Monetary Policy in Real-Time Situations: The Relevance of Simple Instrument Rules

Heinz Glück* and
Stefan P. Schleicher**

There is a long tradition of Austrian, or neo-Austrian, economics within which the scope for policy action is limited on the grounds that the knowledge base of policymakers is insufficient,…

(Sheila Dow, 2002)

Abstract

Policy formulation, evaluation and interpretation by means of simple policy rules, as for instance the popular Taylor rule, have attracted much attention in recent years. Such rules have not only been viewed as guidelines to (the transparency of) policy decisions, but also as benchmarks for predicting future policy and as a tool to judge whether current or past policy has been appropriately set. Furthermore, they have an important role in inflation targeting.

It has been pointed out, however, that results will be misleading, if policy reaction functions, whose parameters are estimated on the basis of "final"data, are used for understanding how policymakers react in real-time situations (Orphanides, 2001). The problem is aggravated by the fact that in monetary policy the necessity to take into

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* *Heinz Glück, Oesterreichische Nationalbank, Austria.*

** *Stefan P. Schleicher, University of Graz, Austria.*

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account long lags leaves the policymaker with rather long-term forecasts for the variables entering his reaction function.

In order to obtain a better understanding of these real-time data issues we evaluate accuracy and efficiency of OECD's forecasts for the G7 countries, paying attention to ex-post data revisions. Apart from a rather disappointing forecast performance over horizons of more than one year, we identify significant biases in the forecasts and a rather different behavior among countries as to data revisions. We find significant differences between Taylor rules estimated over revised data as compared to those estimated over real-time data that are still subject to later revisions.

Further, we suggest methods to correct forecast data for some of these defects, thus enabling a policymaker to use more efficiently the information set available at a certain moment of time. We propose procedures to control for distorting influences on the rule's data input and show that policy errors can be reduced. Generally, however, our results support scepticism against the use of simple instrumental rules in practical monetary policy, mainly because they imply large policy errors if they are based on unadjusted real-time input data.

Keywords: monetary policy rules, economic forecasting, OECD, real-time data
JEL Classification: C53, E52

1 Introduction

In approaching the European Union (EU) and, in further course, the Economic and Monetary Union (EMU), considerations concerning the conduct of monetary policy and exchange rate policy are important issues. There are numerous papers dealing with exchange rate strategies which could be useful for preparing the ground for convergence and final entrance into the Exchange Rate Mechanism (ERM II).

Monetary policy will have to support these endeavours by designing and implementing a framework which should be conducive for the fulfillment of the well-known Maastricht criteria, most of all the inflation criterion. In this context, the currently very much advocated strategy of inflation targeting is a policy option. Some of the new member states of the EU, namely Poland, the Czech Republic and Hungary, follow policies of this kind.

Inflation targeting – sometimes also inflation-forecast targeting – is to be regarded as an approach to the conduct of monetary policy that focuses on a clearly defined target for the inflation rate which has to be hit or not exceeded. In following such a strategy, an important role is assigned to quantitative projections of the economy’s future evolution, and there is a strong commitment to a high degree of transparency and communication as to the goals, the decisions and the principles guiding this policy (Woodford, 2004).

Inflation targeting is closely related to the concept of “monetary policy rules”, and research on such rules has strongly intensified over the last years. In its simplest form, as for instance the well-known Taylor rule, the monetary policy instrument (mostly a short-term interest rate under the control of the central bank) is a function of a small subset of information relating to the economy’s current (and future) situation (mainly the evolution of inflation and output). Rules of this kind have been termed “simple instrument rules”.

For different reasons, these simple instrument rules have come under critique recently. Svensson (2003) has judged them as “inadequate as a description of real-world inflation targeting” and even their use as mere guidelines as “incomplete and too vague to be operational”. It has become clear that there seems to exist a gap between the academic discussion and the current practice of central banking where the opinion prevails that a mechanical application of instrument rules is not appropriate and that some amount of discretion has to be retained.

Moreover, as monetary policy operates on long and variable lags, current policy decisions are made on the basis of assumptions and forecasts about the state of the economy in the future rather than on the basis of the actual state. When current policies are chosen, policymakers are uncertain about the state of the economy which is to prevail at the time the planned policy is expected to impact.

Thus, the literature on policy rules and, especially, on forecast-based rules, brought the problem of forecast quality and reliability to the forefront. Some authors found that such forecast-based rules seemed to be able to control better for current and future inflation (Batini and Haldane, 1999). Ex post, however, forecasts might turn out to be quite wrong, most likely if also forecasts for national account data enter the rule (as in the case of flexible inflation targeting), implying policy error and welfare losses.

In this context, Orphanides (2001) has pointed out that: "The discussion (on monetary policy rules),…., often does not place proper emphasis on the informational problem associated with some of the advocated policy rules." Taking into account that the policymaker when making a decision has at his disposal only forecast values for the arguments entering his reaction function, Orphanides argues that the weights attached to these arguments when estimated by means of "realised" or revised data could be rather misleading. A voluminous literature on "real-time issues" was elicited by this observation, and there is an ongoing debate about its implications. Thus far, the evidence on whether it really matters if a central bank uses real-time data or final data is not yet clear. Orphanides (2001) finds that revisions of recommendations tend to be "very large" comparing results from these two data sets, whereas Adema (2003) for "quasi-real time" data as well as Bernanke and Boivin (2000) and others cannot find much difference.

In this paper we want to concentrate on a problem which we feel has been somewhat neglected in this context, namely: Is the quality of forecasts for the aggregates in question sufficiently reliable to base rules and monetary decisions with possibly far-reaching consequences on it? We will show that this is not the case and together with the additional fact of frequent and significant data revisions this implies high uncertainty concerning the parameters to be used in such rules, thus increasing potential policy error.

One has to be aware that there exists a complex set of errors and mistakes which threaten to be incurred if monetary policy rules whose parameter values are obtained from estimation over "final" data from the past are applied to real-time decisions. Generally, at least three sources of potential mistakes can be observed:

- Forecast uncertainty: The policymaker wishing to influence some future outcome in an optimal sense has, as mentioned, at his disposal only forecasts for the period in question. These forecasts may be wrong and the mistake usually is the larger the longer the forecast horizon is. Thus, for the sensible application of a monetary policy rule, first of all it has to be asked what the forecast horizon will be starting from which the forecast performance shows some reliability.
- Forecast bias: Errors do not sum up to zero over time, but in many cases forecasts can be shown to be severely biased. If such biases can be identified, is it possible and does it make sense to correct for them in order to bring the policymaker's real-time decision closer to "reality"?
- Data revisions: In some cases – apart from the fact that significant revisions can be observed - there seem to exist systematic components in the revision process. Again, if identifiable, can these be incorporated into some correction mechanism?

