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ABSTRACT

Preliminary Data and Econometric Forecasting:
An Application with the Bank of Italy Quarterly Model*

This Paper considers forecasting by econometric and time series models using preliminary (or provisional) data. The standard practice is to ignore the distinction between provisional and final data. We call the forecasts that ignore such a distinction naïve forecasts, which are generated as projections from a correctly specified model using the most recent estimates of the unobserved final figures. It is first shown that in dynamic models a multistep-ahead naïve forecast can achieve a lower mean square error than a single-step-ahead one, intuitively because it is less affected by the measurement noise embedded in the preliminary observations. The best forecasts are obtained by combining, in an optimal way, the information provided by the model with the new information contained in the preliminary data. This can be done in the state space framework, as suggested in numerous papers. Here we consider two simple methods to combine, in general sub-optimally, the two sources of information: modifying the forecast initial conditions via standard regressions and using intercept corrections. The issues are explored with reference to the Italian national accounts data and the Bank of Italy Quarterly Econometric Model. A series of simulation experiments with the model show that these methods are quite effective in reducing the extra volatility of prediction due to the use of preliminary data.

JEL Classification: C53
Keywords: Bank of Italy quarterly economic model, macroeconomic forecasting and preliminary data

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1. Introduction

The quality of a forecast depends greatly on the quality of the data on which it is based. As the initial conditions play a fundamental role in the evolution of a dynamic system (the econometric model), it is clear that accurate forecasting requires, among else, reliable data.

Macroeconomic data, as produced by the statistical agencies, are routinely revised for a number of periods. Preliminary estimates are often available soon after the end of the period to which they refer; these estimates, however, may contain a great deal of noise and may differ considerably from the definitive figures. Macroeconomic forecasts are therefore potentially strongly affected by the presence of preliminary (or provisional) data. Numerous studies have analyzed the size of the revision errors in economic data, e.g. Zellner (1958), Cole (1969), Mankiw and Shapiro (1986) for US GNP, Di Fonzo et al. (1995) for Italian national accounts data. Gallo and Marcellino (1999) and Patterson (2000) have also suggested combining final and provisional data in a unified statistical framework, a vector error correction model *à la* Johansen (1995).

The purpose of this paper is to try and assess the impact of data revisions on econometric forecasts, and suggest alternative ways to avoid the amplification of prediction errors due to preliminary data.

The standard practice is to ignore the distinction between provisional and final data. We call the forecasts that ignore such a distinction *naïve forecasts,* which are generated as projections from a correctly specified model using the most recent estimates (the preliminary data) of the unobserved final figures. We first show that, in dynamic models, a multistep-ahead naïve forecast can achieve a lower mean square error than a single-step-ahead one. The intuitive reason is that it is less affected by the measurement noise embedded in the preliminary estimates.

Only by taking the measurement noise explicitly into account, can efficient forecasts be obtained. In particular, state space techniques and the Kalman filter permit extracting the information contained in the latest released data in an optimal way and obtaining mininum mean square error forecasts. This approach has been taken in Howrey (1978, 1984), Conrad and Corrado (1979), Harvey et al. (1983), Bordignon and Trivellato (1989), Patterson (1995a,b) and Mariano and Tanizaki (1995), the latter extending the basic construct to the case of nonlinear non Gaussian observations. A simultaneous-equations framework has instead been used by Trivellato and Rettore (1986) to investigate the effects of preliminary data on model estimation and one-step-ahead forecasts.

However, the optimal filtering techniques are not well-suited to large-scale structural econometric models, mainly because these models cannot be easily cast in state space form. We therefore suggest two simpler methods of reducing the impact of the noise in the provisional data: modifying the initial conditions of the forecasts by weighting the preliminary observations with the model predictions and using intercept corrections, i.e. adjustments to the constant term of certain equations of the model.

The first of these methods amounts to regressing the final on the preliminary data and the model's in-sample predictions and using the regression coefficients (weights) to obtain what we may call *weighted preliminary data*; these, in turn, will be our initial conditions for producing out-of-sample forecasts. Note that if we regard a preliminary observation as a forecast of the unobserved true value, our proposal of weighting the provisional data closely resembles the proposal of forecast combination advanced in Bates and Granger (1969).

