriate monetary policy in the past. In the process of conducting monetary policy, it is therefore important for the central bank to evaluate the consequences of the lack of accuracy in the available real-time information.

While lack of accuracy in real-time information may apply to many macroeconomic variables which the central bank assesses when setting the interest rate, the problem is particularly evident for measures of production and growth. First, they are crucial input variables for monetary policy decisions: A good measure of current production is important for forecasting inflation, and the role of stabilizing the real economy under flexible inflation targeting requires a good assessment of the current state of the real economy. Second, production and growth data are normally revised -

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sometimes substantially - over time. For other variables important in the monetary policy making process, like consumer price inflation, credit growth, wage growth and the public deficit, real time observations deviate less from final observations and the problems created by data revision are less severe.[1]

Academics and policy makers have recently invested more resources into this area, and there is a growing literature on the properties of real-time data and their consequences for current practices of monetary policy making. The pioneering work by Croushore and Stark (1999, 2001) (see Croushore and Stark (2000) for a non-technical presentation of the real-time database for the US) has set a standard for the systematic work with real-time data and recent applications include Orphanides (2001), Stark and Croushore (2002) (with comments) and Orphanides and van Norden (2002). Kozicki (2004) provides an overview of this literature in the US and discusses how data revisions may affect the evaluation and conduct of monetary policy.

The output gap is frequently considered as a basic summary measure of the state of the real economy, and as a theoretical concept the output gap is a key variable for monetary policy. In addition to the real-time data problems mentioned above, there are also important methodological problems in finding reliable estimates of it. Orphanides and van Norden (2002) compare a wide range of different models and give an assessment of the reliability of output gap estimates in real-time. They argue that great caution is required and that output gap mismeasurement may pose a serious problem for the correct assessment of the state of the economy. Furthermore, they argue that disregarding this unreliability can lead to flawed policy recommendations. For further analysis of the implications of the mismeasurement of the output gap, see e.g., Orphanides et al. (2000). In some situations it may even be advantageous to base monetary policy on information of output growth, and disregard the output gap. Orphanides (2000) argues that the central bank could chose to react to changes in growth and exclude measures of the output gap in the reaction function. The reason is that the output gap may be burdened with persistent measurement problems, meaning

1 The lack of revision in consumer prices does of course not guarantee that observations are accurate and free of biases that may distort policy decisions, cf. the discussion about whether the CPI takes sufficiently into account the quality changes that are typical for many consumer goods.

that the perceived level of the output gap may be distorted over time. In the presence of a high degree of persistence, growth rates may be more reliable than levels in real-time.

The literature on real-time data and monetary policy has so far been dominated by analysis on US data, typically following up on the seminal work by Dean Croushore and Tom Stark at the Federal Reserve Bank of Philadelphia. This paper provides evidence based on a quarterly real-time database for Norway which consists of vintages of data from 1993Q1 to 2003Q4. Norway has since 2001 adopted a flexible inflation targeting regime. Details about the Norwegian real-time database with a special focus on mainland GDP are presented in Section 2 along with a descriptive summary of data properties. Section 2 also analyzes whether final data can be predicted on the basis of information available in real time. That is, can variables which are available at the same point in time as the preliminary data, help predict the final data or not? The two polar views are that revisions either represent *news*, hence they are unpredictable on the basis of contemporaneous information, or revisions tend to eliminate *noise* which is present in preliminary data. We test the *news* hypothesis in Section 2.3 using standard efficiency tests. In Section 3 we discuss the problem of estimating output gaps facing both model and real-time data uncertainty. We compare results for a class of univariate output gap models which have been considered in the literature (Orphanides and van Norden, 2001) and output gaps estimated using a Cobb Douglas production function. The different output gap estimates obtained from final data are compared with those from real-time data, and we decompose the total revision into the sum of data revisions and revisions due to other sources. Section 4.1 discusses the consequences of inaccurate measurement of output gaps for simple Taylor type interest rate rules. Finally, in section 4.2 we discuss implications of output gap uncertainty for monetary policy using a small New Keynesian macroeconomic model. Section 5 concludes.

2 The real-time database for Norway

2.1 Constructing the database

Since 1993, Norges Bank's macroeconomic model RIMINI has been an important tool for forecasting in Norges Bank. The model is estimated on quarterly data. After each round of forecasting (every third month until 2000 and every four month thereafter) the model's data-base and forecasts have been saved in vintages. This has created an opportunity to construct a real-time database, covering national accounts and other data.

Not all the vintages are complete, however, and additional work has to be done to construct a complete real-time database. So far our main focus has been on GDP for Mainland Norway in market value, measured in fixed prices. For the purpose of estimating output gaps using a production function, labour market, real capital and GDP data for selected mainland sectors were also constructed.

The model's database has been updated twice each year. To construct a quarterly data-base, the starting point was published national accounts figures in Statistics Norway's Economic Bulletin. Figures for 6 to 8 quarters are published when new national accounts are available. Saved data in Norges Bank were appended to these figures.[2]

Some of the saved vintages were not complete, covering only the last three to four years. To construct a complete vintage, growth rates from other vintages with the same base year were used. In some cases, no vintages with the same base year as the incomplete vintage existed. In those cases, growth rates from some vintage with a different base year had to be used. This means that some of the vintages are not completely accurate. That should not, however, constitute major problems, as the change in historical growth rates associated with a new base year normally is minor.

2.2 Description of the database

There are three main sources for national accounts data to change over time. First, the earliest estimates are based on preliminary and incomplete information. Second, the base year is changed each year, and third, the national accounts are occasionally subject to major revisions.

In Norway quarterly, unadjusted national accounts data are published in the third month after the end of the quarter. Each time data for a new quarter are published,

2 Labour market, real capital and GDP data for selected mainland sectors were constructed solely on the basis of saved data in Norges Bank.

earlier data are also revised. In the second quarter of year (t), national accounts data for year (t-3) are final, and year (t-3) is the new base year.[3]

The first published figures are of course based on the most incomplete information, and naturally the figures will change when new information becomes available. The revisions can be quite substantial in the first few quarters after the initial publication. After 10 to 13 quarters, quarterly account figures are final, but year-on-year growth rates are in general fairly close to the final growth rates after 3 to 4 quarters. Changes of the base year obviously entail levels changes in historical national accounts data. To some extent, annual growth is also affected, but the effect is typically minor due to the frequency of the base year switch.

In the last ten years, there have been two major revisions of the national accounts:

- From 1995, the guidelines of the System of National Accounts SNA 1993 and European System of Accounts ESA 1995 were gradually implemented. In the third quarter of 1995, revised quarterly national account figures from 1993 to the second quarter of 1995 were published. Historical national accounts were revised stepwise. In 1997 data going back to 1978 were published. For research purposes, data from 1970 to 1978 have been recalculated by the Research Department in Statistics Norway. These are not official National Account statistics, but were made available for research purposes in the first quarter of 2001.
- Statistics Norway has collected new structural statistics for many industries over the last years. For some service industries the new statistics entailed changes that were deemed too substantial to be included on a continuing basis. Statistics Norway therefore decided to undertake a new revision of the national accounts, incorporating the new structural statistics in a coordinated way from 1991. In connection with this revision, some recalculations and corrections also affected national accounts in the previous decades. The revised figures were published in 2002.

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3 From 2003, the publishing of final national accounts figures and the base year change are moved forward to the first quarter of the year. In principle, the base year is changed every year. In connection with major revisions of the national accounts, however, the base year was kept unchanged for a longer period. The revisions are described below.

The complete national accounts are based on unadjusted figures. Seasonally adjusted figures are presented for some main aggregates, but until recently these series have not been published as historical time series. Accordingly, the vintages that are saved in Norges Bank are all unadjusted. Both the major revisions led to substantial changes in the seasonal pattern.

Figure 1(a) depicts the year-on-year growth (indicated by D4Y) in the unadjusted real-time[4] and final data. The final data is the vintage published in 2003Q4. Growth rates are generally much higher in the final data. The change in the level of GDP after several years of revisions is illustrated in Figure 1(b), showing accumulated revisions over 4, 8 and 12 quarters. For example, in the fourth quarter of 2001, the accumulated growth over the last 12 quarters turned out to be 4 percentage points higher than initially measured at the end of that year.

Looking at changes in average growth rates is another way of illustrating the overall effects of the data revisions. The main impact of the two major revisions on data from 1974 to 2001 is illustrated in Table 1, showing average annual growth rates of Mainland Norway GDP over five-year periods. Base year changes also contribute to revised average growth rates. But compared to the major revisions, these effects are minor. The vintage 1995Q1 is the last published vintage prior to the main revision of 1995, the vintage 2002Q1 is the last published vintage prior to the revision in 2002 and the vintage 2003Q4 is the latest available national accounts at the time of writing.[5]

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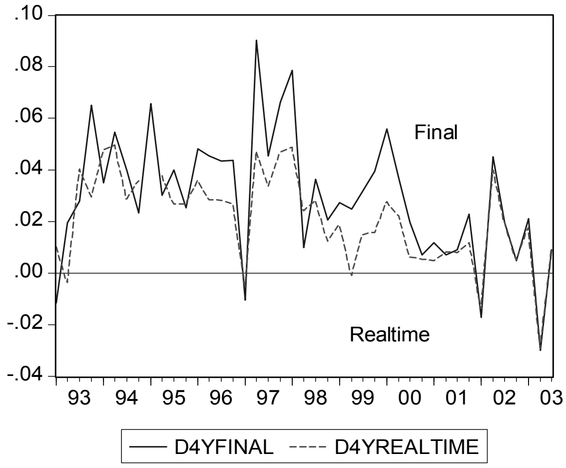
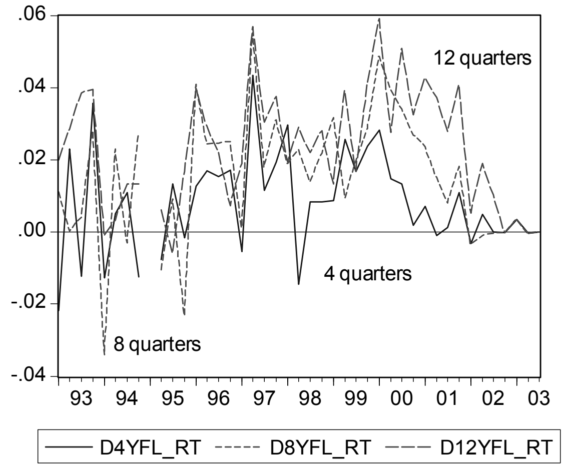
[4] In connection with the major revision in 1995, national account figures were not published in 1995Q1.
[5] Each vintage contains national accounts figures up to and including the previous quarter.

Figure 1: Final and real-time output growth, accumulated revisions over 4, 8 and 12 quarters. Vintages 1993Q1 - 2002Q1



(a) Final and real-time output growth



(b) Accumulated revisions

Table 1: Annual growth rate of Mainland Norway GDP over five-year periods

Vintage Period	1995q1	2002q1	2003q4
1974 to 1979	3,6	3,9	3,8
1979 to 1984	2,0	2,3	2,2
1984 to 1989	1,5	1,8	1,9
1989 to 1994	1,7	2,3	2,3
1994 to 1999		3,1	4,1
1996 to 2001		2,3	3,2

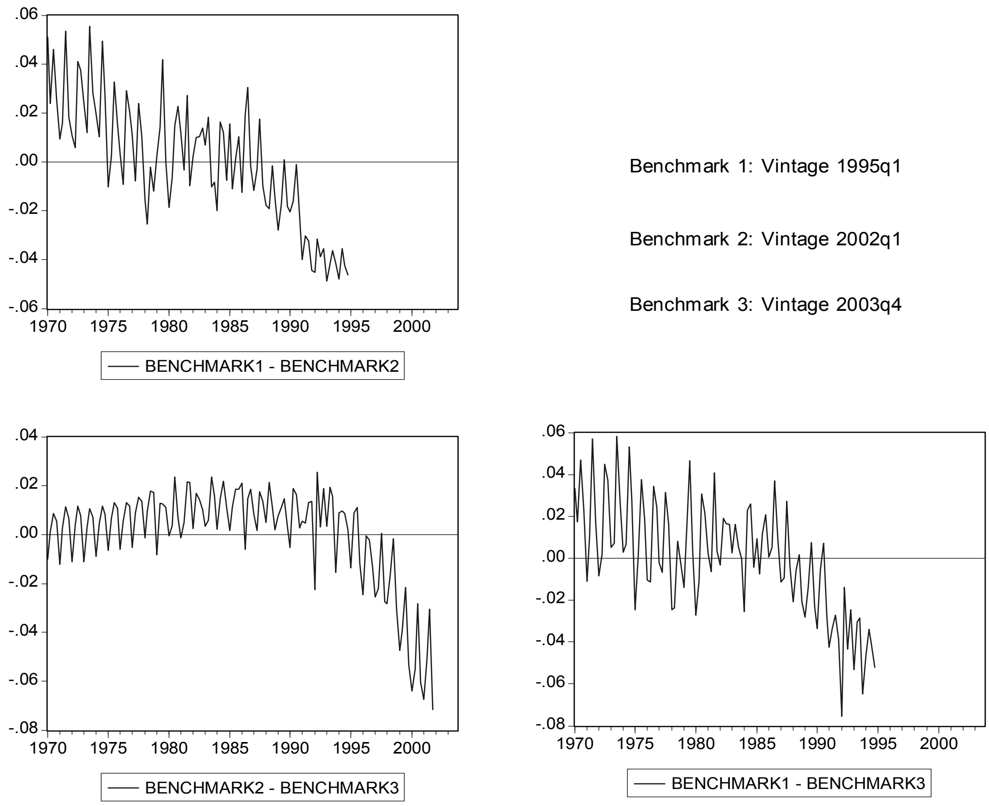
The 1995 revision raised the level of GDP, increasing average annual growth rates in the 1970's and 1980's by 0.3 percentage point. The assessment of the upturn in the first part of the 1990's also changed. Prior to the main revision, the national account figures indicated that the turning point after the pronounced downturn in the last half of the 1980's occurred in 1992. According to the revised account figures, the upswing started already in 1990/91.

In the 2002 revision, new structural statistics were incorporated in the account figures from 1991. The impact of the 2002 revision is highlighted in the last two lines in Table 1. New structural statistics raised the average annual growth rate by 0.4 per cent in the first half of the decade and by 0.9 per cent in the second half. Some additional, partly methodological, changes also affected national accounts figures in the two previous decades.