Neglecting these problems may render simple instrument rules estimated over revised data practically irrelevant for real-time decisions and may lead to an interest rate setting consistently too high or too low with high costs incurred by such policy errors. By close examination of OECD forecasts[1] we try to obtain some estimates of the size and evolution of these mistakes by evaluating forecasts over longer periods, by calculating the forecast errors over changing forecast horizons, by investigating for biases, and by observing the ex-post data revisions. Thus, the policy error incurred by a "final-data Taylor rule" as compared to a "real-time Taylor rule" can be enumerated and procedures be developed to correct for these distortions.

The outline of the paper is as follows: In section 2 we explain the content of our data base and quantify forecast errors and biases. In section 3 we examine the difference between „real-time data" and „last reported data" Taylor rules and we experiment with different procedures to improve the information content of data available in the real-time situation. In section 4 we draw our conclusions.

[1] *See Glück, Schleicher and Catena (2000). We want to point out that it is not our intention to blame anybody for deficiencies of forecast quality. It is our intention here to learn from the observed problems and try to develop procedures to improve upon them.*

2 Dynamics and Bias in Forecasting

There is a vast literature on the evaluation of forecast accuracy trying to discriminate between models based on their relative forecasting record. Although this seems to be potentially an objective criterion, considerable difficulties remain nonetheless.

The first difficulty inherent in such an exercise relates to the measurement of forecast quality. What should be the appropriate metric? As regards *quantitative* measures, there are many to choose from – absolute errors, root mean square errors, Theil's U, etc. Similarly, a number of *qualitative* measures are available. For instance, we might be interested in correctly predicting turning points. Alternatively, we might be more interested in the forecast 'story'. It is widely acknowledged that accurate short-run forecasts are better made by small time series or reduced form models than by structural relations. Such time series models, however, have limited economic content. Policy institutions, by contrast, typically value the economic content of a forecast since it facilitates internal and external communication and allows them to conceptualise risks and scenarios around the forecast.

Second, even if we assume that some suitable forecasting metric can be found, there still remains the question of how one interprets and makes use of that metric. For example, over which horizon do we judge performance? Results will inevitably differ at different forecast horizons. Moreover, ex-post data revisions will change those errors. Indeed, even if we can identify the best (ex-post) performer, there is no guarantee that this will extrapolate into the future. It should also be borne in mind that small forecast failure does not necessarily imply that the model is well-specified; the forecast error is a compound of different errors – specification (i.e. model) errors, errors in residual adjustment and errors in exogenous assumptions, and it is not clear how to disentangle these different aspects. For many projection exercises, the outcome is a combination of model and off-model judgment.

Recent papers[2], however, conclude that more serious problems are involved in forecasting than the simple aspect of accuracy, namely bias, rationality and efficiency as well as the problem of data revisions. It is found that efficiency does not seem to be guaranteed, as shown for instance by Joutz and Stekler (2000) as well as by Loungani (2000), and obviously there are extended periods of bias towards systematic over- or

[2] *A more elaborate review of this literature was given in Glück, Schleicher and Catena (2000).*

underestimation. Whereas Joutz and Stekler in their study of the Fed forecasts find that on average these were unbiased, Loungani (2000) in his investigation on private sector forecasts finds evidence of an upward bias. These results relate predominantly to GDP forecasts, but generally it can be supposed that they also apply to previsions of inflation.

In the following, we put special emphasis on the *dynamic* aspects of the forecasting and data revision processes and on biases as this will provide us with a data base appropriate to deal with some of the problems discussed above. For this purpose, as mentioned, we take under scrutiny the forecasts of the Organisation of Economic Cooperation and Development (OECD).

2.1 Data Base

Since the sixties, the OECD in its *Economic Outlook* has been publishing forecasts for some of its member countries. Projections for the major macroeconomic aggregates are published twice a year, one in June (mid-year forecast) and one in December (end-year forecast). Originally, the first forecast for a particular year was the mid-year forecast one year ahead. This has been extended in the late seventies to the end-year forecast two years ahead. Thus, for instance, the first forecast for 2006 is published in December 2004.

We analyze the gross domestic product (GDP) and consumer price forecasts, both in rates of change, for the G7 countries (USA, Japan, Germany, United Kingdom, France, Italy and Canada). The basic data for this study were taken from every published *Economic Outlook* since 1967. The evolution of forecasts for the particular years as well as the data revisions constitute the data base which is analyzed. That sums up to nine estimates (one two-year-ahead estimate, two one-year-ahead, two current year and two estimates each one year and two years after) for every country. These estimates are compared to the final data, where “final” still means preliminary and should better be termed “last reported” since many countries continue to revise data. The final data in this study are the last reported values for every year that were published in late 2003.

For several reasons, these forecasts are tempting for a thorough analysis. First, the forecasting process in these institutions obviously takes into account a lot of national and international information and political influence cannot be fully excluded. Second, the sequence of these forecasts provides a good documentation of the gradual revisions of the forecasts, since five semi-annual revisions for the predictions of a particular year are available. Third, a very special feature of this data base is the documentation of the data revision process that follows afterwards which can be traced over four additional estimates (revisions) of the data for a particular year.

Some examples of this sequence of forecasts and data revisions are shown in Graphs 1 to 3 on the following page for the evolution of GDP rates and inflation rates from the OECD data set and, for comparison, from IMF. As a first impression we observe large adjustments in the GDP forecasts, but much more stability in the inflation predictions.

This data base offers the possibility to investigate

- if there is an improvement of forecasting accuracy over the sample period and in the data revision process[3],
- if regularities in forecasts and data revisions can be used to adjust the preliminary data in order to obtain estimates that are closer to the final data and
- if there are major differences with respect to the quality of forecasts among the G7 countries.

