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Real-time data and business cycle analysis in Germany

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Abstract:

This paper examines the consequences of using "real-time" data for business cycle analysis in Germany based on a novel data set covering quarterly real output data from 1968 to 2001. Real-time output gaps are calculated. They differ considerably from their counterparts based on the most recent data. Moreover, they are not rational forecasts of the final series. The consequences of using real-time data for inflation forecasts, the dynamic interaction of output gaps and inflation, and stylised facts of the business cycle are also addressed. The results suggest that revisions of data and estimates can seriously distort research and policy implications.

Keywords: E32, C53

JEL-Classification: Real-time data, business cycles, output gap, VAR, inflation, Germany

Non Technical Summary

This paper examines the consequences of using “real-time” data for business cycle analysis in Germany. "Real-time" data are data, which have been available to researchers or policy-makers at a certain point of time. Based on such a data set covering quarterly real output data, real-time output gaps are calculated for each data vintage. These estimates differ considerably from their counterparts based on the most recent data ("final data set"). Moreover, they appear to be no rational forecasts of the final estimate. Using real-time data has also some consequences for describing stylised facts of the business cycle and for estimating the dynamic interaction of important macroeconomic variables. The problematic nature of real-time output gaps is not due to revisions of the underlying data, but due to the end-of-sample problem, which occurs, when trend (ie potential GDP) and cycle (ie the output gap) are distinguished based on the information set represented by the last recent data. Thus, the results suggest that revising estimates has considerable consequences for the diagnosis of the current stance of the business cycle, the assessment of the nature of economic shocks and the prediction of future inflation.

Nicht technische Zusammenfassung

Das Papier untersucht den Einfluss so genannter Echtzeit("Real-Time")-Daten auf die Analyse der deutschen Konjunkturentwicklung. Unter Echtzeit-Daten versteht man Daten, die Konjunkturforschern oder Entscheidungsträgern zu einem bestimmten Zeitpunkt zur Verfügung standen. Auf Basis solcher Daten werden Produktionslücken nach verschiedenen populären Methoden geschätzt. Es zeigt sich, dass Schätzungen von Produktionslücken am aktuellen Rand wenig verläßlich und stark revisionsanfällig sind. Zudem sind die aktuelle Schätzungen keine rationale Vorhersage der jeweils letzten Schätzung. Zudem ist der Informationsgehalt von Produktionslücken für die zukünftige Inflationsrate in Echtzeit recht gering. Auch wird die Darstellung stilisierter Fakten des Konjunkturzyklus und die Schätzung des dynamischen Zusammenhangs zwischen wichtigen makroökonomischen Variablen durch die Verwendung von Echtzeitdaten beeinflußt. Ursache für die problematischen Eigenschaften von Produktionslücken in Echtzeit sind nicht in erster Linie die Revisionen der zugrundeliegenden Ursprungsdaten. Das wichtigste Problem ist vielmehr die Schwierigkeit, auf Basis der am aktuellen Rand tatsächlich verfügbaren Information den Trend (das Produktionspotenzial) angemessen vom Zyklus (der Produktionslücke) zu trennen. Die Studie belegt damit, dass die Verwendung von "Real-Time"-Daten erhebliche Konsequenzen für die Diagnose der jeweils aktuellen konjunkturellen Lage, die Bestimmung der Natur gesamtwirtschaftlicher Störungen und die Prognose der Inflation hat.

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1 Introduction

A correct diagnosis of the stance of the business cycle is crucial both for academic purposes, ie estimating or testing business cycle theories, and policy issues, such as for the decisions on stabilisation policy measures as well as for forecasting. It has been argued, however, that the diagnosis of business cycles might be distorted in real time, ie based on the data set available at a certain point in time (Orphanides and van Norden (1999, 2002)). Though the discussion of this topic has a long tradition in Germany (see eg Rinne 1969 and, more recently, Braakmann 2003), this problem recently has been mainly addressed for US data. The present study tries to figure out how important the problems with real-time data and estimates are for business cycle analysis in Germany.

First, the problem of calculating output gaps is addressed. An output gap is defined as the difference between actual real output and the potential or trend output. The importance of this figure for both macroeconomic theory and practical business cycle analysis can hardly be overstated. Unfortunately, it is not directly observable and hence has to be estimated. A wide range of methods have been suggested for that purpose.[1] Moreover, several criteria for the empirical evaluation of output gaps have been suggested in the literature.[2] Among these, the behaviour of output gaps in real time has gained considerably more attention recently. In this paper, we focus on rather simple methods of estimating the output gap. Nevertheless, these methods are both popular and important for practical business cycle analysis.

Second, the paper deals with the problem of inflation forecasts based on real-time output gaps. Simple forecasting equations are considered. While these equations are

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[1] For comprehensive surveys see Schumacher (2002) and the European Central Bank (2000).

[2] See eg the discussion in Gamba-Mendez and Rodriguez-Palenzuela (2001) and Rünstler (2002).

surely over-simplified, they can still be justified as a crude form of a Phillips-curve relation linking the level of the output gap to future inflation. Additionally, a vector autoregressive (VAR) model is used to discover the dynamic interaction between the stance of the business cycle as it appears on the base of different data sets, short-term interest rates, and the inflation rate.

Third, the robustness of (at least one) famous stylised fact of the business cycle is sketched. To this end, the contemporaneous correlation of prices and output is addressed. The question arises as to whether such a stylised fact remains unaffected by the use of real-time data.

The paper is organised as follows. Section 2 gives a short summary of the literature on real-time data. Section 3 describes the data and the methods used to estimate the output gap. The following section evaluates the real-time estimations. In particular, the following problems are addressed: what are the statistical properties of the real-time estimates and of the revisions, ie the difference of real-time and final output gaps? Are real-time output gaps rational forecasts of the final outcome of this series? Do real-time output gaps provide information regarding future inflation? Do real-time output gaps match business cycle turning points? Does the identification of economic shocks driving the business cycle depend on the use of real-time data? The last section offers some conclusions.

The results of this study strongly support scepticism regarding the reliability of output gap estimates in real time. In particular, it is shown that the first estimates of output gaps are not rational expectations of gaps calculated on the basis of the last available data set. Additionally, the revisions of the first estimates do not behave purely randomly. In contrast, the information content regarding future inflation does not seem to be strongly affected by the use of real-time data. A comparison of output gap measures to results for simple growth rates reveals that the main source of the poor performance of the output gap estimates is not the revision of the underlying data. Rather, the end-of-sample problem inherent in any trend/cycle decomposition seems to be the crucial problem. The modelling of the dynamics of the interaction of inflation and output gaps as well as the correlation of prices and output also appear to be affected by the use of real-time data, though to a much lesser extent.

2 Selected related literature

Economists have recognised the importance of data revisions for a long time. Initial estimates of aggregate output are based on an incomplete set of information. But this is not the only source of data revisions. Following Rinne (2002), one might distinguish three sources of revisions: i) *Statistical revisions*. This kind of revision occurs because the underlying data themselves are still incomplete or estimated when the first figure is published. As regards this point, the statistical office faces a trade-off between an exact and a most timely publication of certain figure. ii) *Revisions due to changing definitions*. From time to time, definitions of the national account statistics change. The last recent example of a revision of this kind is the introduction of the European System of National Accounts (ESA 95). iii*) Methodological revisions*. This category includes revisions due to different methods of price deflation, seasonal adjustment and other transformations of the primary statistics. Beside these categories of revisions, the more recent literature has an even wider understanding of the term revision. For example, Orphanides and van Norden (1999, 2002) call it a revision when an *estimated* figure changes due to additional data, even if the underlying data do not change. [3]

The recent scientific discussion on revisions in that broad sense and their impact on economic research may be summarised as follows (Stark 2002, but see also Rinne 2002). One broad strand of research analyses the magnitude and statistical properties of revisions. For example, this line of research focuses on the question of how large revisions are, both by historical and international standards. Faust, Rogers and Wright (2000) analyse the revisions of the preliminary announcements of output growth rates for the G-7 countries. They conclude that the magnitude of the revisions is quite large, albeit with considerable differences between the countries under investigation. The authors also contribute to a second theme often stressed in this branch of the literature: they present evidence that the revisions are not just white noise but to a surprisingly large extent predictable. This finding is of particular interest, since it suggests that the inclusion of information on the revision process might help to improve the predictability

[3] In other words, the revision of an Output gap estimates might be decomposed in two parts: the revision of the underlying data on the one hand and the revision of the estimate du to additional available information as time goes by.

of the latest data. However, though the authors find such evidence for a number of countries, they also point out that the degree of predictability is rather modest.