The second method, on the other hand, follows an idea originally formulated in Hendry and Clements (1994), where it is argued that intecept corrections can be viewed, among other things, as a device for reducing the effects of data measurement errors on model predictions.

In this paper, simulations run on the Bank of Italy Quarterly Model (BIQM), a large scale structural model containing 96 behavioural equations, are used to show that both methods appear to be highly effective in reducing the extra volatility of predictions due to the utilization of provisional data.

A practical implication of this study is that in many cases it may be wise to underweight the impact of the latest data on the predictions over the future developments of the economy. While it is clear that most professional forecasters regard preliminary data in the right way, i.e. as estimates subject to a degree of error, this is not necessarily the case for the final users of the forecasts, policy makers and market operators, who tend to view the most recently released figures as the best indicators of future trends. Here, instead, we show that factoring in all the data on the current state of the economy may be a significant source of prediction error.

One issue not pursued in this paper is the effect of provisional data on the estimated coefficients, that is it is implicitly assumed that the model parameters are the population ones. Among other things, this simplifies the expression for the mean square error of forecasts by removing the contribution attributable to parameter uncertainty. If the model is correctly specified, the effect on the coefficients is likely to be negligible, because the most recent (noisy) observations are usually not included in the estimation sample but serve for diagnostic checking of the model. In any case, that issue is thoroughly analysed by Trivellato and Rettore (1986).

In summary, the paper proceeds as follows. Section 2 sets out the framework for analyzing the impact of preliminary observations on forecasts. Section 3 shows that if the distinction between provisional and final data is ignored multistep-ahead can be more efficient than one-step ahead forecasts. This occurs when the noise of the provisional data is relatively large with respect to the error in the model equations. Section 4 considers the Italian quarterly national accounts, as produced by the National Statistical Agency (ISTAT), and the Bank of Italy Quarterly Model. We find that the measurement error in the preliminary vintages of data is comparable to the prediction error from the model: by the arguments of the previous sections it follows that the effect on forecasting performance may be substantial. The optimal filtering techniques suggested in much of the literature are reviewed in Section 5, while the suboptimal approach of modifying the forecast initial conditions by weighting the preliminary observations with the model predictions is proposed in Section 6: it is shown that for a simple AR(1) model with noise the two methods are equivalent. The use of intercept corrections as means to mitigate the noise embedded in the preliminary data is advanced in Section 7, where the optimal correction is obtained for the same AR(1) plus noise model. Finally, Section 8 reports the results of a series of simulation experiments with the BIQM, comparing the forecast performance of the model across four scenarios: final data, preliminary data, modified initial conditions and intercept corrections. It is shown that the deterioration in the forecasting performance due to preliminary data is greatly reduced if our suggested methods are used. Concluding remarks are given in Section 9.

2. The framework

Let $\mathbf{x}_t$ be a $n \times 1$ vector time series observed with a delay of $d+1$ periods, and denote by $\mathbf{y}_{t,i}$ the $i-th$ preliminary observation of $\mathbf{x}_t$, $i = 1, ..., d$. We assume that $\mathbf{y}_{t,i}$ is available at time $t+i$, i.e. that a first estimate of $\mathbf{x}_t$ is available at time $t+1$ and this estimate is revised each subsequent period. This approximately corresponds to the case of Italian quarterly national accounts; see Di Fonzo et al. (1995) for details.

Except for the case $d = 1$, it turns out that we have multiple preliminary data, or *vintages*, for each true value of the variable of interest. In particular, at time $t+1$ we have the $d(d+1)/2$ preliminary values $\mathbf{y}_{t,1}$, $\mathbf{y}_{t-1,2}$, $\mathbf{y}_{t-1,1}$, ..., $\mathbf{y}_{t-d+1,1}$; however, the new information is given by only the latest vintage of data.