2.2 Forecast and Revision Dynamics

Formally, we observe the evolution of the value for a variable y at time t for which information is available at time t-τ. We talk about

$$\textit{forecasts} \text{ if } \tau = 0, 1, 2, \ldots$$

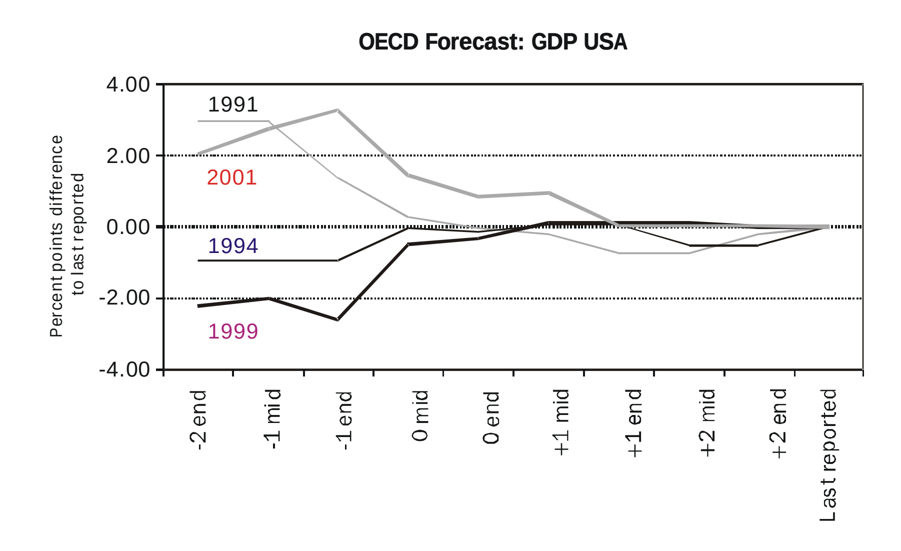
and about

$$\textit{data revisions} \text{ if } \tau = -1, -2, \ldots$$

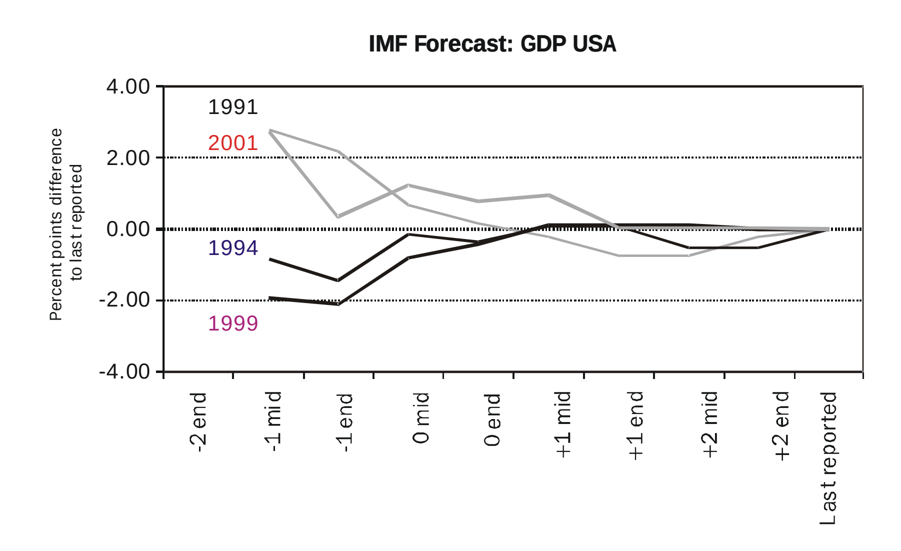
In the following we will treat both cases symmetrically and denote by estimate a particular variable y at time t based on information at *t*-τ by $y^e_{t|t-\tau}$.

[3] *This was extensively analysed in Glück, Schleicher and Catena (2000). No improvement in forecast quality could be diagnosed.*

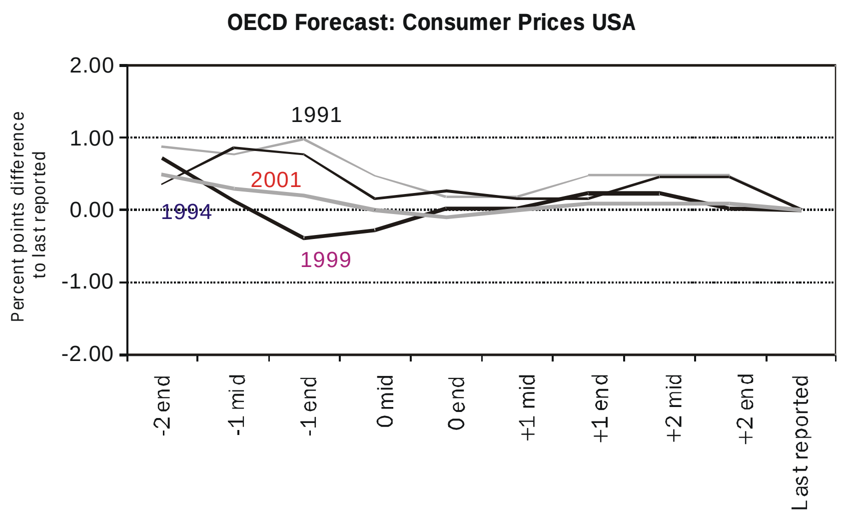
Graph 1. **OECD forecasts and data revisions: GDP USA**



Graph 2. **IMF forecasts and data revisions: GDP USA**



Graph 3. **OECD forecasts and data revisions: Consumer prices USA**



The relationship between the last reported value of variable y_t and the estimate made at different periods τ before (forecast) or after period t (data revision) $y^e_{t|t-\tau}$ and the corresponding estimation error $e_{t|t-\tau}$ is

(1) $$y_t = y^e_{t|t-\tau} + e_{t|t-\tau}, \quad \tau = -2, -1, 0, 1, 2.$$

Tables A.1 and A.2 in the Annex report the error analysis for relation (1). For rates of change of GDP and of consumer price deflators various vintages of estimates and last reported values are compared for the G7 countries, using the following country abbreviations: *United States* (USA), *Japan* (JPN), *Germany* (DEU), *United Kingdom* (GBR), *France* (FRA), *Italy* (ITA) and *Canada* (CAN). The rows in the tables refer to the dates when the corresponding estimates (predictions or data revisions) were published.

The general impression we get from Tables A.1 and A.2 corresponds to what we would expect as to forecast errors which improve with the age of an estimate. But it may not be that plausible that the data revision process continues with remarkably pronounced errors over more than two years after the date a forecast belongs to. From the beginning of the forecast sequence, the precision of inflation forecasts is higher than for GDP growth.

As to GDP, all countries seem to have a tendency towards starting with an overestimation, except the USA. More details will be revealed in the error model which we will present below. For the United States we discover a substantial and systematic underestimation both during the forecast as well as the data revision period. Quite the reverse holds true for Japan. This country's GDP is systematically overestimated (as indicated by negative average errors) in both periods. Compared to this, Germany and France show a very different error behavior: They start with an overestimation of the GDP growth rates but the errors quickly converge to zero and stay there. This means that both countries hardly revise their data afterwards[4]. Italy and the United Kingdom start out with overestimates in their first forecasts but keep underestimating during forecast and data revisions. A similar behavior is exhibited by Canada with a pronounced overestimation of its first forecast.