Many paper address the question whether the use of preliminary data has consequences for the quality of economic forecasts (Stark and Croushore 2002). For example, statistics used to evaluate forecasts differ considerably depending on whether they are calculated based on preliminary or finally revised data. Additionally, the choice of the appropriate model to generate forecasts might be influenced by data revisions.

The most recognised area of research might be seen in the discussion regarding a possible influence of data revisions and output gap mismeasurement on political decisions. In particular, Orphanides (2002) has argued that the course of monetary policy conducted by the Fed can be understood by the means of errors in gauging the true level of the output gap (similar studies using German data are Clausen and Meier 2003 and Gerberding, Seitz and Worms 2004). Nelson and Nikolov (2001) have confirmed this result using data for the UK and the Bank of England. A large part of the papers on policy analysis is devoted to the question of how the decision on short-run interest rates can be understood. In particular, it is argued that the course of monetary policy in the early and mid-seventies is not, in the first place, due to a less inflation-averse central bank, but due to the fact that the real-time data suggest a deep negative output gap for this time (Orphanides 2002). This result cannot be confirmed based on the final data set.

Real-time data are also suitable to analyse the robustness of empirical findings on macroeconomic relationships. For example, as Croushore and Stark (2000) point out, the estimated response of a certain macroeconomic variable to a shock may well depend on the data set from which this response is estimated (Croushore and Evans 2002). Last but not least, the real-time discussion is important for research on financial markets, since financial markets normally respond to news concerning economic fundamentals (see Stark 2000 and the literature cited therein).

3 Data and business cycle measures

3.1 Data

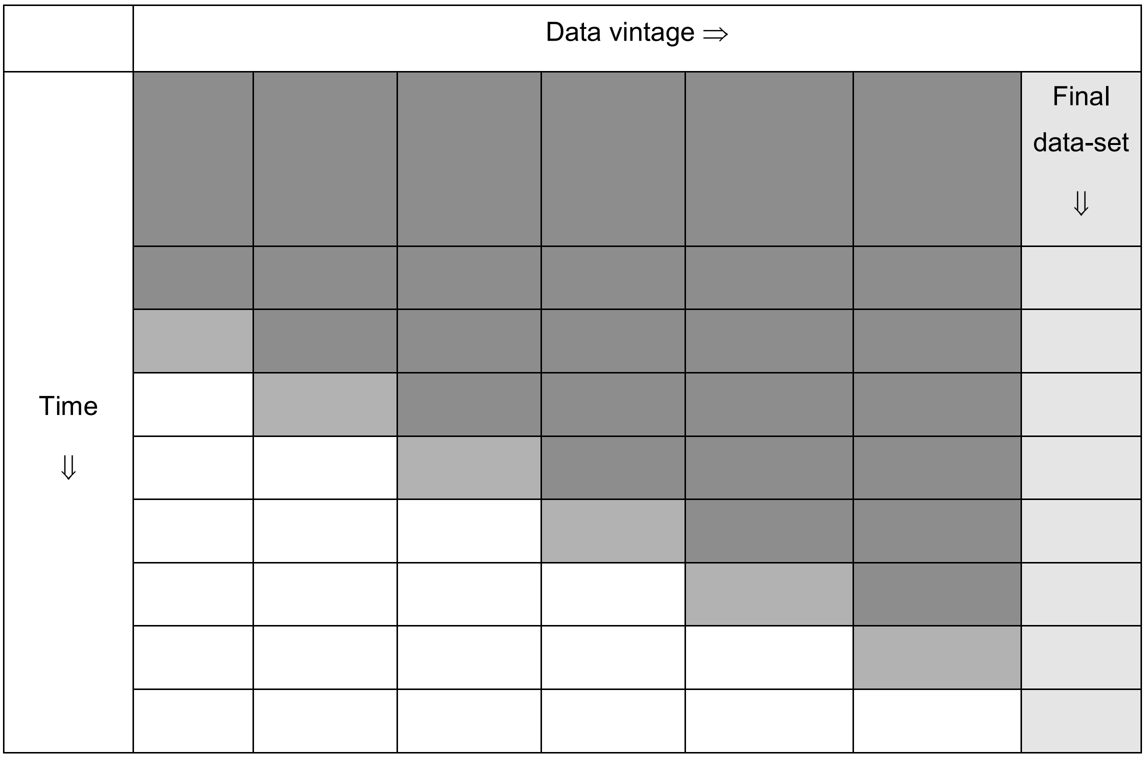
The estimation of output gaps in this paper relies on data on real gross domestic product (GDP). The underlying data are taken from the German Federal Statistical

Office (*Statistisches Bundesamt*), which has regularly published quarterly national accounts statistics from 1968 on. As a general rule, the data are published in March, June, September and December. However, additionally a first rough estimate of the annual growth rate is published. Additional information is provided in the Federal Statistical Office's monthly periodical "*Wirtschaft und Statistik*". Thus, to take into account all possible data revisions, data have been collected for each month of a year. As a consequence, a "real-time" series for real GDP is available for each month.

For Germany, however, there are additional problems compared to the US situation, most of which are related to German unification. To begin with, for the latest data release West German data end in 1991, and unified German data start at the same time. As regards the real-time data, the first estimates of data for Germany as a whole were not available before September 1995. Thus, to make the data comparable and to approximate as closely as possible the situation policymakers faced in the early nineties, we shall refer to western Germany up to 1998. Beginning with 1999 the estimates will be based on unified German data (hereafter German data). To be able to calculate real-time data matching this convention, it is necessary, however, to refer not to the latest possible data release, but the release of 1999. These data provide real GDP for western Germany up to 1998. Unfortunately, these data rely on the "old" system of national accounts instead of the "new" ESA data. Hence, the data available in 1999 have been used as the "final" data set. With the exception of figures giving the change over previous year, all data have been seasonally adjusted using the Census X-11 procedure.

Following Orphanides and van Norden (2002) two types of real-time estimates of the output gap are calculated in this paper. First, data based on the data sets given at a certain point of time, ie real-time data, and estimates based on the last available data set with the estimation period restricted, ie "quasi-real-time data". Figure 1 illustrates the different concepts. For each point in time, ie for each column in figure 1 the output gap is estimated based on the available information at that time, ie based on the data in this column. The result of this task is the real-time data set. The quasi-real time data set is based on the final data set, ie on the last column only, but proceeds recursively, ie row by row to make the data comparable to the Real-time data set. Finally, the final data set refers to the last column only and uses all available data (ie all rows).

Figure 1: Scheme of different data sets



As regards real-time data for output gaps, they are constructed as follows (Orphanides and van Norden 2002: 541). In a first step, each and every data vintage is detrended, ie in every quarter the output gap is estimated using the data available in this quarter.[4] In a second step, a series is constructed containing the latest available output gap estimate for each quarter. This series is the real-time output gap and represents the timeliest estimate that is possible for each quarter. Note, however, that, possibly in contrast to the US experience, the time span between the data release and the latest available quarter for which GDP data have been released may differ sharply over time. Mostly due to German unification, but also due to other changes in data definitions, there have been some periods without regular published GDP data.

[4] Both real-time and quasi-real-time data make use of the maximum of available data, ie *no* "rolling window" approach is applied.

3.2 Business cycle measures

The selection of business cycles measures is mainly motivated by practical purposes, i.e. by the relevance of the respective measure for day-by-day business cycle analysis. Hence, the list of methods comes close to the one considered by the German Council of Economic Experts (2003), though it is restricted by the availability of real-time data. As a consequence, promising multivariate approaches as surveyed by Chagny, Lemoine and Pelgrin (2003) and used in Schumacher (2002a,b) are beyond the scope of this paper.

3.2.1 Changes over previous periods

For the sake of comparison and since these numbers are still by far the most popular measures of the business cycle the changes over previous years and previous quarters are being investigated. As regards the former, the data are not seasonally adjusted. The latter have been seasonally adjusted as described above. They are calculated at an annual rate.

3.2.2 Linear detrending

Linear detrending is widely used for estimating trend and cycle. Moreover, this method is of interest because it is an important input to the production function-based methods of estimating potential GDP. Within these approaches "technical progress", total factor productivity or the potential level of the capital/output ratio are frequently estimated on the basis of a linear trend.[5] Hence, the real-time properties of these methods are strongly affected by the real-time properties of the linear trend model. This can be described as follows: If we let y_t denote the log of real GDP at time t, then the estimation of potential GDP is based on the simple OLS regression

$$y_t=\beta_0+\beta_1 t+u_t \qquad (1)$$

[5] See eg Deutsche Bundesbank (1995).

The fit of this equation gives an estimate of potential GDP and the residual u_t is the estimated output gap. Since we have a logarithmic specification, the estimate $\hat{\beta}_1$ gives the average trend growth over the period under investigation. The estimation implies some normalisation since the residuals have a mean of zero.