Following Croushore and Stark (1999, 2001), the effect of the two main revisions on the level of GDP is also illustrated in Figure 2, depicting the differences between the log levels of the benchmark vintages used in Table 1, adjusted for mean differences between the vintages. The upper left panel illustrates the effect of the main revision in 1995. The lower left panel illustrates the combined impact of the main revision in 1995 and the revision in 2002. The right panel isolates the effect of the 2002 revision.

The log level ratio is decreasing in all three charts, further illustrating the upward shifts of GDP in the major revisions. The changes in the seasonal pattern are pronounced in all the charts, creating a lot of noise in the ratios. The main revision in 1995 increased the GDP level for the whole period, but the upward revision was particularly sharp in 1991, at the beginning of the long upswing in the 1990's. The revision in 2002 further increased the GDP level.

Figure 2: Log output ratios for three different vintages of real-time data



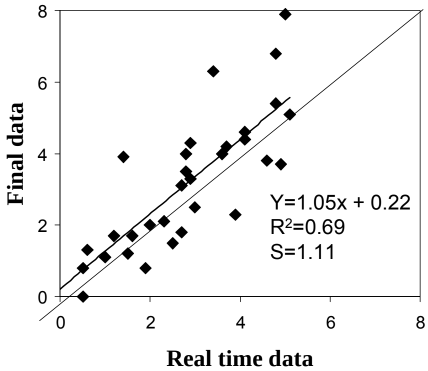
Three main reasons for revisions of national accounts data are described in the previous subsection. Changes due to incomplete information and base-year changes are occurring regularly, while major revisions normally are undertaken more seldom. In this subsection we aim to assess how reliable early estimates of national accounts data are in general, given available information. In the next section we investigate whether final data are predictable, given available information at the time of the first estimate. As major revisions are infrequent, and may lead to changing growth rates several decades after the earliest estimates, it does not seem reasonable to define final data across major revisions. For that reason, we leave out changes due to those revisions. The changes due to major revisions are taken into account partly by leaving out some observations, and partly by considering when growth rates can be judged to be final.

To obtain a broad picture of how growth data evolves over time, Figure 3(a) to 3(d) show real time year-on-year growth data at the time of publication and the revised data in the three subsequent quarters, all four series along with the final revised data. For example, Figure 3(c) shows revised growth data two quarters after the time of publication and final revised data. In the absence of real time measurement problems, all data would lie on the 45-degrees line, meaning that real time data would not be revised. As time evolves, it is expected that the revised data will coincide with the final data, meaning that the numbers will approach the 45-degrees line over time. Note that in the figures the regression line and the standard deviation of the regression have also been included. For all the four regression lines, the hypothesis of a zero intercept and a coefficient equal to one turns out not to be rejected. This supports the view that real time growth rate mismeasurements do not contain a systematic pattern.[6]

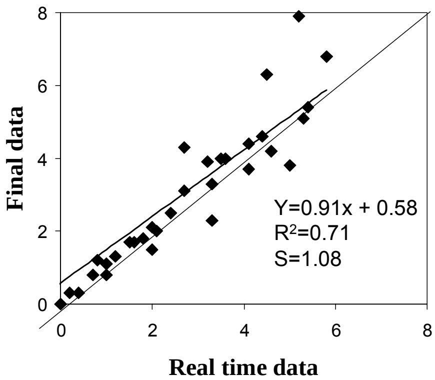
Figure 3(a) shows that real time growth data deviate considerably from final data for some of the observations (the standard deviation of the regression is equal to 1.1 percentage point). For some numbers the difference between real time growth data and final growth data is substantial, meaning that in worst case, incorrect real time information may have serious consequences for monetary policy.

[6] Note the difference between Figure 3 and Figure 1(a). In the former final data is defined across main revisions, while in the latter changes due to main revisions are left out.

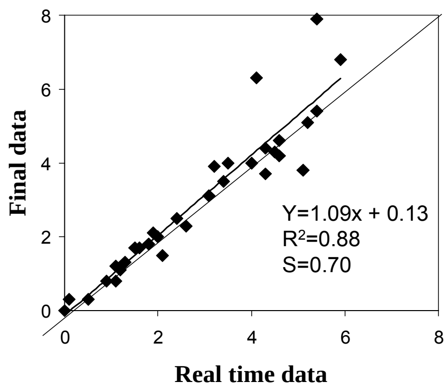
Figure 3: Real-time observations versus final data.
Vintages 1993Q1 - 2002Q3



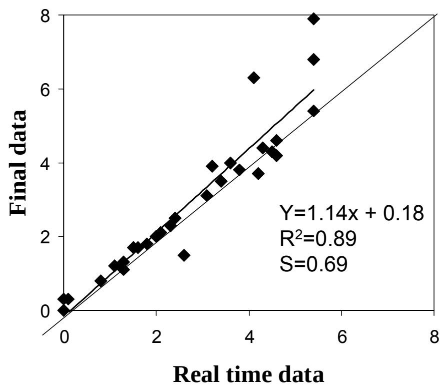
(a) 1. observation versus final data



(b) 2. observation versus final data



(c) 3. observation versus final data



(d) 4. observation versus final data

Turning to the evolution of growth data in the subsequent three quarters, the figures reveal that there are no substantial revisions after one quarter, as the standard deviation of the regression remains broadly unchanged at around 1.1 percentage point. However, this picture changes in the second and the third quarter after first time publication, as the standard deviations then take values of around 0.70 percentage point. Hence while measurement errors are considerably lower a year after the data was published for the first time, some differences between the revised data and the final data remains. After a year, an error of say twice the standard deviation would be around 1.5

percentage point, not insignificant in terms of assessing the consequences for monetary policy.

We now turn to the question of whether final growth data can be predicted on the basis of real time information. The revision process can be characterized in terms of two polar alternatives dubbed *news* and *noise* by Mankiw et al. (1984) and Mankiw and Shapiro (1986). Under the *news* view real time information contain all available information at the time of announcement. Faust et al. (2000) test this hypothesis on real time and final quarterly GDP growth rates for the G-7 countries using a forecast efficiency test. This resembles the well-known efficiency test in finance, where the crucial question is whether future asset prices can be predicted on the basis of all kind of information publicly available at the time the test is performed. In our context, the question is to what extent the difference between the final data and real time data contains a systematic pattern. The test can be conducted on the basis of the regression

$$\Delta y_t^f - \Delta y_t^r = \alpha + \beta \Delta y_t^r + \gamma Z_t^r + \varepsilon_t \qquad (1)$$

where Δy_t^r is the growth rate published in real time (first time publication), Δy_t^f is the final growth rate, Z_t^r is a vector of real time controlling variables, which could possibly have explanatory power on the left-hand side variable and α, β and γ are coefficients to be estimated. Furthermore, ε_t is a disturbance term.

Under the null hypothesis, $\alpha = 0$, $\beta = 0$, $\gamma = 0$ and ε is white noise. Then final growth data do not deviate systematically from real time data, i.e., $\Delta y_t^f = \Delta y_t^r + \varepsilon_t$. If the null hypothesis does not hold, i.e., if at least one of the coefficients differs from zero, or if the disturbance term contains a systematic pattern, deviations from real time data can be predicted. In that case we have some information, not embedded in the real time growth data, which could help us predicting the final revised growth data. This again, could be valuable information in the monetary policy making process.

To test for this, a large set of macroeconomic variables, which could have an explanatory power on the left-hand side variable, were included in the model (one by one). Table 2 shows the F-statistic (and the corresponding probability value) for the joint null hypothesis that the coefficients and the constant term in regression (1) are zero. For all regressions the null hypothesis could not be rejected. Hence available real time macroeconomic information indicate that final revised growth data cannot be predicted beyond the information contained in the numbers published in real time.[7]

Table 2:Omitted variable tests for additional effects on revisions from macroeconomic variables

Labour market variables	
New Jobs	$F_{OVT}(3, 30) = 0.1872$ [0.8303]
Vacancies	$F_{OVT}(3, 30) = 0.2616$ [0.7716]
Employment and vacancies	$F_{OVT}(3, 30) = 0.1814$ [0.8350]
Unemployment	$F_{OVT}(3, 30) = 0.2298$ [0.7961]
Δ(Unemployment)	$F_{OVT}(3, 30) = 1.5212$ [0.2354]
Hours worked	$F_{OVT}(3, 30) = 0.2616$ [0.7716]
Goods market variables	
Industrial production	$F_{OVT}(3, 30) = 0.1144$ [0.8923]
Δ(Industrial production)	$F_{OVT}(3, 30) = 0.3211$ [0.7279]
Retail sales	$F_{OVT}(3, 30) = 0.069$ [0.9338]
Δ(Retail sales)	$F_{OVT}(3, 30) = 0.2422$ [0.7864]
New orders	$F_{OVT}(3, 30) = 0.0671$ [0.9352]
Δ(New orders)	$F_{OVT}(3, 30) = 0.3681$ [0.6952]
Industrial investment	$F_{OVT}(3, 30) = 0.2616$ [0.7716]
Δ(Industrial investment)	$F_{OVT}(3, 30) = 0.4538$ [0.6397]
Bankruptcies	$F_{OVT}(3, 30) = 0.3716$ [0.6928]
Financial market variables	
Credit growth, C1	$F_{OVT}(3, 30) = 0.0700$ [0.9324]
Δ(Credit growth, C1)	$F_{OVT}(3, 30) = 0.6087$ [0.5509]
Credit growth, C2	$F_{OVT}(3, 30) = 0.0698$ [0.9327]
Δ(Credit growth, C2)	$F_{OVT}(3, 30) = 0.7627$ [0.4755]
Credit growth, C3	$F_{OVT}(3, 30) = 0.0682$ [0.9342]
Δ(Credit growth, C3)	$F_{OVT}(3, 30) = 1.1621$ [0.3269]
Nominal effective exchange rate	$F_{OVT}(3, 30) = 0.3213$ [0.7277]
Δ(Nominal effective exchange rate)	$F_{OVT}(3, 30) = 0.3036$ [0.7405]
Slope of the yield curve	$F_{OVT}(3, 30) = 0.8261$ [0.1922]

[7] One should note that the appropriate testing procedure would normally be to include all, or at least some explanatory variables in the regression simultaneously. However, in our case, due to lack of degrees of freedom the additional explanatory variables were included only one by one in the regression.

Similar hypotheses have also been analyzed by Faust et al. (2000) using data for the G-7 countries. The results reported for the period 1988Q1 to 1997Q4 indicate that the *news* hypothesis can be firmly rejected for countries like Germany, Italy, Japan and UK, where GDP-revisions seem to be highly predictable[8]. For Canada, France and US the results in Faust et al. (2000) indicated that revisions were unpredictable at the 10 per cent confidence level over the period 1988Q1 to 1997Q4. This is supportive evidence for the *news* view and holds for the case with no additional variables Z_t, i.e., assuming $\gamma = 0$. When additional variables - available at the same time as the preliminary GDP-figures - were included in the regression, it turned out that one or more of them were significant in the analysis of data for G-7 countries.

3 Output gap estimates in real-time

3.1 Models

The output gap is a concept that has proved useful both as input for analysis and forecasting and for communicating policy. Under flexible inflation targeting, the output gap enters the central bank's loss function directly. In addition, the output gap is an important determinant of inflation.

The output gap is usually defined as the deviation of actual output from potential output. Traditionally, potential output is measured by some sort of trend. From an operational point of view, the output gap is thus the deviation of output from its trend. This measure is, however, not necessarily consistent with the definition from the more recent New Keynesian theoretical framework. The sort of gap the central bank should attempt to close according to theory is the deviation of output from the output level that would have occurred if all prices and wages were fully flexible. Despite the theoretical attractiveness of the flex-price output gap, it is extremely difficult to measure, and most central banks use more traditional methods of detrending.

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8 In fact the results in Faust et al. (2000) yield some support to the *noise* view, i.e., that subsequent revisions tend to remove measurement errors.

As mentioned in Section 2, the national accounts figures in the real-time database are not seasonally adjusted. Estimating output gaps on a quarterly basis, however, requires seasonal adjustments. To remove the seasonal pattern in the GDP figures used in constructing the output gap series, we used the ”quick seasonal adjustment” (X12arima) feature in GiveWin (Doornik and Hendry, 2001). This is not ideal, since the resulting seasonally adjusted series are different from the adjusted series published by Statistics Norway. One important reason for the differences, is that the ”quick seasonal adjustment” does not take account of mobile holidays. This creates an added uncertainty about the quarter-to-quarter development, but it does not severely affect the overall assessment of the economic development. It may, however, exaggerate the noise in the series.

A detrending method decomposes (the log of) real output, y_t, into a trend component, μ_t, and a cyclical component, z_t, see Orphanides and van Norden (2002) for an overview over the relative merits of different detrending methods using final and real time data. Following this, we can write

$$y_t = \mu_t + z_t, \tag{2}$$

where the cyclical component, z_t, may be used as a measure of the output gap, $ygap_t = y_t - \mu_t$. There is considerable uncertainty with respect to the measurement of potential output and in this paper we will use estimates of the trend, , as our estimate of the potential output.

We follow Orphanides and van Norden (1999) and consider a fairly wide range of univariate models of the output gap. In table 3 below, in addition to the production function model, we present seven univariate models of the output gap ranging from simple deterministic trend models through filtering models (Hodrick-Prescott), frequency domain models (band pass) and univariate unobserved components models.[9] Orphanides and van Norden (2001) have also considered bivariate unobserved components models which are estimated with Kalman filter algorithms.

9 The estimation results for the UC-models in Orphanides and van Norden (1999) are based on Kalman filter algorithms in the TSM-module in GAUSS. We are grateful to Simon van Norden for providing access to his procedures written in RATS and Gauss for estimating the univariate models in Table 3.

Table 3: Output gap models

LT	Linear trend	$\mu_t = \alpha + \beta t + \varepsilon_t$
QT	Quadratic trend	$\mu_t = \alpha + \beta t + \gamma t^2 + \varepsilon_t$
WT	Watson (1986) (local level model)	$\mu_t = \delta + \mu_{t-1} + \eta_t$ $z_t = \rho_1 z_{t-1} + \rho_2 z_{t-2} + \varepsilon_t$
CL	Harvey (1985), Clark (1987) (local trend model)	$\mu_t = \delta + \mu_{t-1} + \eta_t$ $\delta_t = \delta_{t-1} + \upsilon_t$ $z_t = \rho_1 z_{t-1} + \rho_2 z_{t-2} + \varepsilon_t$
HP	Hodrick-Prescott (λ=1600)	$\mu_t = \arg\min \sum_{t=1}^{T} \left\{ (y_t - \mu_t)^2 + \lambda \left(\Delta^2 \mu_{t+1} \right) \right\}$
HPUC	Hodrick-Prescott (UC-representation)	$\Delta^2 \mu_t = \eta_t$
BP	Bandpass filter	
PF	Production Function model	$\mu_t = \hat{\alpha} + 0.67 l_t^* + 0.33 k_t^* + tfp_t^*$

Before proceeding, we will have a closer look at the production function method, the method used by OECD for most of the member countries. In contrast to the univariate models, the production function model takes account of the underlying structure of the economy. We follow the approach in Nymoen and Frøyland (2000), basing the calculations on a production function for the sectors manufacturing, construction, services and distributive trade, accounting for about 75 per cent of production for mainland Norway.[10] Potential output may then be interpreted as the supply side of the economy, and output gaps accordingly represent excess demand or supply.