2.3 Error Model of Dated Estimates

Next, we investigate the relationship between dated estimates for forecasts and data revisions and the last reported values by specifying the following error model:

(2) $$y_t = b_0 + b_1 y^e_{t|t-\tau} + u_{t|t-\tau} \quad \tau = -2, -1, 0, 1, 2$$

Thus we estimate the linear relationship between the final (last reported) series y_t and its dated estimates $y^e_{t|t-\tau}$, covering both forecasts (if τ = 2, 1, 0) and data revisions (if τ = -1, -2).

We use model (2) to test the joint hypothesis that the coefficients b_0 and b_1 do not differ significantly from 0 and 1, respectively, and that there is no serial correlation in the errors, as is required for efficiency and unbiasedness. In addition, we would expect that the sequence of these regressions shows convergence both with respect to the parameters b_0 and b_1, the improvement of the overall fit (as reported by R^2) and a lowering of serial correlation (indicated by the *DW* statistic). The results of these regressions for GDP forecasts are reported in Tables A.3 and A.4 in the Annex. A summary of these results expressed by the multiple coefficient of correlation is contained in Tables 1a and b.

[4] *It remains open if this is to be interpreted as proof of an excellent quality of the data generating process or rather as neglect of information coming up later.*

Thus, the impression gained from visual inspection of Graphs 1 to 3 is confirmed by the error model: The forecast record for GDP growth rates is quite disappointing; the first two published forecasts contain hardly any relationship to the last reported values. There is convergence towards b_0 = 0 and b_1 = 1, but only very late in the revision period and not in the forecasting phase.

Estimates for inflation rates, however, are much more accurate than estimates for GDP growth. The end-year inflation forecast two years ahead captures on average more than 50% of the variance of the last reported data. This means that inflation forecasts contain more useful information that can be incorporated into monetary policy rules. Thus, in the following we will concentrate mainly on the GDP forecasts, as they seem to be the source of larger potential errors than the inflation forecasts.

Table 1a. **Error analysis for dated estimates of GDP**

Date of estimate	R^2						
	USA	**JPN**	**DEU**	**GBR**	**FRA**	**ITA**	**CAN**
2 ys. ahead (end)	0.000	0.012	0.050	0.108	0.287	0.100	0.185
1 y. ahead (mid)	0.191	0.071	0.000	0.068	0.035	0.000	0.110
1y. ahead (end)	0.587	0.584	0.428	0.408	0.516	0.416	0.423
Current year (mid)	0.804	0.779	0.769	0.853	0.747	0.627	0.734
Current year (end)	0.883	0.920	0.898	0.871	0.929	0.821	0.837
1 y. after (mid)	0.900	0.954	0.915	0.909	0.908	0.889	0.905
1 y. after (end)	0.947	0.950	0.919	0.919	0.936	0.898	0.914
2 ys. after (mid)	0.947	0.956	0.914	0.918	0.945	0.883	0.923

Source: Calculated from OECD Economic Outlook.

Table 1b. **Error analysis for dated estimates of consumer prices**

Date of estimate	R^2						
	USA	**JPN**	**DEU**	**GBR**	**FRA**	**ITA**	**CAN**
2 ys. ahead (end)	0.525	0.731	0.707	0.711	0.579	0.575	0.683
1 y. ahead (mid)	0.780	0.750	0.537	0.649	0.930	0.941	0.894
1y. ahead (end)	0.850	0.865	0.760	0.884	0.956	0.939	0.936
Current year (mid)	0.987	0.931	0.915	0.906	0.984	0.983	0.962
Current year (end)	0.980	0.929	0.943	0.960	0.992	0.992	0.985
1 y. after (mid)	0.979	0.947	0.940	0.976	0.995	0.992	0.983
1 y. after (end)	0.977	0.945	0.936	0.981	0.994	0.994	0.982
2 ys. after (mid)	0.977	0.940	0.938	0.983	0.994	0.995	0.981

Source: Calculated from OECD Economic Outlook.

We conclude that since all estimates of one-year ahead forecast produced at the end of the preceding year show a significant relationship between estimated data and last reported data, this fact can be exploited for improving both the dated forecasts and the data revisions in order to obtain combined estimates that come closer to the final series. This will be done in the next section.

3 Overcoming Real-Time Data Problems in the Case of Taylor Rules

Given these data problems, a policymaker faces two options:

- to apply parameter values of instrument rules which are estimated from real-time data, or
- to correct real-time data for the known deficiencies like forecasting and revision errors and - if they can be identified - structural breaks and to re-estimate parameter values of instrument rules accordingly.

In this section we first evaluate the extent of parameter uncertainty caused by real-time issues in the case of Taylor rules and then develop operational procedures for overcoming the problem of dated information.

3.1 The Impact of Dated Information on the Parameters of Taylor Rules

If characterised by simple instrument rules, to what extent does central bank behaviour seem different if observed in real-time situations or, alternatively, if extracted from an ex-post information set? Or, put differently, how would policy reactions change if parameter values gained from last reported data were applied instead of those from real-time data?

In order to investigate this, we estimate Taylor rules using forecast values as arguments. Thus, we regress the short-term interest rate of the current period on the forecasts made a certain time span ahead. As indicated, however, GDP forecasts over horizons of more than one year are of no predictive value; therefore, we estimate Taylor rules based on one-year-ahead forecasts for GDP and inflation. In addition, we apply interest-rate smoothing by including the lagged interest rate, i.e. we regress

(3) $$r_{t|t-1} = \alpha_0 + \alpha_1 p^e_{t|t-1} + \alpha_2 y^e_{t|t-1} + \alpha_3 r_{t-1} + u_{t|t-1}$$

with $p^e_{t|t-1}$ being the inflation rate for year t forecast at time t-1, $y^e_{t|t-1}$ being the forecast output gap for the next year (defined as the difference between smoothed GDP growth as a measure for potential GDP growth and forecast GDP growth). We use equation (3) to generate a forecast for the short-term interest rate $r_{t|t-1}$ in period t by using the forecasts for GDP and inflation available in period *(t-1)* for period *t* [5].

The results[6] of this analysis are summarized in Table 2a. It indicates that for all G7 countries current year's short-run interest rates are significantly related to inflation forecasts made at the end of the preceding year. The size of the estimated coefficients varies between 0.4 and 1.4. The impact of the same dated predictions for GDP gap on short-run interest rates is much weaker and only significant for Japan and United Kingdom.