3.2.3 Quadratic detrending

Recently, some authors have argued that quadratic detrending might give a good approximation to the output gap (see eg Galí, Gertler and Lopez-Salido (2001)). The method is implemented by simply regressing the log of output on a trend and its quadrate.

$$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + u_t \qquad (2)$$

Again, the residual u_t provides the estimate of the output gap.

3.2.4 Hodrick-Prescott filter

The Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997) has probably become the most popular way of detrending economic time series in the last recent years. This is mainly due to the fact that it can be very easily calculated and implemented in virtually any econometric software package. If y denotes real GDP, the filter is defined as

$$min \sum_{t=1}^{T} (y_t - y_t^*)^2 + \lambda \sum_{t=2}^{T-1} \left[(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*) \right]^2 \qquad (3)$$

y_t^* being the smooth component which gives the estimate of potential GDP in this context. An HP filter is more or less a "moving average for snobs" (Kuttner 1994). Broadly speaking, the procedure described in [3] contains two commands: (i) minimise the distance between the actual and the trend value of the time series and (ii) minimise the change in the trend value. Obviously, the commands contradict each other. Therefore, a weight has to be given to both aims. This is done by choosing the factor λ. For quarterly data, a smoothing factor of 1600 has become something of an “industrial standard". Though this assumption can be justified,[6] the arbitrary choice of the smoothing parameter is one of the major criticisms of the filter. However, in this paper we follow the most frequently used practice.

It is well known that the Hodrick/Presott filter has an end-of-sample problem, i.e. at the end of the sample the estimates are particular unreliable. To take this fact into account, an approach often adopted by practitioners is also considered here: to make the most recent output gap estimates more reliable forecasted values are added to the filtered series. To calculate the forecasts a simple AR(4) process of the rate of change of real GDP is used.

3.2.5 Band-pass filter

The band-pass filter suggested by Baxter and King (1999) rests on spectral analysis. It assumes that the phenomenon "business cycle" can be described as fluctuations of certain frequencies. For example, the authors argue that the tradition of Burns and Mitchell suggests that a typical business cycle lasts between 6 and 32 quarters. Fluctuations of a shorter length belong to irregular components of the time series, whereas fluctuations of a lower frequency should be attributed to the trend of time series. Once the upper and lower bound of frequencies which shall define the cycle are given, it is still not possible – at least in a finite sample – to calculate the ideal filter which will remove all fluctuations of that length. Instead, it is only possible to approximate this ideal filter by a moving average. The longer the moving average is, the closer the calculated filter comes to the ideal one. Thus, in implementing the band/pass filter, the three parameters need to be set: the upper bound of frequencies, defining the trend of the time series (32 in this paper), the lower bound defining the irregular part of the series (6 in this paper) and the length of the centred moving average (30 in this paper).

A variant of the Baxter and King filter is suggested by Christiano and Fitzgerald (2003). The main difference between the two procedures is, that the optimal filter is

[6] In their original paper Hodrick and Prescott argue that "a five percent cyclical component is moderately large as is a one-eighth of one percent change in the rate of growth in a quarter" (Hodrick and Prescott 1997: 4). This leads to $\left(\frac{5}{1/8}\right)^2 = 1600$. Some studies discuss the appropriate setting of the smoothing parameter. For a full discussion see of this topic see Mohr (2001) and Tödter (2002).

approximated by a *two-sided* filter in case of the Baxter and King (1999) method and a *one-sided* filter in case of the Chistiano and Fitzgerald (2003) approach. Hence, to calculate recent output gaps based on the former method some values have to be forecasted. In this paper, we follow a common approach and make use of a simple AR(3) process to extrapolate the growth rate of real GDP. In contrast, when applying the Chistiano and Fitzgerald (2003) method the cyclical component of the series can be calculated using a one-sided moving average. The authors argue that their filter has better real-time properties as compared to the Baxter and King (1999) variant.

3.2.6 Unobserved component model

As regards the rather broad class of unobserved component approaches to estimate the output gap, this paper refers to the most simple model of Watson (1986). According to his approach, potential GDP is models by a simple random walk with drift (v):

$$y_t^* = v + y_{t-1}^* + \varepsilon_{1,t} \tag{4}$$

with $\varepsilon_{1,t}$ as a white noise error. The output gap, in turn, is assumed to follow an AR(2) process:

$$gap = \alpha_1 gap_{t-1} + \alpha_2 gap_{t-2} + \varepsilon_{2,t} \tag{5}$$

Again, $\varepsilon_{2,t}$ is a white noise error term. Furthermore, it is assumed that the error terms are uncorrelated.

4 Evaluating the measures

Calculations like in the previous sections may be undertaken for several reasons. One might be interested in the long-run trend of economic activity or the current stance of the business cycle, or in a long time series for analytical purposes, eg to estimate an equation. Thus, the criteria to evaluate these data depend on the purpose of the investigation and might hence be quite different. The list of criteria applied in the following section will reveal that the main perspective taken by the present paper is on current business cycle analysis.[7] As a consequence, the main questions are whether real-time business cycle measure are reliable and whether they provide information on possible inflationary pressure.

4.1 Summary statistics

Some summary statistics on the output gap time series are given in table 1. The table compares final, real-time and quasi-real-time estimates as described above. To begin with, the differences in the means of the series are striking in some cases, though the differences between the alternative data sets of the underlying data seem to be of a small magnitude only. For simple detrending methods, the differences are about one percentage point on average. Given a standard deviation of the same order magnitude, this would imply on average a serious misinterpretation of the true stance of the business cycle. It is noteworthy that the filter techniques perform somewhat better according to this criterion. To make things even worse, not even the sign of correction is the same for all methods. Whereas the linear detrending method and, though to a much lesser degree, the band/pass filter lead on average to an upward revision, ie imply an underestimation of the output gap based on real-time data, quite the opposite is true for the estimation based on a quadratic trend.

As regards the standard deviation of the time series, the differences between real-time, quasi-real-time and final estimations are – compared to the means – much less a matter of concern. Whereas the competing methods tell alternative stories of how strong economic fluctuations around a trend are, within a given method these differences seem to be minor. This does not rule out the possibility that for single observations the magnitude of revision might be important. However, as regards the minimum and maximum of the output gaps this does not seem to be the case here. Another interesting bit of descriptive information is the correlation of the real-time and quasi-real-time output gaps with their final counterparts. As a general rule, this correlation is only small compared to the respective correlation of the growth rates.

[7] For other list of criteria compare eg Gamba-Mendez and Rodriguez-Palenzuela (2001).

Table 1: Summary statistics of output gap measures in Germany, 1980 I to 2001 IV

Method	Mean	Standard deviation	Minimum	Maximum	Correlation with final estimate
Change from previous year					
Real-time	1.82	1.75	-3.27	6.07	0.95
Quasi real-time	NA	NA	NA	NA	NA
Final estimate	1.92	1.98	-3.80	6.99	1.00
Change from previous quarter					
Real-time	1.57	3.80	-9.86	10.74	0.89
Quasi real-time	NA	NA	NA	NA	NA
Final estimate	1.84	4.23	-10.63	13.53	1.00
Linear trend					
Real-time	-1.39	2.37	-6.36	3.49	0.77
Quasi real-time	-1.30	2.87	-6.89	6.05	0.82
Final estimate	-0.21	2.56	-4.34	6.54	1.00
Quadratic trend					
Real-time	1.29	2.26	-2.37	6.59	0.42
Quasi real-time	1.43	2.65	-2.36	8.43	0.44
Final estimate	-0.53	2.77	-5.26	6.46	1.00
Hodrick-Prescott filter					
Real-time	-0.07	1.33	-3.63	2.87	0.40
Quasi real-time	-0.02	1.50	-4.38	2.71	0.44
Final estimate	0.02	1.35	-2.42	3.89	1.00
Hodrick-Prescott filter, incl. Forecasts					
Real-time	-0.10	0.81	-2.11	3.38	0.51
Quasi real-time	-0.03	1.62	-5.00	2.93	0.42
Final estimate	-0.04	1.40	-2.42	3.89	1.00
Band-pass (6,32) filter					
Real-time	-0.12	0.70	-2.07	1.97	0.64
Quasi real-time	1.08	0.88	-0.81	3.33	0.68
Final estimate	0.00	1.16	-2.26	2.98	1.00
Unobserved component model					
Real-time	0.05	1.45	-3.53	3.53	0.49
Quasi real-time	-0.66	1.46	-3.59	3.39	0.57
Final estimate	-0.75	2.61	-5.12	5.95	1.00

The table comprises summary statistics on output gap measures for different concepts. See text for additional information.