Denote by $\mathbf{Y}_t = (\mathbf{y}'_{t,1}, \mathbf{y}'_{t-1,2}, ..., \mathbf{y}'_{t-d+1,d})'$ the nd dimensional vector of most recent preliminary observations, as resulting from the latest vintage. Following Howrey (1978) and Harvey et al. (1983), we can write the following model for the data,

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{A}\mathbf{X}_t + \boldsymbol{\varepsilon}_t, \tag{2.1}$$

where $\mathbf{c} = (\mathbf{c}'_1, ..., \mathbf{c}'_d)'$ is a vector of bias, $\mathbf{A} = diag(\mathbf{A}_1, ..., \mathbf{A}_d)$ is a $nd \times nd$ matrix made of $n \times n$ nonzero diagonal blocks, $\mathbf{X}_t = (\mathbf{x}'_t, \mathbf{x}'_{t-1}, ..., \mathbf{x}'_{t-d+1})'$ and $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}'_{t,1}, \boldsymbol{\varepsilon}'_{t-1,2}, ..., \boldsymbol{\varepsilon}_{t-d+1,d})'$ is the vector of measurement errors, which in general can be characterized by some time series model, e.g. an AR(1) in Howrey (1978). For example, with $d = 2$ (2.1) becomes

$$\begin{pmatrix} \mathbf{y}_{t,1} \\ \mathbf{y}_{t-1,2} \end{pmatrix} = \begin{pmatrix} \mathbf{c}_1 \\ \mathbf{c}_2 \end{pmatrix} + \begin{pmatrix} \mathbf{A}_1 & 0 \\ 0 & \mathbf{A}_2 \end{pmatrix} \begin{pmatrix} \mathbf{x}_t \\ \mathbf{x}_{t-1} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon}_{t,1} \\ \boldsymbol{\varepsilon}_{t-1,2} \end{pmatrix}.$$

For the time being, we assume that $\mathbf{x}_t$ follows a vector AR(p) process,

$$\mathbf{x}_t = \sum_{s=1}^{p} \boldsymbol{\Phi}_s \mathbf{x}_{t-s} + \mathbf{u}_t, \tag{2.2}$$

where $\mathbf{u}_t$ is $iid(\mathbf{0}, \boldsymbol{\Omega})$ and the roots of the matrix polynomial $\mathbf{I} - \sum_{s=1}^{p} \boldsymbol{\Phi}_s L$ are outside the unit circle; more general processes for $\mathbf{x}_t$ are considered in Section 5.

If $\mathbf{x}_t$ were observed, its best linear j-step ahead forecast could be written as

$$\widehat{\mathbf{x}}_{t+j|t} = \sum_{s=0}^{\infty} \mathbf{W}_s^{(j)} \mathbf{x}_{t-s}, \qquad j = 1, 2, ... \tag{2.3}$$

where $\mathbf{W}_s^{(j)}$ are appropriate weights that can be computed recursively (over j) starting with $\mathbf{W}_s^{(1)} = \mathbf{\Phi}_{s+1}$, $s = 0, 1, ..., p-1$, and $\mathbf{W}_s^{(1)} = 0$, $s \geq p$. Correspondingly, the forecast mean square error is known to be

$$\mathbf{F}(j) \equiv MSE(\widehat{\mathbf{x}}_{t+j|t}) = \sum_{h=1}^{j} \mathbf{\Psi}_{h-1} \mathbf{\Omega} \mathbf{\Psi}'_{h-1}, \qquad j = 1, 2, ..., \tag{2.4}$$

where $\mathbf{\Psi}_0$, $\mathbf{\Psi}_1$, ... are the coefficients of the moving average representation of the process (2.2); see e.g. Hamilton (1994, page 78).

More generally, if $\mathbf{x}_t$ has a state space representation (which for example includes the cases of ARIMA models and regressions with time varying coefficients) $\mathbf{F}(j)$ can be obtained from the Kalman filter recursions and a weight forecasting formula analogous to (2.3) from the results of Koopman and Harvey (1999); see Section 5.

3. Naïve multistep-ahead forecasts

We call *naïve forecasts* of $\mathbf{x}_t$ those that ignore the distinction between provisional and final data, i.e. that are constructed on the basis of model (2.2) but using the most recent preliminary observations of the unobserved true values. From (2.3), the naïve j-step-ahead forecast, denoted as $\mathbf{x}_{t+j|t}^N$, can then be written as

$$\mathbf{x}_{t+j|t}^N = \sum_{s=0}^{d-1} \mathbf{W}_s^{(j)} \mathbf{y}_{t-s,s+1} + \sum_{s=d}^{\infty} \mathbf{W}_s^{(j)} \mathbf{x}_{t-s}, \qquad j = 1, 2, ... \tag{3.1}$$