Table 2a. **Historical evidence of Taylor rules estimated with end-year forecasts one year ahead**

Country	**Inflation**		**GDP gap**		**Lagged dep. var.**		**Constant**		**R^2**	**DW**
	a_1	**t_1**	**a_2**	**t_2**	**a_3**	**t_3**	**a_4**	**t_4**		
USA	0.973	4.07	-0.377	1.33	0.406	2.66	0.697	0.82	0.847	0.97
Japan	0.796	4.79	-0.580	2.40	0.541	4.83	1.522	2.56	0.895	2.07
Germany	1.394	3.07	-0.302	0.88	0.321	1.45	0.676	0.67	0.709	1.45
United Kingdom	0.789	4.19	-1.078	2.90	0.604	3.75	-0.060	0.04	0.817	1.03
France	0.358	3.04	-0.102	0.24	0.656	4.07	1.229	1.17	0.870	1.72
Italy	0.520	3.83	-0.399	0.98	0.625	5.58	0.956	0.94	0.915	1.87
Canada	1.250	3.37	-0.111	0.19	-0.057	0.17	3.665	1.97	0.742	1.44

Source: Own calculations based on data from OECD Economic Outlook, 1980-2001.

[5] *Given the high error in GDP forecasts, we do not invest more sophistication into the calculation of the output gap.*

[6] *Results for the countries participating in the EMU may be slightly distorted by the fact that they followed a common monetary policy as of 1999.*

Table 2b. **Historical evidence of Taylor rules estimated with last reported values**										
Country	**Inflation**		**GDP gap**		**Lagged dep. var.**		**Constant**		**R^2**	**DW**
	a_1	**t_1**	**a_2**	**t_2**	**a_3**	**t_3**	**a_4**	**t_4**		
USA	0.874	7.42	-0.417	3.34	0.514	5.95	0.278	0.52	0.930	1.76
Japan	0.875	4.67	-0.380	2.26	0.481	3.83	1.548	2.88	0.883	2.28
Germany	0.949	5.02	-0.551	2.86	0.500	3.75	0.993	1.46	0.826	1.64
United Kingdom	0.610	4.81	-0.310	1.30	0.457	3.35	1.834	1.51	0.841	1.38
France	0.368	4.07	-0.146	0.53	0.649	5.32	1.210	1.46	0.895	1.63
Italy	0.362	5.07	-0.700	0.24	0.667	6.84	0.709	0.80	0.928	1.97
Canada	0.912	3.77	-0.132	0.44	0.229	0.85	2.650	1.64	0.782	1.74

Source: Own calculations based on data from OECD Economic Outlook, 1980-2001.

For comparison, the estimation results for the same Taylor rule specification, but with last reported values, are contained in Table 2b. We recognize that the significance of the inflation rate increases. As to the GDP gap, in contrast to the estimates based on predictions, the United States and Germany now show significant impacts, but the United Kingdom does not any more.

Compared to the final data rules, as reported in Table 2b, we recognize that in the real-time data rules of Table 2a the reaction to the inflation rate in most cases is somewhat stronger (though the difference is not always statistically significant), whereas for the real-time output gap the significance is reduced. The coefficients on the lagged interest rates suggest that the desire to keep the interest rate stable seems somewhat stronger than in the final data case.

These results seem to point in the direction that central banks in real-time react more actively to deviations in inflation from their targets than rules estimated over final data would suggest, whereas the reaction to deviations in output in most cases seems less significant than for final data.

Thus, it is confirmed that parameters of estimated Taylor rules are rather sensitive with respect to dated sample information. In addition, our investigations showed that there is evidence from CUSUM tests of structural changes.

3.2 Some Proposals to Handle Dated Information

What can be done? We are proposing a procedure which attempts to deal with a real-time policy decision environment that takes into account both the aspect of dated sample information and possible structural changes in the policy reaction behaviour.

As to the problem of dated sample information, we propose two types of sample strategies:

- The *unadjusted sample* only deals with last reported values but neglects the most recent four values because of the evidence of major data revisions.
- The *adjusted sample* also deals with last reported values but replaces the most recent four values by estimates from the measurement error model. This means that the preliminary values for these values are replaced by bias-corrected values.

As far as structural changes are concerned, we also employ two types of sample strategies:

- *Expanding samples* start with a first sample 1980-1990 and expand in annual increments to the final sample 1980-2000.
- *Moving samples* start with a first sample 1980-1990 and move in annual increments with 11 years sample sizes to the final sample 1990-2000.

For both types of samples, based on the estimated parameters, the one-period outside sample forecast for the short-term interest rate from 1991 to 2001 is estimated.

Thus we design four types of real-time simulations in which we apply the information sets that could have been used by policymakers when calculating adequate policy reactions for short-term interest rates from 1991 to 2001. The policy errors resulting from not using these corrected data, measured in means, variance and mean square errors (MSE) of the short-term interest rate are reported in Tables 3a and b.

The results seem to be quite revealing: In the case of expanding samples as reported in Table 3a, e.g. for the United States, interest rates were set too low over the period under consideration by about 30 basis points on average in the unadjusted sample. Adjusting the sample leads to a reduction of the policy error to about 8 basis points, though the variance increases.

In the case of moving samples as reported in Table 3b, we observe again a reduction of the short-term interest rate policy error from an underestimation of 84 basis points to an overestimation of 46 basis points, but a substantial reduction in variance that also reduces the mean square error.

With only two exceptions (USA and Italy) out of 14 simulations, instead of using unadjusted samples the switch to adjusted samples substantially improves the performance as reflected in the decline of the mean square error.

Switching to moving samples improves in eight out of 14 simulations the forecast performance. The reason for this improvement seems to be the handling of structural changes by moving fixed size samples instead of increasing samples.

Table 3a. **Real-time simulation of Taylor rules using expanding samples estimated with dated data values**

	Unadjusted Sample			Adjusted Sample		
	Mean	**Variance**	**MSE**	**Mean**	**Variance**	**MSE**
USA	0.330	1.065	**1.174**	0.080	3.300	**3.306**
Japan	-1.780	4.283	**7.451**	-1.097	1.527	**2.730**
Germany	-0.067	2.865	**2.869**	-0.615	1.060	**1.438**
United Kingdom	-2.392	6.674	**12.396**	-1.138	2.811	**4.106**
France	-0.841	4.816	**5.523**	-0.819	2.066	**2.737**
Italy	-1.491	3.455	**5.678**	-0.888	3.113	**3.902**
Canada	-0.987	3.672	**4.646**	-1.472	1.503	**3.670**

Source: Own calculations based on data from OECD Economic Outlook, sample starts 1980 and expands from 1991 to 2001.