Table 2: Summary statistics on revisions: Final versus real-time estimates, 1980 I to 2001 IV

Method	Mean	Standard deviation	Noise-to-signal ratio	Minimum	Maximum	Auto-correlation
Change from previous year	0.13	0.64	0.33	-1.42	2.01	0.74
Change from previous quarter	0.32	1.97	0.47	-5.37	6.97	-0.16
Linear trend	1.18	1.67	0.65	-1.30	4.66	0.95
Quadratic trend	-1.95	2.77	1.00	-7.27	1.66	0.98
Hodrick/Prescott filter	0.10	1.48	1.09	-2.68	3.67	0.93
Hodrick/Prescott filter, incl. forecasts	0.12	1.21	0.86	-2.52	3.22	0.84
Band-pass (6,32) filter	0.12	0.89	0.77	-1.75	2.68	0.90
Unobserved component model	-0.79	2.28	0.87	-5.17	5.22	0.78

The table comprises summary statistics on revisions of output and output gap measures for different concepts. Revision is final minus real-time estimation. See text for additional information.

Table 2 shows the summary statistics on the revisions for each time series. The revision is defined as the actual measure minus the first estimate of the measure. Ideally, the revision should have a zero mean, indicating no systematic difference in the output gaps based on different data inventories. Unfortunately, this is not the case for both deterministic trend extraction methods. The filter techniques perform much better in this respect. The standard deviation of the revisions is of roughly the same order of magnitude as the respective standard deviation of the output gap measures itself. This fact is also illustrated by the noise-to-signal ratio of the preliminary estimates. As is done in Orphanides and van Norden (2002), this measure is calculated as the ratio of the standard deviation of the revision to the standard deviation of the final estimate. If this measure exceeds one, the information provided by the initial estimate appears to be rather useless. Though this is the case for the quadratic trend only, some numbers come very close to one. All in all, the results point to a great importance of revisions for gauging the stance of the business cycle. In some particular cases the revision becomes extremely large, as is indicated by the minimum and maximum observations in the series. An upward or downward revision of seven or eight percentage points will lead the business cycle researcher to a completely different judgement of the cyclical situation. Last but not least, it is noteworthy that most of the revision series show a strong degree of autocorrelation, suggesting that revisions are not just white noise but show some systematic behaviour.

4.2 Are real-time output gaps a rational forecast of the final data?

Following Mankiw and Shapiro (1987) and Mankiw, Runkle and Shapiro (1984), we will consider whether the real-time output gaps and the quasi-real time output gaps can be seen as rational forecasts of the results. To this end, the following estimation is used:

$$gap_t^{final} = \alpha + \beta gap_t^{real-time} + u_t \tag{6}$$

In the case of a rational forecast, the null hypothesis $H_0 = \begin{pmatrix} \alpha = 0 \\ \beta = 1 \end{pmatrix}$ cannot be rejected. Table 3 gives the result of such tests for the data under investigation. At the 5% level the rational expectation hypothesis cannot be rejected for the simple rates of change. In the case of the changes over the previous year, the null has to be rejected at the 10% level. These findings are in sharp contrast to the results for the output gap figures. In all cases the null has to be rejected even at the 1% level. This result confirms that the real-time estimate has limited informative value. Moreover, it becomes apparent that the revision of the underlying data is not the main problem.

Table 3: Are preliminary output gaps rational forecasts of the final estimate?

Method	$\hat{\alpha}$	$\hat{\beta}$	R^2	Test (F-value)
Change from previous year	-0.41 (-0.73)	1.26 (5.63)***	0.27	0.71
Change from previous quarter	0.34 (1.50)	0.98 (17.6)***	0.78	1.17
Linear trend	0.96 (4.67)***	0.84 (11.2)***	0.60	24.52***
Quadratic trend	-1.24 (-3.67)***	0.50 (4.03)***	0.17	31.29***
Hodrick-Prescott filter	0.06 (0.43)	0.40 (3.98)***	0.16	17.70***
Hodrick-Prescott filter, incl. Forecasts	0.12 (1.00)	0.89 (5.83)***	0.28	0.84
Band-pass filter	0.12 (1.27)**	1.05 (7.64)***	0.40	0.82
Unobserved component model	-0.79 (-3.22)***	0.89 (5.26)***	0.24	5.58***

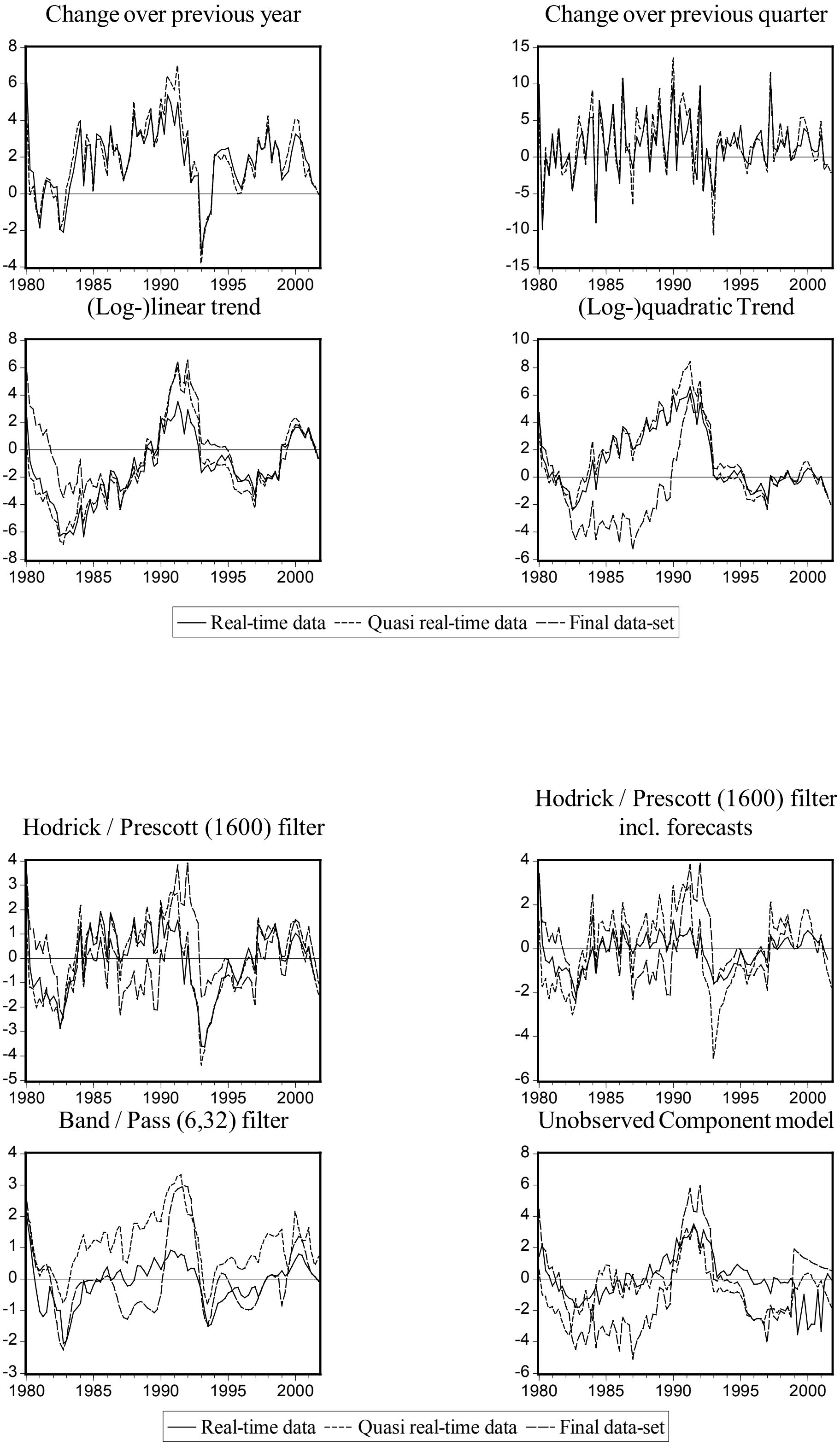
"Test" indicates an F-test on the rationality of the forecast. t-values in brackets. See text for details. *** (**, *) denotes rejection of the null hypothesis at the 1 (5, 10) percent level. Estimation period is 1968:1 to 2001:4.

4. 3 Business cycle turning points

An important feature of real-time data is that they might help to better understand business cycle forecast errors. A full discussion of this topic[8] would require a full real-time data set, which is not available for Germany yet. However, an important part of the problem is the behaviour around business cycle turning points (Dynan and Elemedorf 2001, Chauvet and Piger 2003). The business cycle forecaster might miss the "true" turning point if he relies on real-time data. Therefore, he might misdiagnose the current situation and, as a consequence, be more likely to make the wrong prediction.