The aggregated production function is assumed to be of a Cobb-Douglas type with constant returns to scale[11]:

$$y_t = \alpha_0 + \alpha_1 l_t + (1 - \alpha_1) k_t + e_t \tag{3}$$

where the variables y (production, i.e. value added), l (person-hours) and k (capital stock) are measured in logarithms. e represents total factor productivity, α_1 and (1- α_1) are elasticities and α_0 is a constant. The elasticities are given by the income factor shares

[10] In the univariate methods, we use GDP for mainland Norway.

[11] As in Nymoen and Frøyland (2000), we use the calculation method from the OECD, described in Giorno et. al. (1995).

of the two production factors. The weights can according to the Ministry of Finance be estimated at 0.33 for person-hours and 0.67 for real capital for mainland enterprises.

Potential output is the hypothetical output occurring when capital stock, person-hours and total factor productivity are at their equilibrium, or trend, levels. These levels are not observable and, hence, must be estimated. This is not unproblematic, and the difficulties are compounded when using real time data. Equilibrium values are constructed in the following ways:

- Figures for the capital stock in national accounts are plagued with a high degree of uncertainty. Furthermore, real time data series for capacity utilization are not readily accessible. For these reasons, we assume that the capital stock is fully utilized at any time.
- Potential person-hours, or labor input, is a function of the potential levels of the labor force, unemployment and average working hours per employee. Potential levels of the labor force and unemployment are estimated by smoothing, using a Hodrick-Prescott filter. Potential average working hours are assumed to be equal to actual working hours, implying that average working hours are independent of cyclical variation.
- Total factor productivity is calculated as the residual from estimating equation (3) using the least squares method. The residuals are then smoothed by a Hodrick-Prescott filter.

3.2 Brief overview of the results

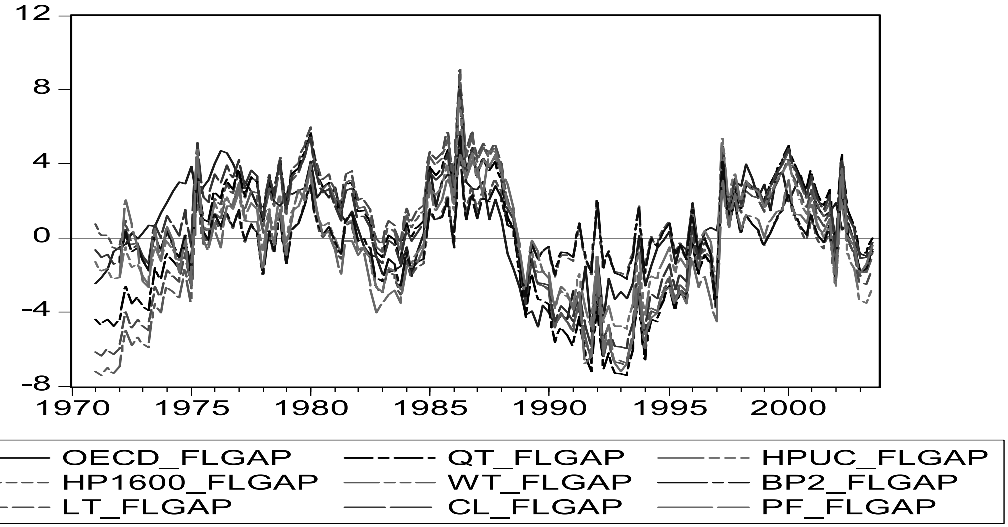
The Real-time database covers the period from 1993. To give a brief overview of the development in the Norwegian economy in the last three decades, output gaps estimated on final data, i.e. vintage 2003Q4, are shown in Figure 4 (FLGAP denotes final gap). The output gaps are estimated for each of the eight different models described above. Output gaps produced by OECD, who uses the production function method to estimate the output gap, are included.

There are no authoritatively determined business cycles, dating of recessions or output gaps in Norway. There is, however, a general agreement that the upswing in the 1990's started in 1991 and peaked in 1998 with the international financial turmoil.

Activity stayed at a high level until 2000. Since then growth has decreased and output is now generally judged to be below potential.

One salient feature is the deep recession in the last half of the 1980s and the following long expansion in the 1990s. Using NBER's definition of a business cycle on the OECD output gap series, and allowing for some uncertainties due to noisy data, the recession starting in the second quarter of 1986 lasted until the second quarter of 1990. The following expansion peaked in the second quarter of 1998. The second quarter of 2003 seems to be the starting point of a new expansionary period.[12]

Figure 4: Final output gaps. Vintage 2003Q4



The period covered by the real-time data base thus starts close to the beginning of a cycle that peaks in the late 1990's and ends with a trough in 2003.

In Figure 5(a) and Figure 5(b) output gaps estimated on final and real-time data for each of the models described in the previous section are presented. Real-time output gaps are calculated for vintages 1993Q1 to 2002Q1.[13]

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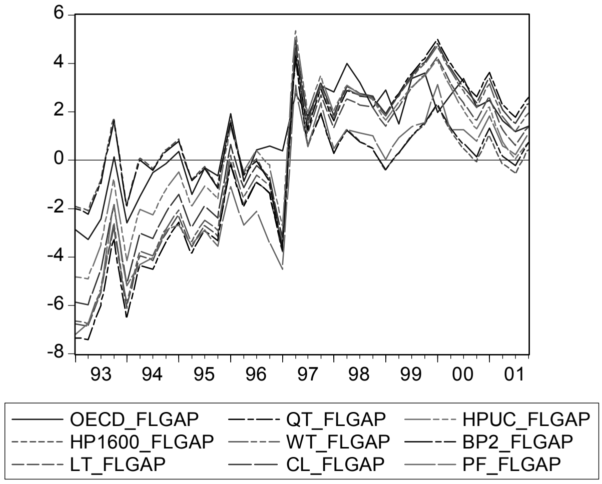
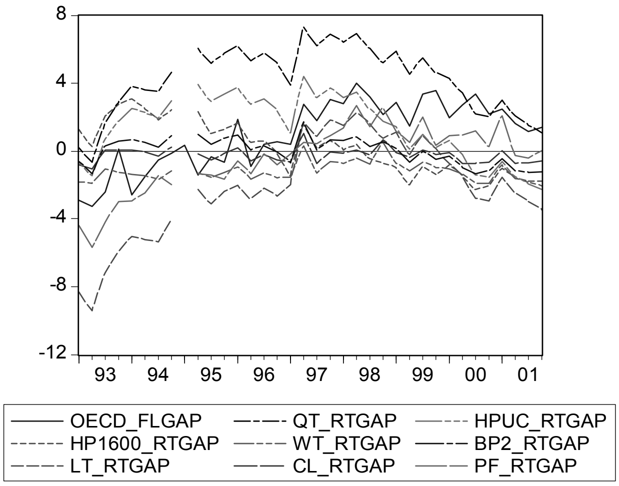
[12] It might perhaps be argued that the period from the second quarter of 1998 to the second quarter of 1999 can be defined as a recession, followed by an expansion lasting for three quarters. On the other hand, this period is hardly characterized by any significant decline in activity.

[13] Real Time estimates are calculated in the following way, described in Orphanides and van Norden (1999): For each vintage, output gaps are estimated. The last value in each of the output gap series is the first available estimate of the output gap for that particular vintage. These estimates are picked from each output gap vintage, and a time series of the Real Time output gaps is constructed.

Figure 5: Final and Real time output gaps. Vintages 1993Q1 – 2002Q1



a) Final



b) Real-time

Some apparent features include:

- Output gaps measured by the alternative models generally move in the same direction, both as real-time and final gaps.
- Measured in real-time, most of the gaps are positive for most of the period, but turn negative the last few years. Calculated on final data, on the other hand, the gaps are negative in the first part of the period and positive in the last part.

- The size of the output gaps covers a wide range, particularly measured as real-time gaps.
- Measured as final output gaps, the difference between most of the models is markedly reduced after the first years of the period.

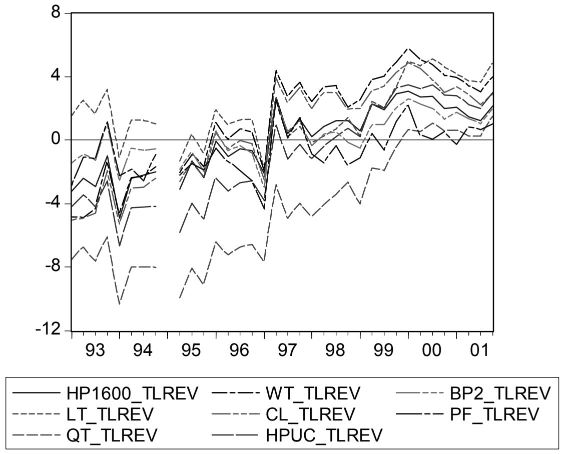
3.3 Revision size and persistence

We follow Orphanides and van Norden (1999), analyzing the revisions of output gaps for each model. Total revisions, calculated as the difference between Final and Real-time estimates of the output gaps, have two main sources: Revision of the national accounts data and new observations. To decompose total revisions, we calculate Quasi-real output gaps. These are constructed in the same way as Real-time output gaps, but instead of using vintages of real-time data, final data are used.

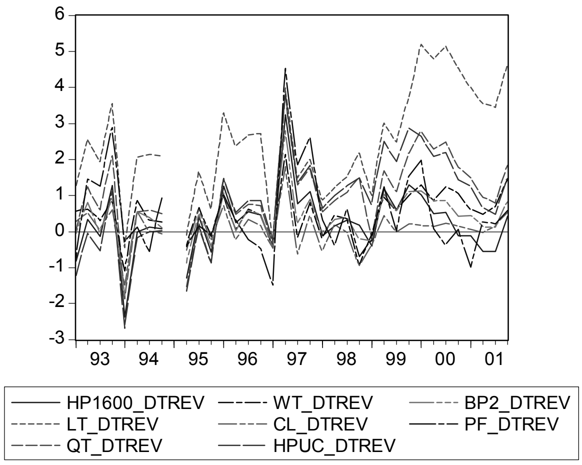
The difference between Quasi-real and Real-time output gaps is entirely due to the different data being used. We define this as Data revisions. The difference between Final and Quasi-real output gaps is only associated with the addition of new data, and we define this simply as Other revisions. Other revisions have different sources in different models. For example: In models with two-sided filters, these revisions are associated with end-point instability problems.[14] In UC models, Other revisions are mainly caused by parameter instability.

[14] This is briefly discussed in the next subsection.

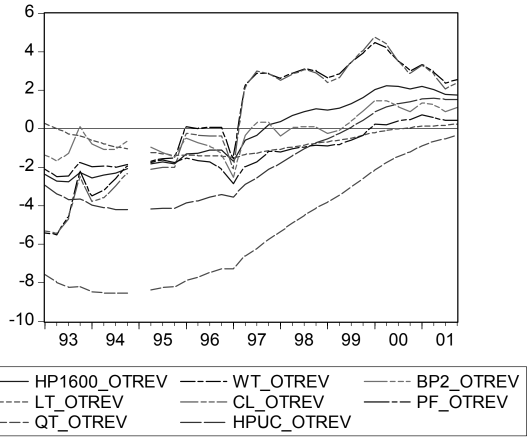
Figure 6. Total revisions, Data revisions and Other revisions. Vintages 1993Q1 – 2002Q1



(a) Total revisions



(b) Data revisions



(c) Other revisions

Total revisions, Data revisions and Other revisions are shown in Figures 6(a) – 6(c) (indicated by TLREV, DTREV and OTREV, respectively). Total revisions are large, generally negative in the first half and positive in the second half of the period. Other revisions are typically larger than Data revisions for most models.

We would expect models with a deterministic trend to be less susceptible to Other revisions and more affected by Data revisions than other models. This is only the case for the LT model. In the QT model, Data revisions are among the largest in parts of the sample, but this model also has large Other revisions.

Parameter instability in UC models is illustrated by Other revisions in the WT and CL models. In both models, the sharp increase in GDP in the second quarter of 1997 leads to a shift in Other revisions.

Following Orphanides and van Norden(1999), descriptive statistics for estimates of Real-time, Quasi-real and Final output gaps and for Total Revisions are provided in Table 4.[15]

In the first column, the mean sizes of the output gaps estimated by the three different methods, together with Total revisions, are reported for each of the eight models. The next three columns report standard deviations of the series, minimum and maximum values. The indicator in the next column is the correlation between the Final

[15] RTGAP is Real Time output gaps, QRGAP is Quasi Real output gaps and FLGAP is Final output gaps.

output gaps and, respectively, Real-time and Quasi-real output gaps. Finally, autoregression coefficients for Total Revisions are shown in the last column.

For five of the models, the absolute value of the mean of the revisions is larger than the absolute value of the mean final output gap. The mean size of the revision is smaller than the mean final output gap in the HP1600 and the PF model, while the two measures are of about equal size in the BP model. The standard deviations of the revisions are larger than the standard deviation of the final output gaps for the HP1600 and HPUC models. Only the LT and the PF models exhibit smaller standard deviations in the Total revisions than in the Final output gaps.

Correlations between Real-time and Final output gaps are higher than 0.80 for the LT and the PF models, while for the rest of the models correlations lie between 0 and 0.46. The revisions are highly persistent. The autocorrelation coefficients vary from 0.62 for the LT model to 0.93 for the QT model. The BP and the Production function models stand out with autocorrelation coefficients of 0.39 and 0.28, respectively.

To facilitate comparisons across models, some measures independent of the size of the gaps are presented in Table 5. The statistics are indications of the reliability of the Real-time output gaps compared to the Final output gaps, in the sense that they are measures of how different Final output gaps are from Real-time output gaps. The statistics do not say anything about how reliable the different models are as measures of the “true” output gap.