Table 3b. **Real-time simulation of Taylor rules using moving samples estimated with dated data values**

	Unadjusted Sample			Adjusted Sample		
	Mean	**Variance**	**MSE**	**Mean**	**Variance**	**MSE**
USA	0.843	5.703	**6.414**	-0.458	2.965	**3.175**
Japan	0.730	1.482	**2.015**	-0.526	1.111	**1.388**
Germany	0.574	2.087	**2.416**	-0.603	0.536	**0.900**
United Kingdom	-0.559	8.516	**8.828**	0.022	7.422	**7.422**
France	0.239	7.898	**7.955**	-0.840	2.619	**3.325**
Italy	-1.398	3.059	**5.013**	-1.243	3.817	**5.362**
Canada	-0.406	9.827	**9.992**	-0.622	4.424	**4.811**

Source: Own calculations based on data from OECD Economic Outlook, moving 11 year sample start with1980-1990 and move to 1991–2001.

Evidently, what might be regarded as the optimal strategy for handling these data problems, differs among countries. Therefore, we performed on the OECD data set a ranking of the four different sampling strategies for dealing with dated information in the context of Taylor-rule-based interest rate decisions. This ranking, using the mean square error as criterion, is shown in Table 4.

Table 4. **Ranking of sampling strategies**

	Ranking			
	1	**2**	**3**	**4**
USA	unadjusted expanding	adjusted moving	adjusted expanding	unadjusted moving
Japan	adjusted moving	unadjusted moving	adjusted expanding	unadjusted expanding
Germany	adjusted moving	adjusted expanding	unadjusted moving	unadjusted expanding
United Kingdom	adjusted expanding	adjusted moving	unadjusted moving	unadjusted expanding
France	adjusted expanding	adjusted moving	unadjusted expanding	unadjusted moving
Italy	adjusted expanding	unadjusted moving	adjusted moving	unadjusted expanding
Canada	adjusted expanding	adjusted moving	unadjusted expanding	unadjusted moving

Source: Own calculations based on data from OECD Economic Outlook.
Data are "adjusted" if they are modified according to the estimated error model, otherwise they are "unadjusted".
Samples are "expanding" if the sample size increases or "moving" if the sample size is kept constant.

4 Conclusions

We started from the general assertion that a useful monetary policy design should be founded on more realistic assumptions about what policymakers can know at the time when policy decisions have to be made.

Applied to simple instrument rules – if they are to be used as an operational and forward-looking device -, we analyze the reliability of the input information for such rules. We use OECD forecasts for inflation and GDP growth rates and investigate the forecasting performance for these variables. We diagnose a much better forecasting record for inflation rates compared to GDP growth rates, which for most countries are almost uninformative at the time a Taylor rule should sensibly be applied. Using this data set, we find clear differences between Taylor rules if estimated over revised ex-post data or over real-time data, and there is evidence that monetary policy seems to react more actively in real time than rules estimated over revised data suggest.

Since the OECD forecasts for GDP growth rates exhibit systematic errors, in a next step we attempted to correct for these forecast biases and checked to which extent this can lower the errors in interest rate policy setting. An ex-ante simulation for the years 1991 to 2001 supports the proposal that correcting for forecast errors and biases based on an error model can lower the resulting policy error in interest rate setting for most countries under consideration. In addition, we investigate to what extent structural changes in the policy reaction behaviour can be handled with moving instead of expanding samples.

Generally, our analysis supports critics and sceptics of the Taylor rule who argue that a mechanical application of this rule will not be appropriate and should at least be accompanied by a careful examination of a broad set of additional information (as is done, of course, in practice by most central banks).

Svensson (2003) presented a long list of what may be wrong with the Taylor rule. Our results additionally point out the fact that the informational basis – when applying such a rule, for instance, in the case of inflation targeting - needs careful examination. Limited forecast quality and significant data revisions recommend a more sophisticated handling of the dated information for which we present an operational procedure that has the potential of reducing the risk of severe policy errors.

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Annex

Table A.1 **Error analysis of GDP**									
	Means of errors of estimates								
	2 y. ahead	**1 year ahead**		**current year**		**1 year after**		**2 years after**	
	end	**mid**	**end**	**mid**	**end**	**mid**	**end**	**mid**	**end**
USA	0.32	0.35	0.41	0.27	0.38	0.34	0.34	0.36	0.32
JPN	-0.71	-0.25	-0.36	-0.07	-0.15	-0.30	-0.30	-0.35	0.04
DEU	-0.76	-0.60	-0.10	0.06	0.07	0.04	-0.03	-0.04	0.05
FRA	-0.72	-0.36	-0.14	-0.09	0.09	0.04	-0.01	-0.03	0.13
ITA	-0.73	-0.49	0.13	0.28	0.53	0.44	0.49	0.49	0.08
GBR	-0.15	0.36	0.28	0.60	0.61	0.55	0.41	0.36	0.21
CAN	-0.65	-0.44	0.11	0.23	0.47	0.40	0.39	0.36	

Table A.1 **continued**									
	Root mean square of errors of estimates								
	2 y. ahead	**1 year ahead**		**current year**		**1 year after**		**2 years after**	
	end	**mid**	**end**	**mid**	**end**	**mid**	**end**	**mid**	**end**
USA	1.58	1.69	1.37	1.01	0.86	0.79	0.64	0.64	0.55
JPN	2.12	1.98	2.24	1.69	1.21	1.08	1.12	0.96	0.66
DEU	1.92	1.73	1.52	0.99	0.79	0.67	0.68	0.69	0.37
FRA	1.77	1.54	1.22	1.00	0.75	0.63	0.53	0.51	0.40
ITA	1.50	1.38	1.77	1.36	1.08	0.84	0.85	0.91	0.24
GBR	1.30	1.43	1.49	0.94	0.93	0.80	0.68	0.66	0.47
CAN	1.86	2.12	1.58	1.10	1.01	0.77	0.74	0.70	

Table A.1 **continued**									
	Standard deviation of errors of estimates								
	2 y. ahead	**1 year ahead**		**current year**		**1 year after**		**2 years after**	
	end	**mid**	**end**	**mid**	**end**	**mid**	**end**	**mid**	**end**
USA	1.60	1.62	1.47	0.85	0.77	0.70	0.49	0.48	0.47
JPN	2.06	1.93	1.34	0.74	0.99	0.76	0.76	0.59	0.59
DEU	1.82	1.73	1.41	0.91	0.72	0.57	0.55	0.54	0.48
FRA	1.67	1.60	1.15	0.72	0.57	0.48	0.50	0.46	0.44
ITA	1.27	1.22	0.84	0.67	0.47	0.26	0.27	0.23	0.23
GBR	1.33	1.26	1.14	0.79	0.54	0.39	0.38	0.39	0.40
CAN	1.79	1.87	1.76	1.19	0.74	0.58	0.48	0.48	