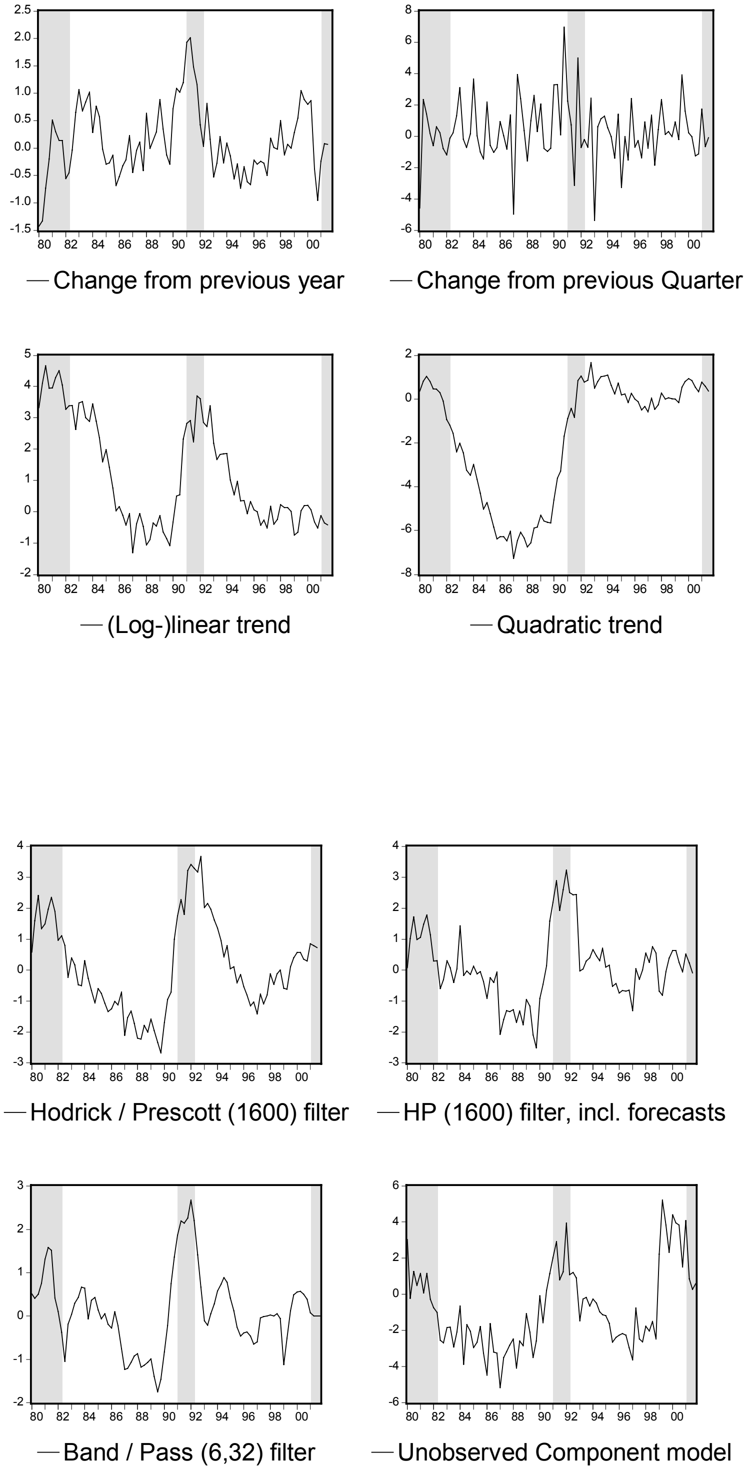
8 See, for example, Stark and Croushore (2002).

Figure 2: Output and output gaps in Germany based on different data sets



Notes: Output gaps are expressed as a percentage of the trend level. See text for additional information.

Figure 3: Revisions of output gap estimates in Germany



Notes: Revisions are expressed as a percentage of the trend level. The shaded areas are recession according to the definition of the Economic Cycle research Institute (2003).

Figure 2 depicts the output growth rates and the output gap measures based on different data sets and compares the implied business cycle turning points. It becomes apparent that the dating of a turning point depend crucially on the use of final, real-time and quasi-real-time data. At least this holds for the detrending methods. It is noteworthy that the growth appears to be much more robust to the choice of the data set. This is also apparent in figure 3. The exhibit shows the revisions of the respective business cycle measure, ie the difference between the first estimate and the final data set. The magnitude of output gap revision is remarkably high and has the same order of magnitude than the output gap measure itself.

Even if the measures based on different data sets differ regarding the level of the output gap, it might still be the case that they tell at least the same business cycle story qualitatively. Thus, the series may show at least the same sign for a certain period. To highlight whether this is indeed the case, we will make use of a test on information content. This test rests on the classification given in table 4.

Table 4: Classification of revisions

		Final data-set		
		Positive output gap	Negative output gap	Sum
	Positive output gap	Oii	Oij	Oi.
Real-time data set	Negative output gap	Oji	Ojj	Oj.
	Sum	O.i	O.j	O

Source: The classification follows the classification of forecast errors, see e.g. Diebold and Lopez (1996, S. 257).

From this classification it is possible to evaluate the information content of the real-time estimate using the measure $I = \frac{O_{II}}{O_{II} + O_{JI}} + \frac{O_{JJ}}{O_{JJ} + O_{IJ}}$. In a "coin flip", we have $O_{II} \approx O_{JI}$ and $O_{JJ} \approx O_{IJ}$ and therefore $I \to 1$. If the real-time estimates fits the final-data set results perfectly than $O_{JI} = O_{IJ} = 0$ and $I = 2$. Therefore, any value of $1 < I \leq 2$ indicates a positive information content. Furthermore, the statistical significance of the information content can be tested (cf. Diebold and Lopez, p. 257): We estimate the expected cell counts under the null of no information content. The consistent estimator for the cell counts is given by $\hat{E}_{ij} = O_{i.}O_{.j} / O$. Finally, one constructs the following test statistic $C = \sum_{i,j=1}^{2} (O_{ij} - \hat{E}_{ij})^2 / \hat{E}_{ij} \sim \chi^2(1)$. If the empirical value exceeds the critical one, the null hypothesis of no information content has to be rejected. The results of this task are given in table 5.

Table 5: Test of information content regarding the sign of the final output gap estimate

Sign of real time estimate:	+	+	–	–	Information	Test value	p-value
Sign of final estimate:	+	–	+	–	content		
		%				χ^2	
Change from previous year	84	2	5	9	1.64	64.41	0.00
Change from previous Quarter	61	9	3	26	1.75	47.05	0.00
Linear Trend	25	17	6	52	1.49	32.50	0.00
Quadratic Trend	34	10	28	28	1.27	9.39	0.00
HP-Filter	33	14	22	31	1.29	8.64	0.00
HP, incl forecast	34	13	16	37	1.43	17.36	0.00
Band-Pass Filter	32	10	15	43	1.50	30.45	0.00
UC model	20	15	27	38	1.16	24.46	0.00

See text for additional information.

The results indicate that there are numerous cases in which the sign of the output gap based on real-time estimates does not match the respective number based on the final data set. However, the null of no information content has still to be rejected for all methods under investigation.

From a practitioner's viewpoint it matters whether the data revisions are random or contain a systematic component. If the latter is the case, the forecast of the final outcome might be improved using information on the revisions. It has already been noted in table 2 that the revisions show a large degree of autocorrelation and, thus, are predictable. A related topic is the question of whether macroeconomic variables may help to forecast revisions. If this were the case, the real-time properties of the output and output gap measures might be improved by looking at these variables. To test whether this is the case, tests for Granger non-causality have been performed. As macroeconomic variables linked to the stance of the business cycle, the short-term interest rate (as a prominent leading indicator) and survey data on capacity utilisation are used. Both series have the advantage of not being subject to revision.

The results of tests for Granger-non-causality are given in table 6. Unfortunately, neither series helps to predict revisions. In some cases, however, at least a feedback relationship can be established. This points to the possibility that additional data may help to interpret the current stance of the cycle.

Furthermore, for the purposes of business cycle forecasting it particularly matters whether revisions make it difficult to detect a business cycle turning point. A good deal of forecasting rests on the stylised facts, ie on the assumption that, once a turning point has been reached, the forecaster can rely on a "typical" pattern of, say, an upswing. Thus, table 7 compares the order of magnitude of revisions around major business turning points according to the NBER-style definition of turning points.[9] To this end, the revisions' means are calculated for the quarters in which a turnaround has emerged plus and minus one quarter. The results are not clear-cut, however. Some numbers suggest that revisions might be larger in these periods, but no systematic evidence can be found. From this it follows that the problems in detecting turning points are not related to the turning point itself. If the method of determining turning points is independent of the output gap measure, no systematic bias occurs. Again, this points to the conclusion that the problems arise from detrending the series, rather from the underlying stance of the cycle.