The first column repeats the correlation statistics between real-time and final estimates from Table 4. The correlations between the Real Time and Final estimates vary considerably, from 0.87 for PF to -0.01 for HP1600. In the second column a noise-to-signal ratio, the ratio of the root-mean-squared revisions divided by the standard deviation of the final estimates of the output gap, is reported (N/S). The higher is the value of N/S, the noisier are the Real Time estimates compared to the Final estimates. For most models, N/S ratio is larger than 1, indicating a high degree of noise in the Real-time output gaps. The exceptions are LT and PF, where the ratios are 0.79 and 0.58, respectively. In the next column, OPSIGN measures the frequency with which real-time and final estimates have opposite signs. The last column (XSIZE) shows the frequency with which the absolute value of the total revision is larger than the absolute value of the final output gaps. For most of the models, real-time and final estimates produce opposite signs with a frequency of around 0.50. The PF model is a notable exception, with opposite signs occurring with a frequency of only 0.06. In 75 per cent of the time, the absolute value of the total revision is larger than the absolute value of the final output gaps using HP1600. At the other end of the spectrum, the frequency is only 0.17 using the PF model.

The statistics in Tables 4 and 5 support visual impressions from Figures 5(a) and Figure 6(a) – 6(c). The reliability of the various models is in general poor. Total revisions are large and persistent, and the correlations between real time and final estimates are low. Output gaps estimated by the Production Function model exhibits somewhat more favorable statistics than output gaps produced by univariate filtering models. Compared to the US data analyzed by Orphanides and van Norden, the real-time estimates of the Norwegian data seem in general even less reliable than the real time estimates for the US.

In addition, as pointed out in Orphanides and van Norden (1999), the approach taken here probably overestimates the precision and accuracy in all the detrending models. The size of the revision errors measured here must be interpreted as the lower limit of the real revision errors.

Figure 7 shows the estimated growth rates of potential output in the eight models. Broadly speaking the results fall into three different categories. First we have the two polynomial trend models LT and QT which has constant and linear growth rates respectively. The local level model WT (Watson, 1986) also has constant growth, slightly lower than LT while the QT growth rate declines linearly over the period 1993Q1 to 2003Q3. These three models are all characterized by *inflexible* trends. The other two categories we see from Figure 7 can be denoted as *moderately flexible* (CL and HPUC) and *strongly flexible* (HP1600, PF and BP).

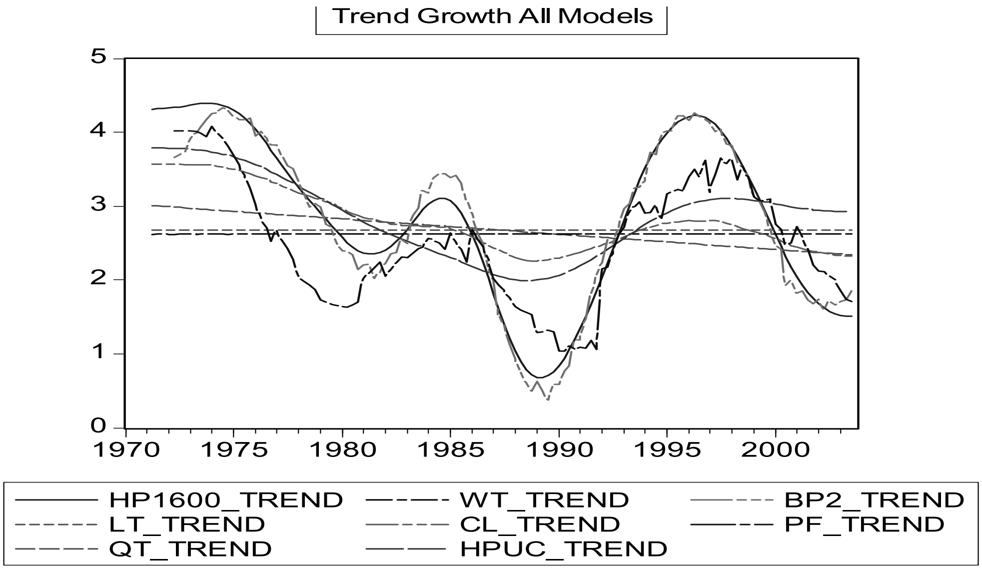
Table 4: Summary Statistics: Levels. Output Gaps and Total Revisions. Vintages 1993Q1 – 2002Q1

Method	Mean	SD	Min	Max	Corr	AR
Linear Trend (LT)						
RTGAP	-2.16	2.90	-9.41	2.28	0.83	
QRGAP	0.32	3.27	-7.06	5.71	0.98	
FLGAP	-0.42	3.25	-6.89	4.37	1.00	
Total revisions	1.79	1.86	-1.84	5.13		0.82
Quadratic Trend (QT)						
RTGAP	4.23	2.00	-0.67	7.30	0.33	
QRGAP	5.22	2.26	0.22	11.10	0.64	
FLGAP	-0.22	3.70	-7.43	4.97	1.00	
Total revisions	-4.39	3.57	-10.35	1.51		0.94
Watson (WT)						
RTGAP	-1.20	0.57	-2.08	0.50	0.46	
QRGAP	-0.71	0.82	-2.46	2.43	0.65	
FLGAP	-0.09	3.37	-6.77	4.70	1.00	
Total revisions	1.17	3.18	-4.89	5.77		0.86
Clark (CL)						
RTGAP	-0.25	0.43	-1.06	1.02	0.22	
QRGAP	-0.17	0.72	-1.41	2.81	0.30	
FLGAP	0.28	3.14	-5.98	4.95	1.00	
Total revisions	0.58	3.10	-5.28	4.91		0.83
HP1600						
RTGAP	0.16	1.56	-2.25	3.09	-0.01	
QRGAP	0.41	1.70	-2.35	4.83	0.39	
FLGAP	0.20	1.39	-3.59	4.23	1.00	
Total revisions	0.02	2.13	-4.92	3.06		0.73
HPUC Trend						
RTGAP	1.41	1.91	-2.27	4.39	0.08	
QRGAP	2.24	2.18	-1.85	8.22	0.60	
FLGAP	0.42	2.57	-4.92	5.34	1.00	
Total revisions	-0.96	3.08	-6.68	3.49		0.88
Band Pass Filter (BP)						
RTGAP	-0.00	0.79	-1.34	1.72	0.28	
QRGAP	0.38	1.06	-1.13	4.52	0.71	
FLGAP	0.20	1.41	-3.66	4.18	1.00	
Total revisions	0.19	1.43	-2.96	2.58		0.41
Production Function (PF)						
RTGAP	-0.43	1.96	-5.69	2.68	0.87	
QRGAP	0.06	2.20	-5.10	5.05	0.95	
FLGAP	-1.08	2.83	-7.21	3.12	1.00	
Total revisions	-0.65	1.51	-4.34	2.55		0.38

Table 5: Summary Statistics: Levels. Reliability. Vintages 1993Q1 – 2002Q1

Method	CORR	N/S	OPSIGN	XSIZE
Linear Trend	0.83	0.794	0.25	0.33
Quadratic Trend	0.33	1.530	0.44	0.64
Watson	0.46	1.005	0.50	0.53
Clark	0.22	1.005	0.53	0.53
HP 1600	-0.01	1.532	0.53	0.75
HPUC Trend	0.08	1.253	0.56	0.61
Band Pass Filter	0.28	1.022	0.56	0.64
Production Function	0.87	0.580	0.06	0.17

Figure 7. Growth rates of potential output in eight models



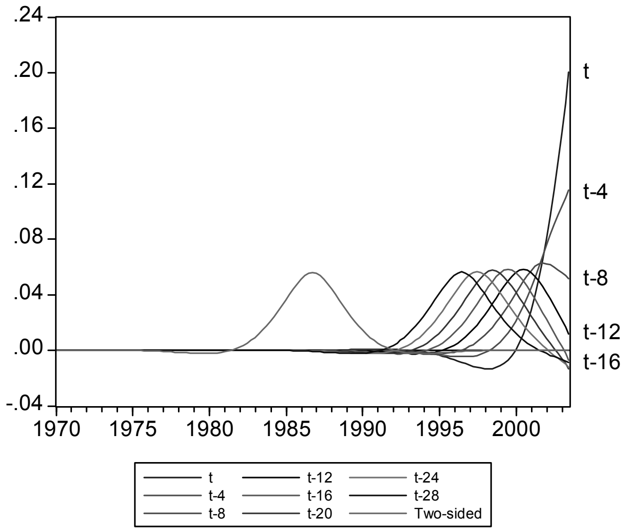
3.4 Two-sided filtering (HP-models) and the end-point-problem

Figure 8 shows how the weights in HP-filter models change as we move from mid-sample (*denoted two-sided*) to end-of-sample where the weights change and turn the two-sided mid-sample filter into a one-sided filter end-of-sample. Figure 8 shows this transition as we move in steps of four quarters towards end-of-sample. The two upper figures (8(a) and 8(b)) show the MA-weights for the HP-filter with $\lambda = 1600$ and the two lower figures (8(c) and 8(d)) show the MA-weights for the HP-filter with $\lambda = 50000$. The estimated HPUC-model can be shown to be very close to the HP-filter with $\lambda = 50000$. Since $\lambda = 1600$ offer larger variation in trend growth rate it is not surprising that the weights are less responsive towards the end-of-sample since it essentially puts less weight on observation far behind or far into the future. Weight instability is clearly a more serious problem for a HP-filter with $\lambda = 50000$, where the weights change considerably over a period of five years. It is also of great importance for assessing trend growth over the last two years when $\lambda = 1600$, and the changes in the weights over this period are also of a larger magnitude. The overall implication is that end-of-sample estimates are unreliable estimates of potential output growth and deviations from trend, cf. the properties of the growth rates of potential output in the HP1600 and HPUC models in Figure 7 above. Similar conclusions are drawn in St-Amant and van Norden (1997), who compare different approaches to measuring the output gap.

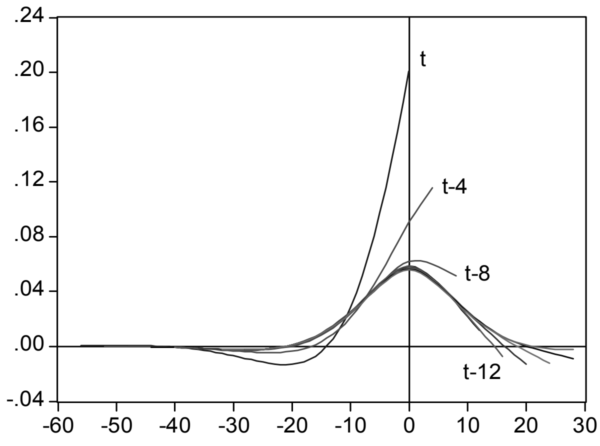
3.5 Unobserved components models - a note

So far we have only considered univariate UC-models in local level and local trend versions. Orphanides (2002) have also compared bivariate UC-models suggested by Kuttner (1994) and Gerlach and Smets (1997) respectively, in which a Phillips curve is added to either the local level model (Watson, 1986) or the local trend model, cf. Harvey (1985) and Clark (1987). The results indicate, however, that adding a Phillips curve does not appear to enhance the reliability of the output gap estimates. On the other hand, Claus et al (2000) report that univariate UC-models typically turn out to be unstable and frequently cannot be estimated due to convergence problems. So far we have only limited experience with multivariate UC-models on Norwegian data, and we have only considered the models suggested by Kuttner (1994) and Gerlach and Smets (1997), where the models are extended with a Phillips curve. In both cases we experienced severe convergence problems which did not arise in the context of the univariate models. Convergence problems in multivariate UC-model may indicate that more work is needed on the model specification. For example, instead of adding a Phillips curve it may be advantageous to incorporate equations for cyclical variations in the rate of capacity utilization and the unemployment rate like in the trivariate UC-model considered by Claus et al. (2000).

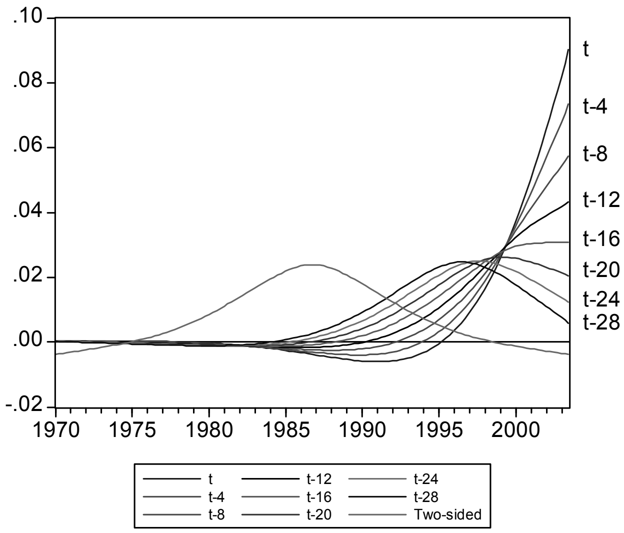
Figure 8: Two-sided filtering (HP-models) and the end-point problem



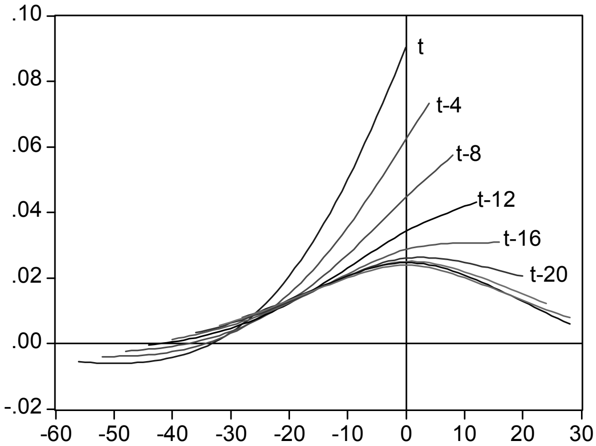
(a) HP-weights (1600)



(b) Centered HP-weights (1600)



(c) HP-weights (50000)



(d) Centered HP-weights (50000)

3.6 Decomposition of output gap revisions

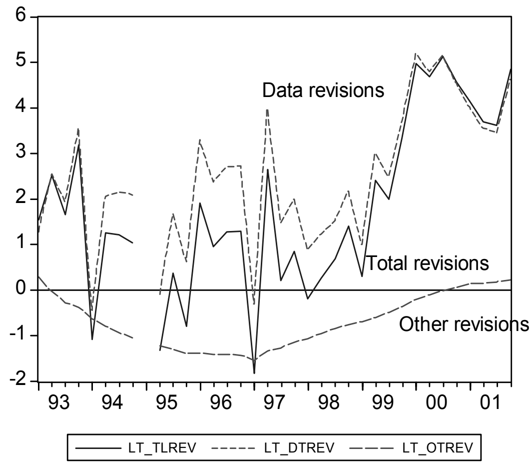
Table 6 offers descriptive statistics for the Total revision of the output gap and its decomposition into Data revisions and Other revisions for each of the eight models. Figures 9(a) – 9(d) and 10(a) – 10(d) give a detailed picture of the development in the Total revision and its subcomponents over the period 1993Q1 to 2002Q1.