Table A.2 **Error analysis of consumer prices**

	Means of errors of estimates								
	2 y. ahead	1 year ahead		current year		1 year after		2 years after	
	end	mid	end	mid	end	mid	end	mid	end
USA	-0.55	-0.63	-0.28	-0.07	0.03	0.09	0.01	-0.03	-0.10
JPN	-0.53	-0.63	-0.36	-0.21	-0.06	0.03	0.01	0.02	-0.02
DEU	-0.12	-0.24	-0.09	-0.11	-0.13	-0.12	-0.09	-0.09	-0.15
FRA	0.00	-0.01	0.14	0.04	0.06	0.22	0.21	0.22	0.20
ITA	0.88	0.64	0.92	0.40	0.31	0.21	0.20	0.19	0.21
GBR	0.03	-0.03	-0.02	0.15	0.45	0.44	0.40	0.44	0.34
CAN	-0.40	-0.34	-0.10	-0.07	0.09	0.12	0.09	0.09	

Table A.2 **continued**

	Root mean square of errors of estimates								
	2 y. ahead	1 year ahead		current year		1 year after		2 years after	
	end	mid	end	mid	end	mid	end	mid	end
USA	1.01	1.01	1.01	0.31	0.37	0.37	0.37	0.37	0.38
JPN	0.92	1.12	0.96	0.77	0.71	0.63	0.63	0.57	0.59
DEU	0.80	1.01	0.91	0.60	0.54	0.48	0.48	0.40	0.41
FRA	0.62	0.80	0.87	0.51	0.36	0.38	0.39	0.53	0.30
ITA	1.45	1.16	1.67	0.84	0.58	0.47	0.48	0.42	0.35
GBR	1.33	1.27	1.28	1.19	0.88	0.79	0.69	0.69	0.63
CAN	1.23	1.12	1.02	0.84	0.67	0.57	0.58	0.44	

Table A.2 **continued**

	Standard deviation of errors of estimates								
	2 y. ahead	1 year ahead		current year		1 year after		2 years after	
	end	mid	end	mid	end	mid	end	mid	end
USA	0.88	0.60	0.83	0.31	0.30	0.26	0.23	0.26	0.31
JPN	0.70	0.79	0.80	0.63	0.51	0.51	0.50	0.52	0.52
DEU	0.58	0.64	0.58	0.38	0.37	0.42	0.44	0.43	0.43
FRA	0.65	0.55	0.54	0.32	0.32	0.25	0.27	0.21	0.19
ITA	1.19	1.01	0.92	0.36	0.42	0.30	0.31	0.24	0.26
GBR	1.38	1.37	0.97	1.13	0.88	0.79	0.66	0.64	0.64
CAN	0.81	0.51	0.53	0.44	0.36	0.33	0.30	0.30	

Table A.3 **Error model for GDP**

USA GDP

Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	-0.03	0.1	3.00	2.1	0.000	1.48
1 y. ahead (mid)	1.05	2.2	0.21	0.2	0.191	1.36
1y. ahead (end)	0.89	7.2	0.71	1.8	0.587	1.94
Current year (mid)	0.83	12.0	0.75	3.1	0.804	1.78
Current year (end)	0.85	16.3	0.78	4.3	0.883	1.74
1 y. after (mid)	0.87	17.5	0.69	4.0	0.900	1.48
1 y. after (end)	0.87	24.5	0.67	5.3	0.947	1.69
2 ys. after (mid)	0.89	24.3	0.65	5.0	0.947	1.74

Table A.3 **continued**

JAPAN GDP

Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	0.17	0.4	1.44	1.3	0.012	1.03
1 y. ahead (mid)	0.41	1.3	1.37	1.4	0.071	1.09
1y. ahead (end)	0.83	7.1	0.39	0.6	0.584	1.78
Current year (mid)	0.83	11.1	0.63	1.6	0.779	1.87
Current year (end)	0.81	20.1	0.64	2.8	0.920	1.70
1 y. after (mid)	0.82	26.5	0.51	2.8	0.954	1.95
1 y. after (end)	0.81	25.5	0.53	2.8	0.950	1.91
2 ys. after (mid)	0.86	26.8	0.30	1.6	0.956	1.93

Table A.3 **continued**

GERMANY GDP

Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	-0.78	0.9	3.89	1.6	0.050	1.26
1 y. ahead (mid)	-0.06	0.1	2.02	1.2	0.000	1.05
1y. ahead (end)	1.00	5.2	-0.09	0.5	0.428	1.64
Current year (mid)	0.88	10.7	0.33	1.4	0.769	1.94
Current year (end)	0.81	17.2	0.48	3.1	0.898	1.98
1 y. after (mid)	0.85	19.1	0.38	2.6	0.915	1.80
1 y. after (end)	0.84	19.5	0.35	2.5	0.919	1.71
2 ys. after (mid)	0.83	18.8	0.38	2.5	0.914	1.64

Table A.3 **continued**

UNITED KINGDOM GDP

Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	0.93	1.3	0.01	0.0	0.108	1.22
1 y. ahead (mid)	0.59	1.2	1.28	1.1	0.068	0.86
1y. ahead (end)	0.82	5.0	0.67	1.6	0.408	1.45
Current year (mid)	1.04	14.3	0.53	3.0	0.853	1.84
Current year (end)	0.93	15.3	0.74	4.7	0.871	1.83
1 y. after (mid)	1.03	18.4	0.50	3.5	0.909	2.57
1 y. after (end)	1.02	19.7	0.36	2.6	0.919	2.96
2 ys. after (mid)	1.01	19.2	0.34	2.4	0.918	3.17

Table A.3 **continued**						
FRANCE GDP						
Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	-1.78	2.5	6.67	3.4	0.287	1.14
1 y. ahead (mid)	-0.38	0.8	2.95	2.6	0.035	0.93
1y. ahead (end)	0.85	6.2	0.29	0.7	0.516	1.50
Current year (mid)	0.75	10.2	0.60	2.4	0.747	1.25
Current year (end)	0.86	21.1	0.38	2.8	0.929	1.21
1 y. after (mid)	0.81	18.3	0.55	3.6	0.908	1.45
1 y. after (end)	0.80	15.0	0.60	3.4	0.936	1.22
2 ys. after (mid)	0.85	22.8	0.37	2.8	0.945	0.91
2 ys. after (end)	0.93	10.1	0.26	1.3	0.879	1.12

Table A.3 **continued**						
ITALY GDP						
Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	-1.06	1.3	4.46	2.2	0.100	1.21
1 y. ahead (mid)	-0.02	0.1	1.88	2.0	0.000	1.16
1y. ahead (end)	0.69	5.1	0.95	2.1	0.416	1.42
Current year (mid)	0.88	7.7	0.57	1.6	0.627	1.74
Current year (end)	0.88	12.7	0.76	3.5	0.821	1.61
1 y. after (mid)	0.97	16.5	0.49	2.6	0.889	1.12
1 y. after (end)	0.95	17.3	0.58	3.3	0.898	1.20
2 ys. after (mid)	0.89	15.8	0.75	4.0	0.883	1.39