[9] See Economic Cycle Research Institute (2003) for a discussion of different concepts of turning points. This implies that the turning point do not themselves depend on real-time data.

Table 6: Tests for Granger non-causality of output gap revisions and macroeconomic variables

	H0: Variable does not Granger-cause revision	H0: Revision does not Granger-cause variable	Test decision
Variable		Change from previous year	
Short-term interest rate	0.82	1.43	No causality
Survey data on capacity utilisation	0.54	1.36	No causality
Variable		Changes from previous quarter	
Short-term interest rate	0.06	2.04*	Revisions Granger-cause variable
Survey data on capacity utilisation	1.41	1.24	No causality
Variable		Linear trend	
Short-term interest rate	2.78*	1.13	Variable Granger-causes revisions
Survey data on capacity utilisation	2.58*	4.90***	Feedback
Variable		Quadratic trend	
Short-term interest rate	0.40	1.34	No causality
Survey data on capacity utilisation	6.21***	1.51	Variable Granger-causes revisions
Variable		Hodrick-Prescott filter	
Short-term interest rate	2.16*	1.38	Variable Granger-causes revisions
Survey data on capacity utilisation	3.99***	4.08***	Feedback
Variable		Hodrick-Prescott filter; incl forecasts	
Short-term interest rate	1.80	0.78	No causality
Survey data on capacity utilisation	1.49	6.47***	Revisions Granger-cause variable
Variable		Band-pass filter	
Short-term interest rate	3.38**	2.23*	Feedback
Survey data on capacity utilisation	1.87	7.16***	Revisions Granger-cause variable
Variable		Unobserved component Model	
Short-term interest rate	1.75	2.06*	Revisions Granger-cause variable
Survey data on capacity utilisation	1.41	2.81**	Revisions Granger-cause variable

*** (**, *) denotes rejection of the null hypothesis at the 1 (5, 10) percent level.

Table 7: Revisions around business cycle turning points, 1980 I to 2001 IV

Method	Mean of revision series "Normal" periods	Around turning points
Change from previous year	0.12	0.17
Change from previous quarter	0.23	0.81
Linear trend	1.00	1.96
Quadratic trend	-1.99	-0.30
Hodrick-Prescott filter	-0.06	0.92
Hodrick-Prescott filter, incl forecasts	0.01	0.66
Band-pass (2,32) filter	0.04	0.55
Unobserved component model	-1.03	0.46

Business cycle turning points are: 1973, 3rd quarter (peak), 1975, 2nd quarter (trough), 1980, 1st quarter (peak), 1982, 2nd quarter (trough), 1991, 1st quarter (peak), 1992, 2nd quarter (trough) and 2001, 1st quarter (peak). These data are from: Economic Cycle Research Institute (2003).

4. 4 Information content for future inflation

Another empirical criterion for evaluating estimates of the output gap is whether they contain information about future inflation (Claus 2000). The underlying argument is that the output gap is an indicator of excess demand or supply in the aggregated goods market. Thus, if excess demand increases, inflationary pressures should also increase. To analyse this aspect, a simple VAR containing inflation and the respective output or output gap measure equation is estimated (see also Orphanides and van Norden 2003).

$$X_t = \begin{bmatrix} \pi_t \\ gap_t \end{bmatrix};\ X_t = \Theta(L)X_{t-1} + \varepsilon_t \tag{7}$$

If there is information content stemming from the respective gap series, the system in (7) should produce significantly better inflation forecasts than a simple autoregressive process. To test this implication, ex ante forecasts have been computed. To this end, I refer to the end-year data available from 1977 to 1997. These data include the third quarter of the respective year. Thus, for each vintage, data running up to the second quarter of the previous year are available. Based on these data sets, both the VAR and a simple autoregressive process are used to compute forecasts for the period until the end of the next year, ie for the coming five quarters. For these forecasts the mean squared error (MSE) is computed. With these numbers at hand, it is possible to obtain the loss differential

$$\bar{d} = MSE^{autoregressive} - MSE^{gap} \tag{8}$$

If the inclusion of the gap variable improves the forecasts, the loss differential should be lower than zero. Diebold and Mariano (1995) have developed a test of whether this improvement is significant. In practice, the loss differential is regressed on a constant. If it is significantly higher than zero, the VAR forecast is significantly better, and the output gap measure provides information with regard to future inflation. To ensure white-noise residuals an autoregressive moving average (ARMA) process is added to the test equation. This is likewise recommended by Diebold (1998).

Table 8 presents the results of the analysis. In general, the methods perform quite well according to this criterion. Except the one based on a quadratic trend output gap measures seems to be significantly helpful in forecasting German inflation. Thus, the results presented here are in some contrast to the findings of Orphanides and van Norden (2003), who argue that virtually no output gap measure is useful to predict inflation. It is noteworthy, however, that survey data are also useful in predicting inflation. Since these variables are not revised at all, it seems to be reasonable at least to double-check an inflation forecast using this variable.

Table 8: Inflation content for future inflation, 1980 to 1998

Forecasted year	Changes over previous year	Changes over previous quarter	Linear trend	Quadratic trend	Hodrick-Prescott filter	Hodrick-Prescott filter, incl. forecasts	Band-pass filter	UC Model	Survey data
1980	0.05	-0.03	0.16	0.09	0.03	0.01	0.11	-0.14	0.13
1981	-0.01	-0.02	-0.17	0.25	0.10	0.13	0.24	0.01	-0.12
1982	0.18	0.01	0.29	0.17	0.14	0.07	0.29	-0.02	0.29
1983	0.10	0.04	0.22	-0.03	0.03	0.04	0.02	0.02	0.18
1984	0.21	0.05	0.25	0.04	0.07	0.10	0.19	0.02	0.20
1985	0.04	0.01	0.09	-0.13	-0.06	-0.01	-0.05	0.01	-0.04
1986	0.40	0.11	0.32	-0.67	-0.24	-0.13	0.55	0.03	-0.06
1987	-0.10	-0.05	0.02	0.04	0.03	0.03	-0.15	-0.06	0.01
1988	0.19	0.13	0.15	0.02	0.12	0.13	0.13	0.07	0.17
1989	0.01	0.00	0.00	0.03	0.01	0.01	0.02	0.01	0.02
1990	0.01	0.02	0.03	-0.21	0.03	0.04	0.04	0.01	-0.12
1991	0.06	0.06	0.07	-0.05	0.05	0.05	0.04	0.06	0.06
1992	-0.01	0.01	-0.15	-0.47	-0.04	-0.08	-0.17	-0.14	-0.13
1993	0.00	0.00	0.06	0.03	0.05	0.06	-0.07	0.03	0.02
1994	0.19	0.16	0.10	0.06	0.13	0.12	0.14	0.07	0.13
1995	0.00	-0.01	-0.04	-0.10	-0.01	-0.01	-0.01	-0.04	0.05
1996	0.01	0.01	0.00	-0.02	0.00	0.00	0.00	0.01	-0.01
1997	-0.03	-0.01	-0.01	0.00	0.00	0.00	-0.02	0.00	-0.01
1998	0.23	0.16	0.25	0.12	0.10	0.14	0.17	0.10	0.15
DM statistic	0.07***	0.04**	0.07***	-0.02	0.03*	0.03***	0.07**	0.01	0.04**
Non-param- test	5.21***	4.16***	4.17***	0.26	3.35***	3.54***	3.35***	2.01**	2.04*

The table shows the mean loss differential of a forecast based on the lagged inflation rate only (benchmark model) and a VAR forecast based on the inflation rate and the respective output or output gap measure. A positve number indicates that the latter forecast is better. *** (**, *) denotes rejection of the null hypothesis of equal forecast accuracy at the 1 (5, 10) percent level according to the modified Diebold and Mariano (1995) test