Figure 9(a) shows results for the LT model. Total revisions are positive in most periods, and this means that the output gaps are revised upwards. The revisions are quite large the last years, turning initially negative output gaps positive. The substantial revisions in 2000 and 2001 are entirely due to data revisions. Data revisions lead to irregular quarterly changes in the output gaps, while the addition of new data changes the output gaps more gradually. This is to be expected in a model with a deterministic trend, since the addition of new data changes the trend only gradually.

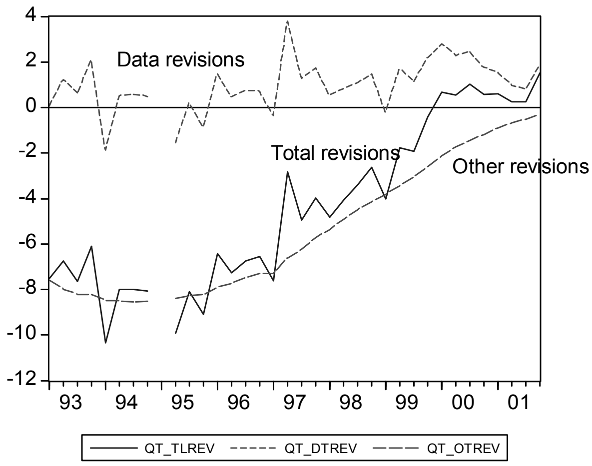
The summary statistics in Table 5 indicated that the difference between the Real-Time and the Final estimates in the LT model were smaller than for most of the other models. Figure 9(a) reveals that the relatively favorable results are due to the period before 2000. After 2000, revised national accounts data led to revisions in Real-Time output gaps by more than 4 percentage points.

The final output gaps for the local level model WT are very close to those of the linear model with a deterministic trend. The Real-Time estimates of the output gaps calculated by the WT model shown in Figure 5(b), however, are very different. These estimates are negative over the whole period, except for two separate quarters where the gaps are just above zero. In contrast to the LT model, data revisions, see Figure 9(c), play a minor part in the total revisions. The addition of new data, on the other hand, changes the output gaps quite dramatically for almost the whole period, the exception being 1996.

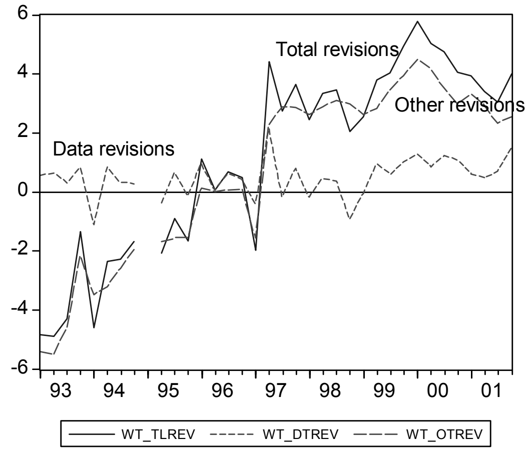
Figure 9: Total revisions, Data revisions and Other revisions. Vintages 1993Q1 - 2002Q1 (Panel I)



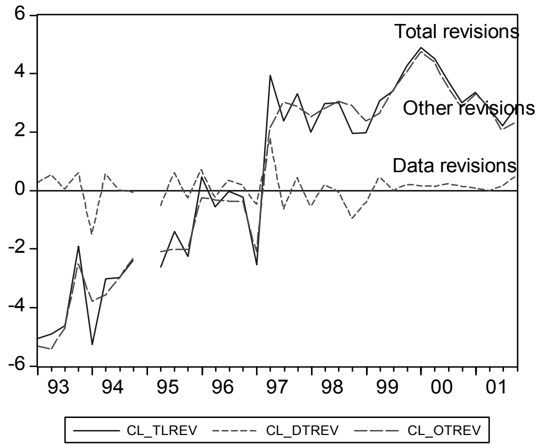
(a) Linear trend



(b) Quadratic trend

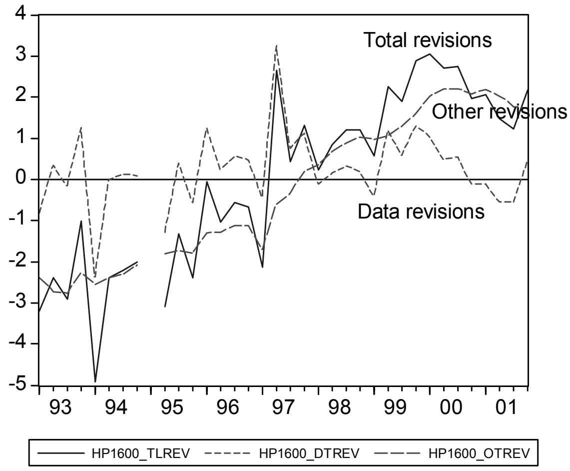


(c) Watson (local level)

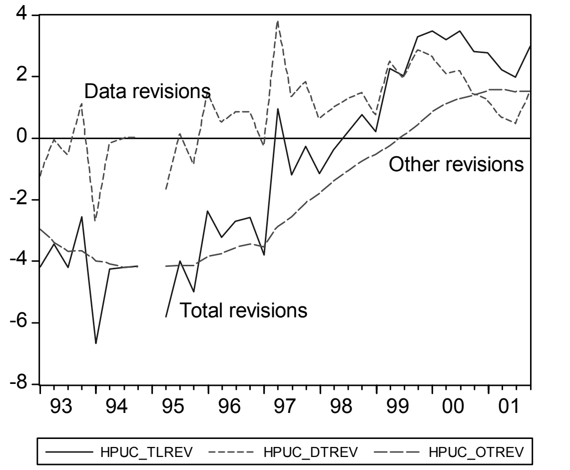


(d) Clark (local trend)

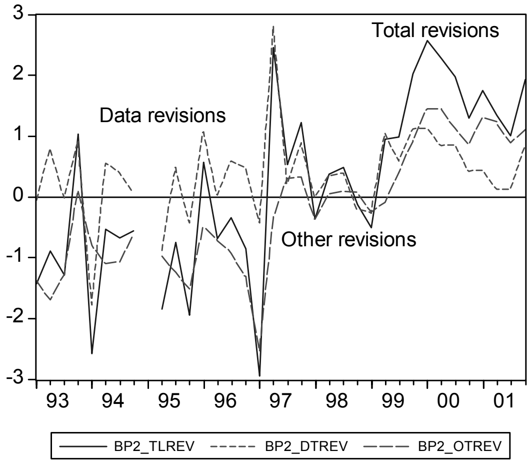
Figure 10: Total revisions and its decomposition into Data revisions and Other revisions. Vintages 1993Q1 - 2002Q1 (Panel I)



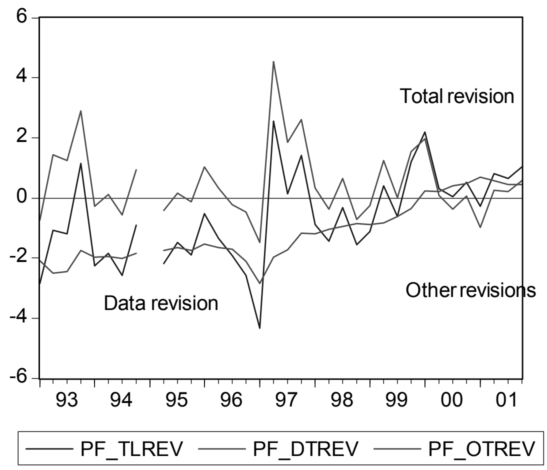
(a) HP filter (λ = 1600)



(b) HP filter (estimated λ)



(c) Bandpass filter



(d) Production function

Table 6: Revision Statistics: Levels. Details. Vintages 1993Q1 – 2002Q1

Method	Mean	SD	Min	Max	AR	N/S
Linear Trend (LT)						
Total Revision	1.79	1.86	-1.84	5.13	0.82	0.794
Data Revision	2.48	1.48	-0.45	5.19	0.87	0.889
Other Revision	-0.69	0.58	-1.54	0.28	0.95	0.277
Quadratic Trend (QT)						
Total Revision	-4.39	3.57	-10.35	1.51	0.94	1.530
Data Revision	0.99	1.14	-1.87	3.79	0.53	0.407
Other Revision	-5.38	2.87	-8.58	-0.33	0.98	1.648
Watson (WT)						
Total Revision	1.17	3.18	-4.89	5.78	0.86	1.005
Data Revision	0.49	0.64	-1.10	2.14	0.27	0.240
Other Revision	0.68	2.93	-5.52	4.49	0.91	0.894
Clark (CL)						
Total Revision	0.58	3.10	-5.28	4.91	0.83	1.005
Data Revision	0.08	0.55	-1.49	1.79	-0.41	0.176
Other Revision	0.50	3.03	-5.45	4.75	0.91	0.979
HP1600						
Total Revision	0.02	2.13	-4.92	3.06	0.73	1.532
Data Revision	0.25	0.91	-2.37	3.25	0.04	0.679
Other Revision	-0.23	1.75	-2.77	2.21	0.96	1.270
HPUC Trend						
Total Revision	-0.96	3.08	-6.68	3.49	0.88	1.253
Data Revision	0.84	1.31	-2.69	3.83	0.57	0.603
Other Revision	-1.80	2.15	-4.2	1.56	0.88	1.089
Band Pass Filter (BP)						
Total Revision	0.19	1.43	-2.96	2.58	0.41	1.022
Data Revision	0.39	0.73	-1.78	2.80	0.05	0.583
Other Revision	-0.20	1.01	-2.54	1.45	0.77	0.730
Production Function (PF)						
Total Revision	-0.65	1.51	-4.34	2.55	0.38	0.580
Data Revision	0.49	1.20	-1.50	4.53	0.23	0.458
Other Revision	-1.14	1.00	-2.84	0.70	0.95	0.536

Revisions from the QT Model are shown in Figure 9(b). Output gaps from this model are subject to large downward revisions. In real time output gaps are positive and quite large for the whole period, but the final estimates are in line with estimates from the other models. The difference between the real time and the final estimates are mainly due to the addition of new data and are decreasing over the sample period. Like in the LT Model, data revisions lead to irregular quarterly changes in the output gaps, while the addition of new data changes the output gaps more gradually.

Revisions of the output gaps from the CL model are shown in Figure 9(d). This model produces real-time output gaps very close to zero, see Figure 5(b). The addition of new data changes the gaps considerably, while data revisions have very small impact.

HP1600 produces a very flexible trend in the Norwegian data and, accordingly, small output gaps. Data revisions are an important source of revisions in some quarters, but the addition of new data over time is the main reason for the revised level of the output gaps. The autocorrelation coefficients are 0.04 and 0.96 for Data Revisions and Other Revisions, respectively.

The revisions of the output gaps from the Band Pass filter, with upper cutoff frequency = 2 and lower cutoff frequency = 32, are shown in Figure 10(c). This filter produces results similar to HP1600. The final output gaps are almost identical. The revisions are generally smaller, however, particularly in the first part of the period.

The results from the Hodrick-Prescott filter in its unobserved components form (HPUC) are shown in Figure 10(b). Compared to HP1600, the output gaps are quite large. The estimated trend in the HPUC model is not as flexible as the trend in the HP1600 model, cf. Figure 7. When using the unobserved component form, the implied smoothing parameter is estimated to approximately 50000. Revisions are quite substantial, and in the last few years of the period data revisions are more important than for models with a more flexible trend.

Finally, Figure 10(d) depicts revisions in the PF model. The addition of new data, as summarized in Other Revisions, tends to reduce the output gap considerably, particularly in the first half of the period. These revisions are strongly autocorrelated. Data Revisions, on the other hand, contribute to reduce the autocorrelation in Total Revisions.

We have described revisions of output gaps estimated by eight different models in some detail in figures and tables. The main conclusions are that revisions to real time output gaps are large and persistent, and that the addition of new data is the main source of revisions for all the models except the LT model. These findings are in line with results from analyzing U.S. data, see for instance Orphanides and van Norden (1999).

In real time, all models except LT and PF produce negative output gaps from the first quarter of 2000, and for most of the models output gaps are negative from late 1998. Many of the models indicate positive output gaps in the first half of the 1990s, which is clearly unreasonable. After the recession in the last half of the 1980s and the turning point in 1991, there was excess capacity in the Norwegian economy at least through 1995, with unemployment levels still at historically high levels.

Of the models considered here, the Production Function model exhibits somewhat better properties than the univariate models. The reliability of the real time output gaps are higher than for the other models considered here, even if revisions in this model also are substantial. It remains to be tested, however, how well real time output gaps behave in the context of a larger model.

Figures 5(a) and 5(b) revealed that output gaps calculated as real time and final output gaps generally move in the same direction. Revisions of the *change* in the output gap may therefore be better behaved than revisions of the *level* of the output gaps. Orphanides et al. (2000), Orphanides (2003) and Walsh (2003a,b) have investigated this for U.S. data, and Cayen and van Norden (2004) study revisions in the change in output gaps for Canadian data.