Table A.3 **continued**						
CANADA GDP						
Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	1.23	1.8	-1.39	0.6	0.185	1.22
1 y. ahead (mid)	0.92	1.6	-0.18	0.1	0.110	1.24
1y. ahead (end)	1.10	5.1	-0.21	0.3	0.423	2.09
Current year (mid)	1.03	9.8	0.12	0.3	0.734	1.75
Current year (end)	0.87	13.4	0.84	3.6	0.837	1.38
1 y. after (mid)	0.93	18.0	0.60	3.2	0.905	1.31
1 y. after (end)	0.94	19.0	0.58	3.2	0.914	1.34
2 ys. after (mid)	0.94	19.9	0.55	3.1	0.923	1.32

Table A.4 **Error model for consumer prices**

USA Consumer Prices

Date of estimate	Estimated variable		Constant		R2	DW
	b_1	t_1	b_0	t_0		
2 ys. ahead (end)	0.65	3.9	0.47	0.9	0.525	1.25
1 y. ahead (mid)	0.67	8.6	0.51	1.7	0.780	1.65
1y. ahead (end)	0.93	11.7	-0.03	0.1	0.850	1.21
Current year (mid)	1.02	41.9	-0.16	1.5	0.987	1.63
Current year (end)	1.02	34.1	-0.07	0.5	0.980	1.48
1 y. after (mid)	1.06	33.2	-0.10	0.7	0.979	1.27
1 y. after (end)	1.06	32.2	-0.20	1.3	0.977	1.32
2 ys. after (mid)	1.06	31.3	-0.25	1.6	0.977	1.57

Table A.4 **continued**

JAPAN Consumer Prices

Date of estimate	Estimated variable		Constant		R2	DW
	b_1	t_1	b_0	t_0		
2 ys. ahead (end)	0.89	6.2	-0.46	2.3	0.731	1.20
1 y. ahead (mid)	0.74	8.0	-0.30	1.6	0.750	2.19
1y. ahead (end)	0.91	12.4	-0.23	1.2	0.865	2.82
Current year (mid)	0.94	18.0	-0.13	0.9	0.931	1.96
Current year (end)	1.07	17.7	-0.14	1.0	0.929	1.52
1 y. after (mid)	0.99	20.7	0.32	0.2	0.947	1.56
1 y. after (end)	1.04	20.4	-0.01	0.8	0.945	1.64
2 ys. after (mid)	1.02	19.0	0.01	0.1	0.940	1.68

Table A.4 **continued**

GERMANY Consumer Prices

Date of estimate	Estimated variable		Constant		R2	DW
	b_1	t_1	b_0	t_0		
2 ys. ahead (end)	1.03	5.8	-0.20	0.5	0.707	1.72
1 y. ahead (mid)	0.91	4.9	-0.06	0.1	0.537	1.52
1y. ahead (end)	1.19	8.9	-0.57	1.5	0.760	1.53
Current year (mid)	1.10	16.1	-0.37	1.9	0.915	1.72
Current year (end)	1.00	19.9	-0.14	0.9	0.943	1.94
1 y. after (mid)	0.98	19.3	-0.11	0.7	0.940	1.89
1 y. after (end)	0.97	18.7	-0.03	0.2	0.936	1.72
2 ys. after (mid)	0.97	18.7	-0.05	0.3	0.938	1.67

Table A.4 **continued**

UNITED KINGDOM Consumer Prices

Date of estimate	Estimated variable		Constant		R2	DW
	b_1	t_1	b_0	t_0		
2 ys. ahead (end)	1.65	5.9	-2.12	2.2	0.711	1.68
1 y. ahead (mid)	0.92	6.2	0.31	0.5	0.649	0.78
1y. ahead (end)	1.06	13.5	-0.33	0.7	0.884	1.06
Current year (mid)	0.92	15.2	0.52	1.3	0.906	1.66
Current year (end)	1.03	24.1	0.29	1.1	0.960	1.28
1 y. after (mid)	1.02	31.1	0.30	1.4	0.976	1.77
1 y. after (end)	0.99	35.0	0.41	2.2	0.981	1.93
2 ys. after (mid)	0.99	36.3	0.47	2.5	0.983	1.47

Table A.4 **continued**						
FRANCE Consumer Prices						
Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	1.23	4.4	-0.44	0.8	0.579	1.17
1 y. ahead (mid)	0.91	16.7	0.28	1.2	0.930	2.31
1y. ahead (end)	1.04	22.8	-0.58	0.2	0.956	1.98
Current year (mid)	0.98	39.0	0.12	0.8	0.984	2.41
Current year (end)	0.99	55.7	0.79	0.7	0.992	1.69
1 y. after (mid)	0.99	0.2	0.24	2.6	0.995	1.82
1 y. after (end)	1.01	62.5	0.12	1.2	0.994	1.23
2 ys. after (mid)	1.01	64.1	0.12	1.2	0.994	1.31

Table A.4 **continued**						
ITALY Consumer Prices						
Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	0.94	4.4	1.09	1.4	0.575	1.48
1 y. ahead (mid)	0.94	18.3	0.96	2.8	0.941	2.33
1y. ahead (end)	1.09	19.2	0.37	0.8	0.939	0.86
Current year (mid)	0.96	37.0	0.69	2.9	0.983	2.52
Current year (end)	0.98	54.6	0.45	2.7	0.992	1.72
1 y. after (mid)	0.98	53.0	0.30	1.6	0.992	1.58
1 y. after (end)	0.99	63.5	0.21	1.3	0.994	1.74
2 ys. after (mid)	0.99	71.3	0.22	1.6	0.995	2.08

Table A.4 continued						
CANADA Consumer Prices						
Date of estimate	**Estimated variable**		**Constant**		**R2**	**DW**
	b_1	**t_1**	**b_0**	**t_0**		
2 ys. ahead (end)	0.69	5.5	0.40	1.1	0.683	1.26
1 y. ahead (mid)	0.83	13.3	0.24	0.9	0.894	1.45
1y. ahead (end)	1.04	18.7	-0.24	0.9	0.936	1.20
Current year (mid)	0.98	24.7	0.52	0.3	0.962	1.68
Current year (end)	0.97	39.7	0.20	1.6	0.985	2.18
1 y. after (mid)	0.96	37.0	0.34	2.4	0.983	1.78
1 y. after (end)	0.95	35.7	0.38	2.7	0.982	1.60
2 ys. after (mid)	0.95	34.7	0.38	2.5	0.981	1.51