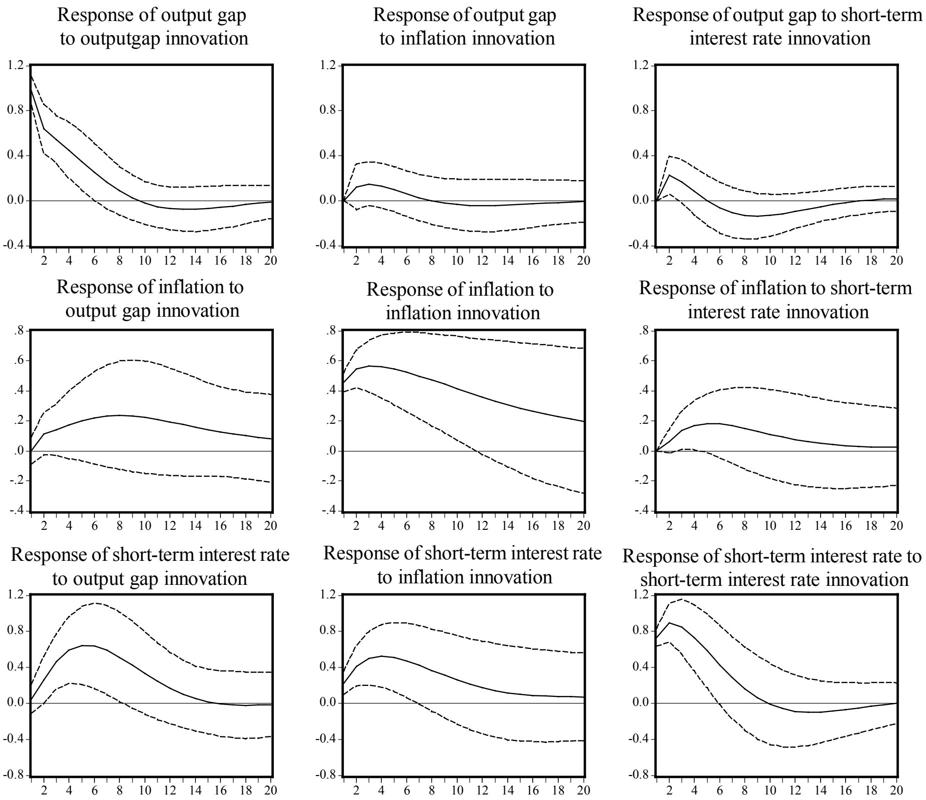
4. 5 Identification of macroeconomic shocks

To gain further insight into the importance of the use of real-time data for output gaps for macroeconomic research, a vectorautoregressive (VAR) model is considered (Croushore and Stark 2000). The model analysed in this paper can be justified on the grounds of the Taylor consensus (Taylor 2000). This model can be seen as the workhorse of modern macroeconomics. In a benchmark system this model is built on three equations: an IS function relating the output gap to a real interest rate, a simplified Phillips curve equation linking the development of inflation to the output gap, and a monetary reaction function which stipulates that the authorities react to both the inflation rate and the level of the output gap. Thus, the dynamic interaction of three variables is of particular interest: the inflation rate (π_t), the short-term interest rate (i_t), and the output gap (gap_t). Consequently, the vector of endogenous variables is given by $X_t = \begin{bmatrix} \pi_t \\ gap_t \\ i_t \end{bmatrix}$. The reduced-form VAR model takes the form:

$$X_t = \Theta(L)X_{t-1} + \varepsilon_t \tag{9}$$

In (9), the matrix polynomial $\Theta(L)$ contains the coefficients to be estimated, and the residuals (ε_t) have the variance-covariance matrix $Var(\varepsilon_t) = \Sigma_\varepsilon$. To begin with, the VAR is estimated for a given sample and data vintage, namely for the period 1968-1998 and based on data available in 1998. The length of the lag polynomial was set equal to 2. This choice was based on information criteria and on lag exclusion tests, which are not reported here but are available upon request from the author. Figure 3 depicts the impulse response functions of the VAR obtained in the following order: output gap, inflation, and interest rate (see also Rudebusch and Svensson 1998 and Giordani 2001). In a nutshell, the response functions match the results of previous studies. Hence, it is useful to check, whether these impulse response functions depend on the data set used.

Figure 4: Impulse-response functions of three variable VAR (quarters after shock)



The output gap responds positively to innovations in the output equation, slightly and insignificantly positively to shocks in the inflation equation and negatively to shocks in the interest rate equation. This impulse response function is, however, positive in the first quarters after the shock, which is at odds with an interpretation of this innovation as a monetary shock. Despite the difficult-to-understand short-run behaviour, the medium-term response meets economic prejudice: a higher interest rate lowers the output gap for a while, but not permanently, since the output gap is a stationary variable. As the negative impact is relatively small, the model might still serve as a benchmark.

As regards the inflation rate, two impulse response functions are in line with common expectations: the inflation rate responds positively to its own innovations, which reflects the well-documented fact of inflation persistence, and it also responds positively to output gap innovations, ie booms tend to increase the inflation rate. The last impulse response function confirms a puzzle frequently documented in the relevant literature. An increase in the short-run interest rate tends to raise rather than lower the inflation rate. Several explanations have been offered for this puzzle (see Giordani 2001 for a survey). For the purpose of this analysis, it is not necessary to "solve" this puzzle. Rather, this analysis will check whether the use of real-time data helps us to understand this puzzle – or makes it even less comprehensible.

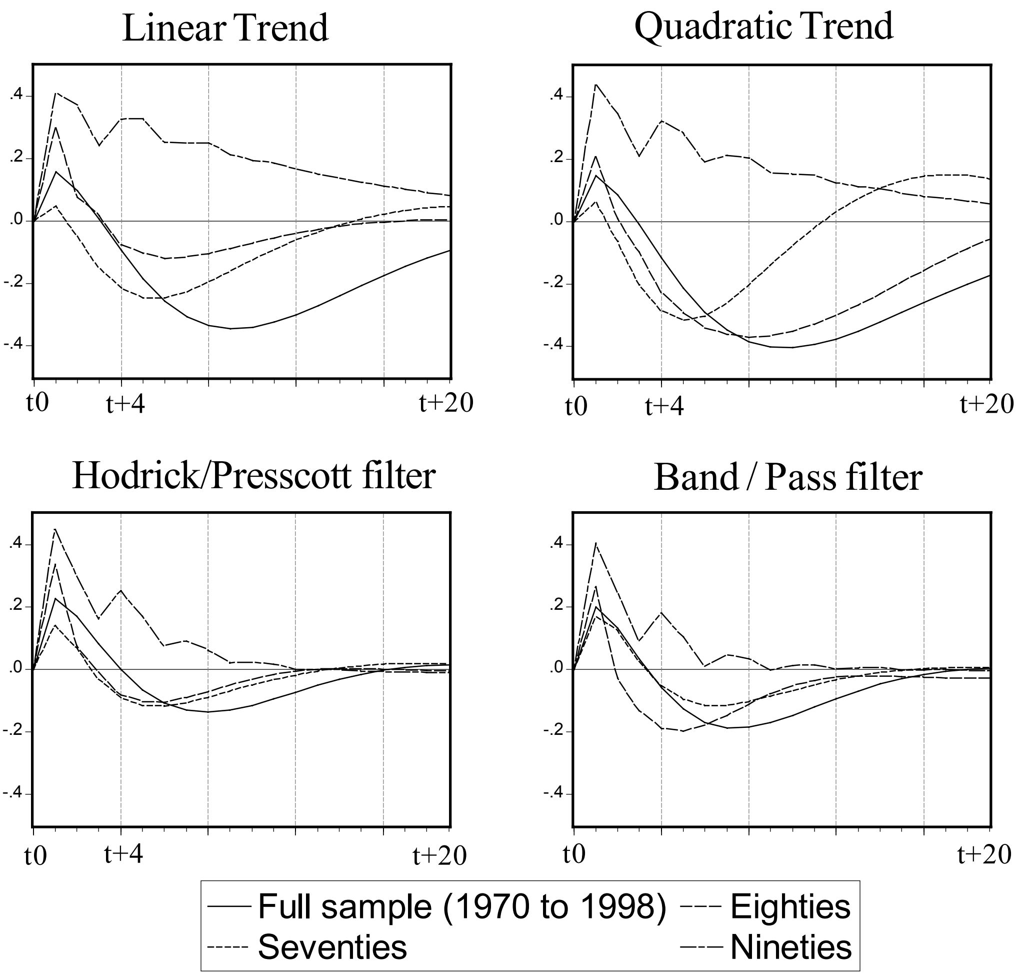
The responses of the short-term interest rate to innovations also unveil a prominent puzzle, the "liquidity puzzle". While an increase in the interest rate in the light of a positive output gap and inflation innovations is plausible, the strong persistence of short-term interest rates raises the question as to why monetary authorities respond to their own decisions on short-term rates with yet another interest rate move in the same direction. Again, we will leave the puzzle for now and discuss instead whether real-time data are helpful in explaining it.

The first question is whether the dynamic interaction between the three variables at hand has changed over time. To illustrate this point, figure 5 compares the response of the output gap to an innovation in the short-term interest rate. The results suggest that, first, the choice of the output gap measure matters for the judgement on the dynamics of the VAR. Even for a given data set, the impulse-response function differs considerably. Second, the estimations show clearly that the impulse-response function changes over time. The responses for a given method differ for alternative time periods.

This fact, however, is not a clear-cut indication that the real-time problem has any influence on the impulse-response functions. Rather, the possibility of a structural break cannot be ruled out, ie the dynamics captured in the VAR itself may have changed. To gain further insights into this problem, a VAR for a given sample (the 1970s) has been estimated based on different data vintages. For this purpose, the impulse-response functions that represent the two puzzles mentioned above have been chosen.