In Table 7 we present some statistics comparing revisions of differences and levels for the Norwegian data. For most of the models, mean values for the revisions of the change in the output gap are smaller than the corresponding figures for revisions in output gap levels. The exception is the HP1600 model, where the mean value is higher for the change in the output gap than for its level. Standard deviations of the revisions are also generally smaller for changes than for levels, except for the BP and PF models where standard deviation increases. Compared with the findings for U.S. and Canadian data, the gains of converting real time output gap levels to changes in the output gaps seem very small. The mean values and standard deviations of revisions in the changes in the output gaps are still substantial. This is confirmed by the statistics in the four last columns of the table. The maximum revisions are higher for differences than for levels, except for the LT model. The auto-correlation coefficients lie in the area -0.5 to -0.7 for

Table 7: Total Revisions: Levels versus Differences. Vintages 1993Q1 – 2002Q1

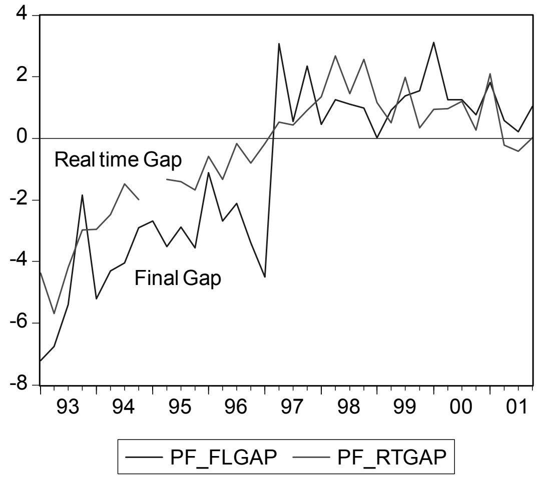
FORM	Mean	SD	Min	Max	AR	N/S
Linear Trend						
Level	1.79	1.85	-1.84	5.13	0.82	0.794
Difference	0.10	1.68	-4.27	4.48	-0.63	0.842
Quadratic Trend						
Level	-4.39	3.57	-10.35	1.51	0.94	1.530
Difference	0.26	1.59	-4.02	4.80	-0.59	0.806
Watson						
Level	1.17	3.18	-4.89	5.77	0.86	1.005
Difference	0.24	1.68	-3.24	6.38	-0.53	0.851
Clark						
Level	0.58	3.10	-5.28	4.91	0.83	1.005
Difference	0.21	1.67	-3.38	6.47	-0.54	0.844
HP1600						
Level	0.02	2.13	-4.92	3.06	0.73	1.532
Difference	0.14	1.51	-3.91	3.69	-0.67	0.767
HPUC Trend						
Level	-0.96	3.08	-6.68	3.49	0.88	1.253
Difference	0.21	1.54	-4.13	4.76	-0.62	0.777
Band Pass Filter						
Level	0.19	1.43	-2.96	2.58	0.41	1.022
Difference	0.09	1.57	-3.60	5.41	-0.63	0.792
Production Function						
Level	-0.65	1.51	-4.34	2.55	0.38	0.580
Difference	0.12	1.79	-3.40	6.89	-0.48	0.945

all models. Improvements in the noise-to-signal ratio are small, and for some models the noise-to-signal ratio increases.

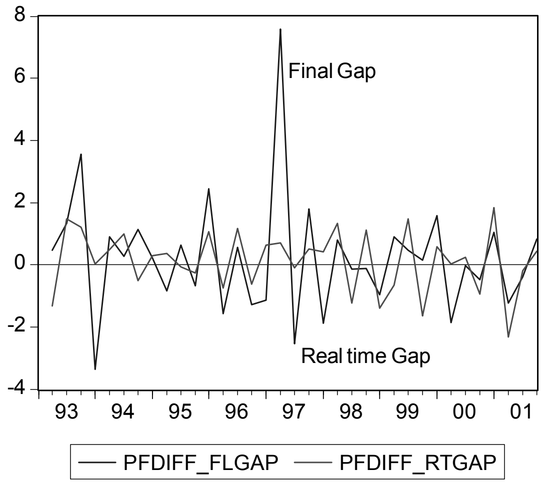
One reason for the substantial remaining volatility in the revisions of the change in the output gaps can be traced to the development in 1997 [16]. Figure 11 illustrates this for the PF model, which is extreme in the sense that the noise-to-signal ratio increases by more than 60 per cent moving from levels to changes. The level of the output gap increases from -4.5 per cent in the first quarter to 3.1 per cent in the second quarter in the final data, while in real-time the output gap increases by less than 1 per cent. The change in the output gap moves from -1.1 per cent to 7.6 per cent in the final data – around 1 percentage point more than for the level. The increase in the real-time output gap is less than 1 measured both as level and change, meaning that revisions are higher for the change than for the level.

[16] The development in 1997 cannot be explained by our rough seasonal adjustment, cf. figure 1 where unadjusted figures are used. Looking at 1996 and 1997 together, it is a puzzle that output growth in

Figure 11: Real-time and Final output gaps calculated by the production function model. Levels and changes. Vintages 1993Q1 - 2002Q1



(a) Levels



(b) Percentage change

The deteriorating properties of the PF model moving from output gap levels to changes in the output gap is a nice illustration of the point made in Walsh (2003b). Walsh shows that only if the autocorrelation coefficient of the revisions is bigger than

the first quarter of 1997 is slightly reduced while output growth in 1996 and, in particular, the rest of 1997 is markedly increased.

0.5, the measurement error in the change in the output gaps is smaller than that in the level. The autocorrelation coefficient of the revisions of the output gap level in the PF model is 0.38.

In conclusion, improvements in reliability after transforming revisions of output gap levels to revisions of the change in output gaps seem less than those reported from investigating Canadian and U.S. data. The most reliable model, the PF model, exhibited worse properties moving from levels to changes. This is probably due to the fact that this model was the most reliable one when considering the levels, and autocorrelation of the revisions were markedly lower than for the other models.

In the next section, we consider the impact of output gap uncertainty for monetary policy.

4 Monetary policy in real-time - output gap uncertainty

4.1 Taylor rules

The output gap is an important determinant of the interest rate under inflation targeting. When the interest rate is set, the central bank needs to have an assessment about whether the level of activity differs from the potential level, irrespective of whether this assessment takes the form of an explicit output gap or not. Measuring the output gap incorrectly is therefore a potentially important source of ex post monetary policy errors. In Section 4.2, we will illustrate how output gap measurement errors of the size experienced in Norway can affect the trade-off between inflation variability and output variability. We will, however, first give an indication of the implications for monetary policy by considering the simple classic Taylor rule, which is given by

$$i_t = r^* + \pi^* + 1.5(\pi_t - \pi^*) + 0.5(y_t - y^*) \tag{4}$$

where r^*, π^*, π_t, y_t and y^* is the equilibrium real interest rate, the inflation target, the current rate of inflation[17], production (GDP) and trend-GDP respectively. The coefficients in (4) are the same as those suggested by Taylor (1993). Although no central bank follows a simple Taylor rule in practice, the rule may serve as a rough

[17] Inflation is measured as changes in consumer prices adjusted for tax changes and excluding energy products.

proxy for how central banks behave, and the Taylor rule as a normative benchmark has proved to work reasonably well across various models, see e.g., the articles in Taylor (1999).

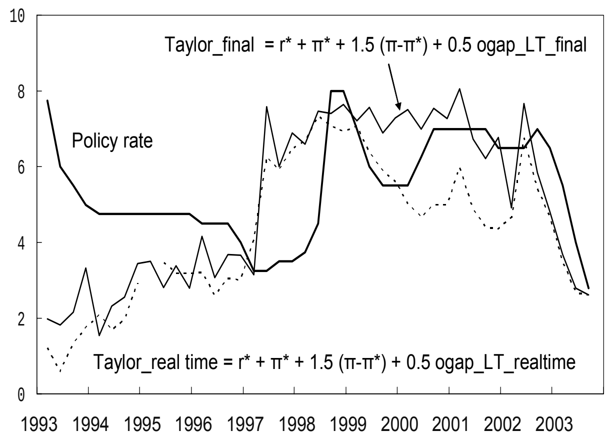
In his path-breaking article, Orphanides (2001) shows that calculated on real time data, i.e. data available to the policy maker at the time policy is decided, the Taylor rule describes the US key rate considerably poorer compared to the case where ex-post final data is used. Because policy makers have only real time information at their disposal, it may be of utmost importance to distinguish between real time estimates of the output gap and estimates based on final revised data.

We estimate the output gap by the eight models discussed in section 3, on both real time data and final data. With regard to the rate of inflation, the other component in the Taylor rule, real time problems are less severe as inflation data is normally not revised. Therefore, the differences in interest rates given by the alternative Taylor rules, is simply a transformation of the alternative output gaps into an interest rate and does hence not provide any new insights beyond the analysis of output gaps in Section 3. However, it is easier to relate output gap uncertainty to actual monetary policy when "translated" into Taylor rules. Moreover, though focus will be on real time data versus final data performance of Taylor rates, the analysis also cast some light on Taylor rules in general and to what extent they track the evolution of the policy rate, irrespective of whether real time data or final data is used.

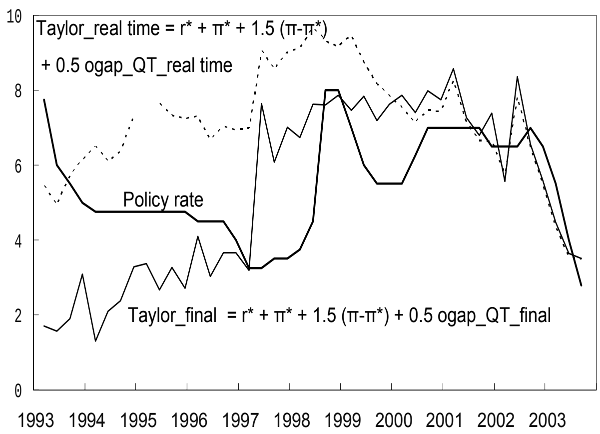
To discuss this issue further, for each of the eight models used to estimate the output gap, Figures 12(a) – 12(d) and 13(a) – 13(d) show the policy rate[18] and rates implied by the eight corresponding Taylor rules calculated on both real time data and final data. As explained in section 2, data for 1995Q1 do not exist. One should note that up until 1997-1998 the Taylor rule gives a poor description of the policy rate. The

[18] The policy rate is the sight deposit rate, which is the overnight interest rate on banks' deposits in the central bank

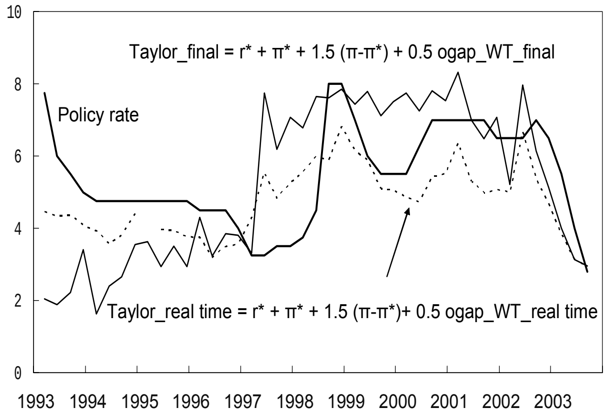
Figure 12: Taylor-rules based on different Real-time and Final output gaps. Vintages 1993Q1 - 2003Q4



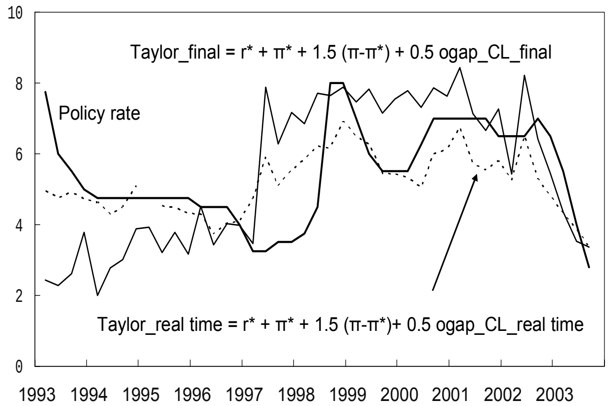
(a) Linear trend



(b) Quadratic trend



(c) Watson (local level)



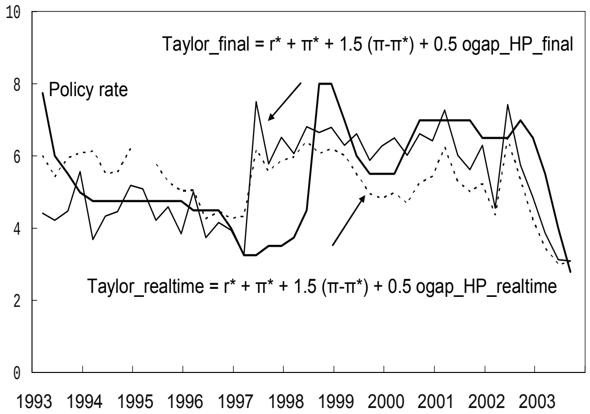
(d) Clark (local trend)

reason may be that prior to this period monetary policy in Norway was oriented towards exchange rate stabilization and less focused on reacting to measures of current and expected inflation and the output gap. Furthermore, towards the end of the sample the rates implied by the Taylor rules estimated on real-time data and final data coincide as the latest data has not yet been revised.

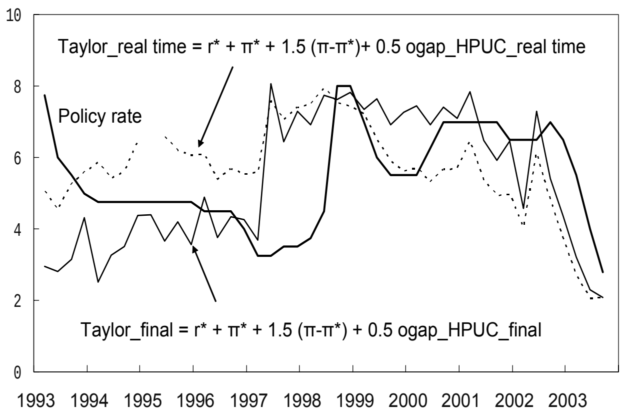
The figures reveal that real time Taylor rates in periods may deviate considerably from rates calculated on final data. For most of the models used to estimate the output gaps the two series differ by up to 2-3 percentage points and for the quadratic trend the differential is enormous. The general picture indicates that evaluated in terms of Taylor rules, lack of real time information may impose serious challenges for monetary policy. In particular, having a closer look at the period 1999-2000, we notice that real time Taylor rates to a relatively large extent follow the path of the policy rate, falling in 1999 followed by a rise in 2000. On the other hand, rates inferred by rules calculated on final data imply a more stable policy rate. However, one should note that the rate implied by the Taylor rule is not generally the "optimal" one, and there could be a number of reasons why a central bank would choose to deviate from it. For example, though the Taylor rule captures the effects of the exchange rate and other asset prices like house prices to the extent they influence the inflation gap and the output gap, the central bank could in some situations choose to put more weight on these. This applies in particular for small open economies, where the exchange rate is frequently considered to have a large impact on the economy (see Taylor, 2001).

To obtain a more summarized picture, Table 8 shows the mean and the standard deviation of absolute differences between Taylor rates calculated on real time data and final data. The lower is the calculated mean, the less the Taylor rates calculated on real time data and final data deviate. The methods implying the lowest mean are the BP, the production function model, the HP-filter and the linear trend, with means equal to 57, 72, 84 and 92 basis points respectively. The corresponding standard deviations vary between 39 and 76 basis points. Hence, based on these methods the difference between Taylor rates calculated on real time data and final data, as measured by the mean multiplied by say one time the standard deviation, would be something between 100 and 170 basis points. Looking at the HPUC, the Clark and the Watson model and the quadratic trend, rates calculated on real time data deviate even more from rates estimated on final data, with average differences equal to 126, 129, 134 and 199 basis points. With differences up to say 3 percentage points, real time Taylor rates may be a highly misleading tool in monetary policy.

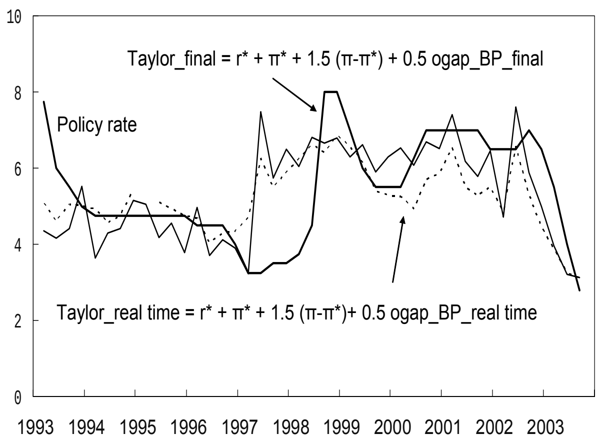
Figure 13: Taylor-rules based on different Real-time and Final output gaps. Vintages 1993Q1 - 2003Q4



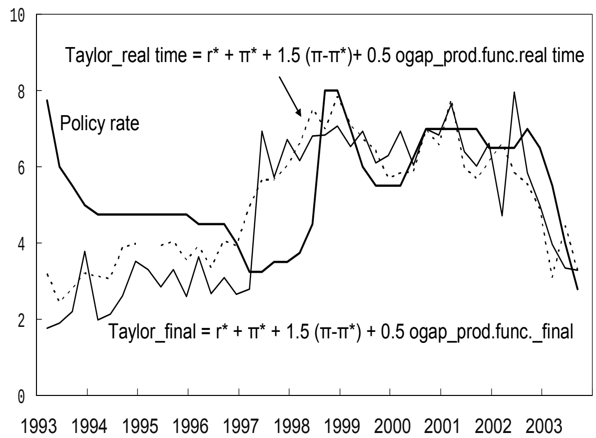
(a) HP filter (λ = 1600)



(b) HP filter (estimated λ)



(c) Band pass filter



(d) Production function

Table 8: Mean and standard deviation (in parenthesis) of absolute differences between Taylor rates estimated on real time data and final data. Basis points. Vintage 1993Q1 – 2003Q4

LT	QT	Clark	Watson	HP1600	HPUC	BP	PF
92 (76)	199 (167)	129 (74)	134 (82)	84 (53)	126 (80)	57 (39)	72 (54)

The mean is calculated as $\mu=(1/N)\ \Sigma\ |Tr - Tf|$, where Tr and Tf are the rates implied by Taylor rules calculated on real time data and final data respectively.
The standard deviation is calculated as $s = \{(1/N)\ \Sigma\ [(Tr - Tf) - \mu]^2\}^{0.5}$

The second issue to be discussed is to what extent the Taylor rules give a reasonable description of the policy rate. As explained above, on this matter we should concentrate on the period after 1999. For the period1999-2000 we have already noted that Taylor rates calculated on final data do not follow the U-shaped path of the policy rate, proposing a more stable policy rate. Real time Taylor rates, however, seem to move in the same direction as the policy rate, though the level may differ. Turning to the period from the beginning of 2001 to the autumn 2002, Taylor rates, in particular those calculated on real time data, seem to be consistently lower than the policy rate (except for the quadratic trend). Hence overall, the policy rate in Norway seems to have deviated from Taylor rates to a considerable extent. However, we should keep in mind rates implied by Taylor rules are not in any sense optimal and central banks might have very good reasons to deviate from them.[19]

Table 9 shows the mean and the standard deviation of absolute differences between the policy rate and Taylor rates for the period 1999Q1-2003Q4, calculated on real time data and final data, respectively. The lower is the calculated mean, the less the Taylor rates deviate from the policy rate. Overall, irrespective of whether real time data or final data are used to calculate the Taylor rules, the implied rates deviate from the policy rate, on average, by around one percentage point. In some periods, however, as indicated in Figures 12(a) – 12(d) and 13(a) – 13(d), the difference is substantially higher. This is also evident from the standard deviations of the means, which, overall,

[19] The interest rate decisions of Norges Bank are explained in the annual reports. In particular, monetary policy in 2003 is extensively discussed in "Report on monetary policy in 2003 - the first eight months". See www.norges-bank.no for further details.

vary between 50 and around 150 basis points. Comparing the real time Taylor rate and the Taylor rate based on final data, we see that, except for the Taylor rules based on the Clark gap and the production function gap, the Taylor rule based on final data tracks the actual policy rate somewhat better than the real time Taylor rule. This result is also in line with the results in Orphanides (2001), although the classic Taylor rule of course describes Fed's behavior better than Norges Bank's behavior.

Table 9: Mean and standard deviation (in parenthesis) of absolute differences between rates implied by Taylor rules and the policy rate. Basis points. Vintage 1999Q2- 2003Q4

	LT	QT	Clark	Watson	HP1600	HPUC	BP	PF
Real	126 (85)	115 (87)	76 (58)	109 (64)	123 (69)	127 (90)	93 (66)	73 (61)
Final	104 (62)	108 (65)	106 (62)	107 (62)	85 (53)	115 (72)	80 (49)	82 (54)

The mean is calculated as $\mu=(1/N)\ \Sigma\ |F - T|$, where F and T is the policy rate and the rate implied by the Taylor rule, respectively. The standard deviation is calculated as $s = \{(1/N)\ \Sigma\ [(F - T) - \mu]2\}0.5$

Finally, one should note that the results and our discussion are based on a specific sample with macroeconomic data for Norway. It may be difficult to generalize beyond the sample at hand. Still, however, the results clearly indicate that lack of real time information may be a substantial challenge to monetary policy as final data in retrospect may give other paths for the policy rate compared to those suggested by real time data.

4.2 Implications of output gap uncertainty for monetary policy

The output gap is a key variable in interest rate decisions. First, the output gap affects inflation, so that the central bank must respond to the gap in order to stabilize inflation. Second, the output gap is an independent term in the loss function under flexible inflation targeting. In the short and medium run, tradeoffs between stabilizing inflation around the target and stabilizing the output gap can arise, and the central bank must strike a balance between the two objectives. Due to the importance of the output gap in the conduct of monetary policy, mismeasurements have potentially large consequences for how well the central bank achieves its objectives.

Evidently, output gap uncertainty increases, *ceteris paribus*, the welfare loss. An important question is, however, whether such uncertainty has implications for how central banks should respond to its estimate of the gap, that is, whether certainty equivalence holds. Svensson and Woodford (2003) show that in models with forward-looking variables, the optimal response to an optimal estimate of potential output displays certainty equivalence. They find, however, that the optimal response to an imperfect observation of output depends on the noise in this observation. Given the considerable revisions in the GDP series documented in Section 2, the results by Svensson and Woodford suggest that one should put somewhat less weight on the first releases of the GDP figures than implied by the real time estimates of the gap discussed in Section 3.

Monetary policy is often described by simpler instrument rules, like the Taylor rule, rather than the complex optimal rules considered by Svensson and Woodford. It is well known that certainty equivalence does not hold if the central bank follows simple rules, and Smets (2002) finds that the optimal coefficients in the Taylor rule are smaller under output gap uncertainty. There is an ongoing debate on whether monetary policy should be described by minimizing a loss function (optimal policy) or whether it is better described by simpler Taylor-type instrument rules, and we will not follow up this debate here. However, due to the intuitive appeal of simple rules like the Taylor rule, we will discuss the challenges of output gap uncertainty for monetary policy using such rules. Specifically, we use a calibrated version of a fairly standard aggregated New Keynesian macroeconomic model for illustration. The model is given by

$$\pi_t = 0.8\pi_{t-1} + 0.2E_t\pi_{t-1} + \gamma(y_t - y^*) + 0.1z_t + \varepsilon_t^{\pi} \tag{5}$$

$$y_t = 0.85y_{t-1} + 0.1E_t y_{t-1} - 0.1(i_{t-1} - E_{t-1}\pi_t) + 0.05z_{t-1} + \varepsilon_t^{y} \tag{6}$$

$$z_t = 0.4z_{t-1} + 0.6E_t z_{t-1} - 0.2\{(i_t - E_t\pi_{t+1}) - (i_t^f - E_t\pi_t^f)\} + \varepsilon_t^{z} \tag{7}$$

$$i_t = \alpha_i i_{t-1} + \alpha_\pi \pi_t + \alpha_y y_t^0 + \alpha_{\Delta y}\Delta y_t^0 \tag{8}$$

$$y_t^0 = y_t + \varepsilon_t^0 \tag{9}$$

$$\varepsilon_t^0 = \rho\varepsilon_{t-1}^0 + \eta_t^0 \tag{10}$$

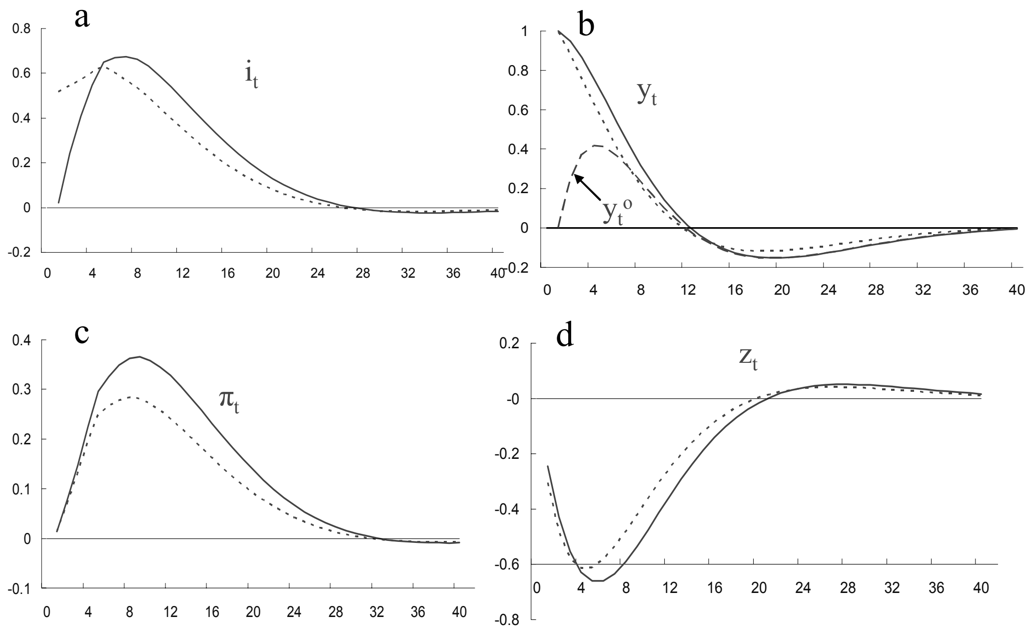
The first equation is a "hybrid" open-economy New Keynesian Phillips curve, where π_t is the rate of (CPI) inflation, y_t is the "true" (but unobservable) output gap, z_t is the (log of) the real exchange rate, measured as deviation from the equilibrium real exchange rate, and ε_t^{π} is a cost-push shock. The second equation represents aggregate demand, where i_t is the nominal short-term interest rate. $i_t - E_t\pi_{t+1}$ is then the real interest rate, and the neutral real interest rate is for simplicity normalized to zero. Equation (7) is the UIP condition, where a lag is introduced to better capture observed dynamics in the real exchange rate (short-run deviations from UIP). The coefficient of 0.2 on the real interest rate differential ensures that UIP holds in steady state. Equation (8) represents the monetary policy rule, which is a generalized Taylor rule. Since the central bank cannot observe the true output gap, it responds to its real time estimate of the gap, y_t^0. The most notable difference between equation (8) and the classic Taylor rule is the inclusion of the change in the output gap. The motivation for this is twofold. First, as shown by Woodford (1999), optimal monetary policy under commitment in forward-looking models is characterized by history-dependence (inertia). By responding the change in the gap, one achieves history-dependence in monetary policy. Such history-dependence gives more stable inflation expectations and thereby stabilizes actual inflation, as expectations of future inflation affect current inflation. Second, if there is persistence in the output gap mismeasurement, Orphanides e al. (2000) show that there is a case for responding the change in the gap, since, with high degree of persistence, the errors in the estimate of the change is less severe than the errors in the level of the gap. Equation (9) states that the central bank's estimate of the output gap is subject to errors, represented by ε_t^0. For simplicity, we assume that these errors are exogenous to the rest of the model and follows an AR(1) process given by equation (10).

Since we cannot observe the true output gap, the process for the true measurement error ε_t^0 cannot be estimated. This is an important, but unsolvable, problem for monetary policy; one never knows the true magnitude of the output gap mismeasurement. The best one can do is to use the difference between the real time estimate and the estimate based on final data, with larger data set and revised historical data, as a proxy for the true measurement error. This is the approach taken in this paper. Since the gap estimates vary depending on which model is used, we must make a choice of model (or combination of estimates) when estimating equation (5). Since the output gap estimates presented in the Norges Bank's Inflation Reports are based on the HP(1600) filter, we will use this as our benchmark. When estimating the process for the difference between the real-time estimate and the final estimate, we find

$$\varepsilon_t^0 = 0.7\varepsilon_{t-1}^0 + \eta_t^0 , \quad \hat{\sigma}_{\eta_t^0} = 1.3 \tag{11}$$

The degree of persistence is somewhat less than what Orphanides et al. (2000) find for the US data, while the standard error of η_t^0 is somewhat higher. To illustrate the challenges for monetary policy in practice resulting from output gap mismeasurements, we shall first consider a specific case where the true output gap increases due to a temporary decrease in potential output, while the central bank does not immediately observe this drop in potential output and estimate the gap to be unchanged. The central bank is here assumed to set the interest rate according to the classic Taylor rule. The impulse-responses following such a shock are illustrated in Figure (14).

Figure 14: Unobserved increase in the true output gap (productivity slowdown). Number of periods on the horizontal axis.