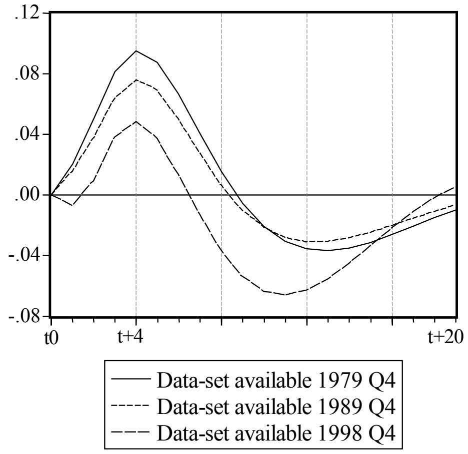
Figure 6 shows the amount of the price puzzle in a VAR estimated for the 1970s. Qualitatively, the results do not differ at all. Quantitatively, however, the response of inflation to interest rate shocks differs depending on the data set used. The price puzzle is largest for the most recent data set and becomes smaller the more data have been used to estimate the gap.

Figure 5: Impulse responses of the output gap to innovations in the interest rate equation based on different data sets and alternative methods of estimating the output gap



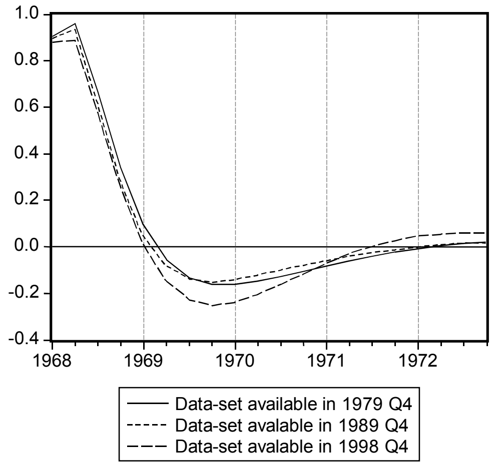
Note: The figure depicts the dynamic response of the output gap to a one standard deviation innovation in the interest rate equation.

Figure 6: Data vintage and impulse-response functions: the "price puzzle"



Note: The figure depicts the dynamic response of the inflation rate to a one standard deviation innovation in the interest rate equation.

Figure 7: Data vintage and impulse-response functions: interest rate persistence



Note: The figure depicts the dynamic response of the interest rate to a one standard deviation innovation in the interest rate equation.

As can be seen from figure7, the persistence of short-run interest rates is almost completely independent of the underlying data set. Thus, taking the evidence together, the impact of different data sets on the qualitative behaviour of impulse responses seems to be quite small, though sometimes the impact might be quantitatively important. All in all, the results are broadly in line with the findings of Croushore and Evans (2003), who conclude that "(…) the use of revised data in VAR analyses of monetary shocks may not be a serious limitation".

4. 6 The robustness of stylised facts

Given that real-time and final estimates differ considerably, the question arises as to whether well-established stylised facts of the business cycle are robust against the choice of a data vintage. Following Stark (2000), the discussion will focus on the contemporaneous correlation of the output gap and the detrended price level and the inflation rate. Authors who argue that supply-side shocks might be important for business cycle fluctuations have stressed this correlation. Table 9 shows the correlation of real-time and final output gaps with the respective price figure.

Table 9: Real-time data and the output-price correlation, 1980 I to 2001 IV

	Contemporaneous correlation based on	
Method	Real-time data	Final data
	With detrended price level	
Change from previous year	-0.43*	-0.42*
Change from previous quarter	-0.15	-0.20*
Linear trend	-0.54*	-0.27*
Quadratic trend	-0.51*	-0.26*
Hodrick-Prescott filter	-0.46*	-0.16
Hodrick-Prescott filter, incl forecasts	-0.57*	-0.16
Band-pass (6,32) filter	-0.62*	-0.20*
Unobserved component model	-0.24*	-0.29*
	With inflation rate	
Change from previous year	-0.34*	-0.29*
Change from previous quarter	-0.20*	-0.20*
Linear trend	-0.05	0.50*
Quadratic trend	-0.07	0.37*
Hodrick-Prescott filter	-0.47*	0.24*
Hodrick-Prescott filter, incl forecasts	-0.32*	0.25*
Band-pass (6,32) filter	-0.20*	0.26*
Unobserved component model	0.22*	0.39*

Notes: The table gives contemporaneous correlation coefficients. * a correlation significantly different from zero according to the rule of thumb $2/\sqrt{n} = 0.18$.

As regards the correlation with the detrended price level, nothing changes qualitatively when real-time data are used in place of the latest data. The picture is less clear for the correlation with the inflation rate. In this case, the differences are generally large. Sometimes even the sign of the correlation changes. Hence, the results suggest that major stylised facts of the business cycle might not be robust against the use of real-time data.

5 Conclusions

As usual, the most obvious conclusion of this paper is, that it points to the need of further research. The first and most urgent item on the agenda is the inclusion of additional methods of estimating the output gap in the analysis. However, the results of Orphanides and van Norden (2002) suggest that the problems with real-time output gaps cannot be resolved by using more sophisticated methods. Moreover, the simple trend extraction methods used in this paper are of some practical relevance for the analysis of the German business cycles, since production function approaches (which are the dominant method of estimating Germany's output gap) depend heavily on the assumed trend model. Second, more real-time data are necessary. The availability of such data would make it possible to use multivariate methods to estimate potential GDP. Furthermore, the discussion of the stability of prominent empirical results and stylised facts of the business cycle would rest on more solid footing if all involved data were real-time data. Third, on the methodological side, possibilities of reducing the measurement error of output gaps should be discussed. For example, it is well known that the end-of-sample properties of filters may be improved by using forecast data (Mohr 2001). Fourth, the consequences of real-time data for both policy decisions and forecasting must be addressed more carefully. Given the preliminary nature of this paper, all these topics are left for further research.

Given the limitations mentioned above, it would be premature to draw too far-ranging conclusions from the results. However, some conclusions can and should be drawn. First, the notion that the quality of real-time estimates of the output gap is rather poor is strongly confirmed by the German data. Hence the results strongly support the scepticism on the usefulness of output gaps estimates in real time raised by Orphanides and van Norden (2002), among others. Of course, the methods differ in respect to the alternative criteria, which are used to evaluate the real-time estimates as it is summarised in table 10. However, it is not possible to find a single method that dominates that others according to all criteria. From this it might be concluded, that the problem lies in output gap estimates itself, or, more precisely, in the information available in real-time, when estimating a gap, rather than in the limitation of one particular method applied.

Table 10: Overview over selected results

Method	Revisions [1]	Rational Expectation?	Information Content for final estimate?	Information Content for Inflation? [2]
Change from previous year	Small	Yes	Yes	High
Change from previous quarter	Small	Yes	Yes	Medium
Linear trend	Medium	No	Yes	High
Quadratic trend	Large	No	Yes	None
Hodrick/Prescott filter	Large	No	Yes	Low
Hodrick/Prescott filter, incl. Forecasts	Large	Yes	Yes	High
Band-pass (6,32) filter	Large	Yes	Yes	Medium
Unobserved component model	Large	No	Yes	None

[1] Small: Noise-to-signal ratio < 0.5, Medium: 0.5 < Noise-to-signal ratio 0.75, Large: Noise-to-signal ratio > 0.75 (see table 1). — [2] High: DM-test significant at the 1 % level, Medium: DM-test significant at the 5 % level, Low: DM test significant at the 10 % level, None: DM-Test insignificant (see table 8).

Second, it should be noted that the main source of the revisions of the output gap measures is *not* the revision of the underlying data set but the end-of-sample problem of the estimators used. For example, the results regarding simple growth rates appear to be much more robust to changes in the data vintage than output gap estimates. Third, the information content for future inflation, the dynamic interaction between inflation and the output gap and some stylised business cycle facts are apparently affected by the use of real-time data. However, the impact on these techniques seems to be rather limited and less systematic.

To sum up, the degree of uncertainty regarding the level of the current output gap is enormous. This is, of course, a challenge for stabilisation policy. If the current business cycle position is not clear, stabilisation policy is hard to justify. It would be premature, however, to argue that policy authorities should ignore the output gap. There are several ways we can try to improve our knowledge. For example, one can try to find methods of estimating the output gap with better real-time properties. But even if one has to admit that estimating the current level of the output gap is likely to remain difficult, this does not imply that this series should be ignored completely. A broad strand of the literature addresses the question of how to deal with output gap uncertainty. For example, it is possible to refer to a so-called “speed limit” policy, ie a policy relying on the change of the output gap rather than on its level (see Orphanides and Williams 2002).

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