Since the central bank does not observe the increase in the output gap, it does not raise the interest rate as a direct response to this. The increase in the true output gap gives, however, an increase in inflation, which the central bank responds to by raising the interest rate. The central bank therefore interprets the shock as a cost-push shock. Since inflation is persistent, the effect of the shock becomes amplified in the subsequent periods, so that inflation and thus the interest rate continue to rise (see figures 14(a) and 14(b)). The initial rise in the interest rate is, however, insufficient compared to what the central bank would have done if it observed the gap perfectly, as illustrated by the dotted line in Figure 14. Since the process for the measurement error is stationary, such that the central bank gradually "learn" about the true gap, the central bank's estimate of the gap becomes adjusted upwards, as illustrated by the dashed line in Figure 14(b). Without this feature, y_t^0 would have become negative due to the higher real interest rate and thereby stronger exchange rate.

Within the New Keynesian literature, the output gap measure that enters the welfare loss function is the deviation of output from the level that would have occurred if prices and wages were fully flexible. Estimating potential output by various trending techniques, as discussed in Section 3, implies in practice a smoother series for potential output than what is likely to be the case with the theoretical flex price concept, which would tend to jump around as, e.g., technology shocks occur. The case discussed above, where the true output gap changes, while the central bank's estimate of it remains (almost) constant, is likely to be a case that could happen quite frequently. The above impulse-responses depend of course crucially on the model and parameter values, and one should therefore be cautious when generalizing the results. However, the above figures illustrate a more general point, namely that the main welfare costs associated with failing to capture movements in potential output may arise because monetary policy does not respond quickly enough to changes in the true output gap, thereby letting inflation move too far away from the target and closing the output gap too slowly.

In the above exercise, the comparison between monetary policy with and without output gap mismeasurements was done within the same monetary policy rule. However, the optimal coefficients on the variables in the interest rate rule depend on the degree of uncertainty. In order to analyze optimal simple rules, we apply the following standard (period) loss function:

$$L = \pi_t^2 + \lambda y_t^2 + \omega(\Delta i_t)^2 \tag{12}$$

We then find the coefficients in the simple rule (8) that minimizes the unconditional expectations of the loss for various weights in the loss function. As discussed in Section 3, the revisions of the gap estimates based on the production function method displays less persistence than the estimates based on HP(1600). To illustrate the role of persistence in output gap mismeasurements, we therefore consider optimal coefficients when the true mismeasurements are assumed to follow the same process as the revisions in the PF gaps, i.e.

$$\varepsilon_t^0 = 0.38\varepsilon_{t-1}^0 + \eta_t^0 , \quad \hat{\sigma}_{\eta_t^0} = 1.41 \tag{13}$$

The optimal simple rules are reported in table 10 (HP-1600) and table 11 (PF), while table 13 reports the optimal coefficients in the hypothetical case with perfectly observable output gaps.

Table 10: Optimal Simple Rules. Hodrick-Prescott (HP-1600)

	Loss Function			Optimal Weights				Measures of Macro Variability		
	λ	ω	E{L}	α_i	α_π	α_y	$\alpha_{\Delta y}$	σ_π	σ_y	$\Sigma_{\Delta i}$
0.	0.00	0.50	1.25	0.40	3.10	0.20	0.00	0.87	1.50	0.99
1.	0.50	0.50	2.13	0.20	2.40	0.30	0.00	0.93	1.25	0.99
2.	1.00	0.50	2.86	0.10	2.10	0.30	0.00	0.99	1.17	0.99
3.	1.50	0.50	3.51	0.10	2.00	0.40	0.00	1.03	1.13	1.04
4.	2.00	0.50	4.13	0.00	1.90	0.40	0.00	1.06	1.10	1.10
6.	0.00	0.00	0.50	0.00	4.60	0.40	0.00	0.71	1.53	1.64
7.	0.50	0.00	1.44	0.00	3.50	0.80	0.90	0.81	1.25	3.40
8.	1.00	0.00	2.15	0.00	2.70	0.70	0.90	0.91	1.15	3.20
9.	1.50	0.00	2.78	0.00	2.30	0.60	0.90	0.98	1.10	3.03
10.	2.00	0.00	3.37	0.00	2.10	0.60	1.00	1.03	1.07	3.25

Table 11: Optimal Simple Rules. Production Function Approach

	Loss Function			Optimal Weights				Measures of Macro Variability		
	λ	ω	E{L}	α_i	α_π	α_y	$\alpha_{\Delta y}$	σ_π	σ_y	$\Sigma_{\Delta i}$
0.	0.00	0.50	1.24	0.40	3.00	0.20	0.00	0.88	1.48	0.97
1.	0.50	0.50	2.09	0.30	2.40	0.40	0.00	0.93	1.21	1.00
2.	1.00	0.50	2.76	0.30	2.10	0.50	0.00	1.00	1.12	1.02
3.	1.50	0.50	3.35	0.30	2.00	0.60	0.00	1.03	1.07	1.08
4.	2.00	0.50	3.90	0.30	1.90	0.60	0.00	1.06	1.05	1.07
6.	0.00	0.00	0.49	0.00	4.60	0.60	0.00	0.70	1.44	1.86
7.	0.50	0.00	1.28	0.00	3.70	1.20	0.60	0.79	1.15	4.07
8.	1.00	0.00	1.87	0.00	2.80	1.20	0.60	0.90	1.03	4.02
9.	1.50	0.00	2.37	0.00	2.50	1.20	0.60	0.96	0.98	4.00
10.	2.00	0.00	2.84	0.00	2.30	1.20	0.60	1.01	0.96	3.99

Table 12: Optimal Simple Rules. No output gap uncertainty

	Loss Function			Optimal Weights				Measures of Macro Variability		
	λ	ω	E{L}	α_i	α_π	α_y	$\alpha_{\Delta y}$	σ_π	σ_y	$\Sigma_{\Delta i}$
0.	0.00	0.50	1.12	0.70	4.00	1.40	1.90	0.84	1.24	0.91
1.	0.50	0.50	1.69	0.60	3.30	1.90	1.70	0.89	0.95	0.94
2.	1.00	0.50	2.08	0.60	3.10	2.40	2.00	0.96	0.84	0.96
3.	1.50	0.50	2.40	0.60	3.00	2.80	2.20	1.01	0.77	0.99
4.	2.00	0.50	2.67	0.60	2.90	3.00	2.40	1.05	0.73	1.01
6.	0.00	0.00	0.37	0.00	9.90	3.00	2.00	0.61	1.28	3.22
7.	0.50	0.00	0.96	0.00	9.90	6.80	3.20	0.75	0.90	5.37
8.	1.00	0.00	1.30	0.00	7.90	7.60	2.60	0.86	0.75	4.96
9.	1.50	0.00	1.56	0.00	7.10	8.20	2.20	0.92	0.69	4.83
10.	2.00	0.00	1.77	0.00	6.50	8.60	2.00	0.98	0.64	4.80

A striking result is that output gap mismeasurements reduce the optimal coefficients considerably compared to the full information case. Although the quantitative magnitude of the reduction depends on, among other things, the particular parameter values in the model, the qualitative result confirms results by Smets (2000) and thus seems quite robust. Another result is that in the loss function with zero weight on interest rate smoothing, the relative importance of the change in the (observed) output gap becomes greater when the degree of persistence in output gap mismeasurements increases, as seen by comparing tables 10 and 11. This result thus confirms the results by Orphanides et al. (2000). Note, however, that the coefficient on the change in the output gap is strictly positive in the case with perfectly observable gaps. This reflects the role of history-dependence in forward-looking models. Since the optimal coefficient on the lagged interest rate is positive only when interest rate smoothing enters the loss function, we have that in this particular model history-dependence is more efficiently introduced through responding to the change in the output gap rather than smoothing the interest rate directly. This result is, however, likely to be less robust to alternative model specifications.

The expected losses, E{L}, in tables 10 - 12 suggest that there is a substantial excess loss stemming from output gap mismeasurements. Improving existing measures of the output gap may therefore have significant welfare effects through better monetary policy.

5 Conclusions

Interestingly, the tests of the *news* hypothesis indicate that future revisions to output growth for the Norwegian mainland economy are unpredictable. When we augmented the tests with macroeconomic variables which were observable at the same time as the preliminary growth estimates, none of these turned out to be significant (at the 10 per cent level of significance).

The different output gap estimates obtained from final data were compared with those from real time data and we have decomposed total revision into the sum of data revisions and other revisions. In general, other revisions are relatively more important the data revisions for most models.

The reliability of the various output gap models is poor. Total revisions are large and persistent, and the correlations between real time and final estimates are generally low. Compared to the US data analyzed by Orphanides and van Norden, the real-time estimates of the Norwegian data seem even less reliable than the real time estimates for the US.

None of the models considered stands out as an obvious choice for estimating output gaps in real time. Most of the models generate positive output gaps in the first half of the 1990s and negative output gaps from late 1998. This is clearly unreasonable. On the other hand, we find that changes in the real time output gaps in most of the models are more reasonable.

When we assess the implications for Taylor type interest rates the results clearly indicate that the inaccuracy of real time information may be a substantial challenge to monetary policy as final data in retrospect may give other paths for the policy rate compared to those suggested by real time data.

Finally, analyzing the consequences for monetary policy within a small New Keynesian macroeconomic model, the main welfare costs associated with failing to capture movements in potential output arise because monetary policy does not respond quickly enough to changes in the true output gap, thereby letting inflation move too far away from the target and closing the output gap too slowly. Furthermore, output gap mismeasurements reduce the optimal coefficients in generalized Taylor rules considerably compared to the full information case.

References

Cayen, J.-P. and S. van Norden 2004. The Reliability of Canadian Output Gap Estimates. Unpublished paper. Ecole des Hautes Etudes Commerciales, Montreal, Bank of Canada, CIRANO and CIREQ.

Clark, P. 1987. The cyclical component of U.S. economic activity. *Quarterly Journal of Economics, 102*(4), 797 -814.

Claus, I., P. Conway and A. Scott 2000. The output gap: measurement, comparisons and assessment. Research paper no. 44/2000, Reserve Bank of New Zealand.

Croushore, D. and T. Stark 1999. A real-time data set for macroeconomists. Working paper 1999/4, Federal Reserve Bank of Philadelphia.

Croushore, D. and T. Stark 2000. A funny thing happened on the way to the data bank: A real-time data set for macroeconomists. Business review september/october 2000, Federal Reserve Bank of Philadelphia.

Croushore, D. and T. Stark 2001. A real-time data set for macroeconomists. *Journal of Econometrics, 105*, 111-130.

Croushore, D. and Stark, T. 2002. Forecasting with a real-time data set for macroeconomists. *Journal of Macroeconomics, 24*, 507-531.

Doornik, J. and Hendry, D. F. 2001. GiveWin: An interface to empirical modeling. Timberlake Consultans, London.

Faust, J., J. H. Rogers and J. H. Wright 2000. News and noise in G-7 GDP announcements. International Finance Discussion Paper 2000/690, Federal Reserve Board of Governors.

Gerlach, S. and F. Smets 1997. Output gaps and inflation: Unobservable components estimates for the G-7 countries.

Giorno, C., P. Richardson, D. Roseveara and P. van den Nord 1995. Estimating potential output, output gaps and structural budget balances, Working papers 152, OECD.

Harvey, A. C. 1985. Trends and cycles in macroeconomic time series. *Journal of Business and Economics Statistics, 3*, 216-227.

Kozicki, S. 2004. How do data revisions affect the evaluation and conduct of monetary policy? Economic review first quarter 2004, Federal Reserve Bank of Kansas City.

Kuttner, K. N. 1994. Estimating potential output as a latent variable. *Journal of Business and Economics Statistics, 12*(3), 361-368.

Mankiw, N. G., D. E. Runkle and M. D. Shapiro 1984. Are preliminary announcements of the money stock rational forecasts? *Journal of Monetary Economics, 14*, 15-27.

Mankiw, N. G. and M. D. Shapiro 1986. News or noise: An analysis of GNP revisions. *Survey of Current Business*, (May), 20-25.

Nymoen, R. and E. Frøyland 2000. Output gap in the Norwegian economy – different methodologies, same result? *Economic Bulletin 2000/2, 71*, 46-52.

Orphanides, A. 2001. Monetary policy rules based on real-time data. *American Economic Review, 91*(4), 964-968.

Orphanides, A. 2003. Monetary policy evaluation with noisy information. *Journal of monetary economics*, 50, 605-631.

Orphanides, A. and S. van Norden 1999. The reliability of output gap estimates in real time. Unpublished Paper, Board of Governors of the Federal Reserve System and Ecole des Hautes Etudes Commerciales, Montreal.

Orphanides, A., R. D. Porter, D. Reifschneider, R. J. Tetlow and F. Finan 2000. Errors in the measurement of the output gap and the design of monetary policy. *Journal of Economics and Business, 52*, 117-141.

Orphanides, A. and S. van Norden 2001. The reliability of inflation forecasts based on output gap estimates in real time. Unpublished Paper, Board of Governors of the Federal Reserve System and Ecole des Hautes Etudes Commerciales, Montreal and CIRANO.

Orphanides, A. and S. van Norden 2002. The unreliability of output-gap estimates in real time. *Review of Economics and Statistics, 84*(4), 569-583.

Smets, F. 2002. Output gap uncertainty: Does it matter for the Taylor rule?, *Empirical Economics*, 27 (1) pp. 113-129

St-Amant, P. and S. van Norden 1997. Measurement of the output gap: A discussion of recent research at the Bank of Canada. Unpublished manuscript, Bank of Canada, July 1997.

Svensson, L. and M. Woodford 2003. Indicator Variables for Optimal Policy. *Journal of Monetary Economics, 50*, 691-720.

Taylor, J. B. 1993. Discretion versus policy rules in practise. *Carnegie-Rochester conference series on public policy, 39*, 195-214.

Taylor, J. B. 1999. *Monetary Policy Rules*. Chicago: The University of Chicago Press.

Taylor, J. B. 2001. The Role of the Exchange Rate in Monetary Policy Rules. Unpublished manuscript, Stanford University.

Walsh, C. 2003a. Minding the speed limit. FRBSF Economic Letter. 2003-14, 3 p.

Walsh, C. 2003b. Implications of a changing economic structure for the strategy of monetary policy, in Monetary Policy and Uncertainty: Adapting to a Changing Economy, Federal Reserve Bank of Kansas City, 2003.

Watson, M. 1986. Univariate detrending methods with stochastic trends. *Journal of Monetary Economics, 18*, 49-75.

Woodford, M. 1999. Optimal monetary policy inertia. NBER working paper no. 7261.

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Applicants are requested to send a CV, copies of recent papers, letters of reference and a proposal for a research project to:

Deutsche Bundesbank
Personalabteilung
Wilhelm-Epstein-Str. 14

D - 60431 Frankfurt
GERMANY