Consider first the important case of $\mathbf{c} = \mathbf{0}$, $\mathbf{A} = \mathbf{I}_{nd}$, which corresponds to *unbiased preliminary observations,* in the sense that they are unbiased estimates of the true values. In this situation, (3.1) can be rewritten as

$$\begin{aligned} \mathbf{x}_{t+j|t}^N &= \sum_{s=0}^{d-1} \mathbf{W}_s^{(j)} \left(\mathbf{x}_{t-s} + \boldsymbol{\varepsilon}_{t-s,s+1} \right) + \sum_{s=d}^{\infty} \mathbf{W}_s^{(j)} \mathbf{x}_{t-s} \\ &= \widehat{\mathbf{x}}_{t+j|t} + \sum_{s=0}^{d-1} \mathbf{W}_s^{(j)} \boldsymbol{\varepsilon}_{t-s,s+1}. \end{aligned}$$

The mean square error of the naïve forecast is then

$$\mathbf{F}_N(j) \equiv MSE\left(\mathbf{x}_{t+j|t}^N\right) = \mathbf{F}(j) + \mathbf{G}(j), \qquad j = 1, 2, ..., \tag{3.2}$$

where $\mathbf{F}(j)$ is given by (2.4) and

$$\mathbf{G}(j) = \sum_{s=0}^{d-1}\sum_{h=0}^{d-1} \mathbf{W}_s^{(j)} E\left(\boldsymbol{\varepsilon}_{t-s,s+1}\boldsymbol{\varepsilon}'_{t-h,h+1}\right)\mathbf{W}_h^{(j)\prime}.$$

It is shown in Appendix A that $\mathbf{G}(j+1) - \mathbf{G}(j)$ is a negative semidefinite matrix for all $j = 1, 2, ...$ As $\mathbf{F}(j+1) - \mathbf{F}(j)$ is clearly positive semidefinite, we may have regions where the mean square error of the naïve forecast is decreasing as the forecast horizon grows; for example it can happen a 2-step ahead forecast is better, in the MSE sense, than a 1-step ahead. This is likely to occur when the prediction variance of the model is small relative to the variance of the preliminary data; intuitively, a multistep-ahead naïve forecast can be more attractive than a single-step-ahead one, as it is based on more reliable observations.

EXAMPLE: AR(1)+NOISE, d=1. Let $\mathbf{x}_t$ follow a univariate AR(1) process with parameter ϕ and suppose that $d = 1$, $\mathbf{A}$ =1 and that $\boldsymbol{\varepsilon}_{t,1}$ is serially uncorrelated with variance σ_e^2. As $\mathbf{W}_0^{(j)} = \phi^j$ and $\mathbf{W}_s^{(j)} = 0$ for $s \neq 0$, we have $\mathbf{F}_N(j) = \sigma_u^2 \sum_{h=1}^{j} \phi^{2(h-1)} + \phi^{2j}\sigma_e^2$, where σ_u^2 is the variance of $\mathbf{u}_t$. Thus a 2-step-ahead forecast is better (in the MSE sense) than 1-step-ahead, provided $\sigma_u^2 < (1-\phi^2)\sigma_e^2$. [1]

For general $\mathbf{c}$ and $\mathbf{A}$, the naïve forecast MSE can be written as

$$\mathbf{F}_N(j) \equiv MSE(\mathbf{x}_{t+j|t}^N) = \mathbf{F}(j) + \mathbf{G}^*(j), \qquad j = 1, 2, ...,$$

where $\mathbf{F}(j)$ is as before and $\mathbf{G}^*(j+1) - \mathbf{G}^*(j)$ is a negative semidefinite matrix; see the appendix. Then similar arguments on the behaviour of the forecast mean square error apply.[2]

4. Revision errors and forecasting errors of the BIQM

We have seen that when the prediction variance of the model is small enough, projecting the model into the future can be better than running it using preliminary

[1] This result also appears in Harrison et al. (2003).

[2] Analogous considerations apply also when the data generating process for $\mathbf{x}_t$ is a cointegrated VAR of order p: by writing the error correction representation with the disequilibrium term lagged p times instead of the usual representation with one lag, it is clear that for large enough p the impact of preliminary data on that term is negligible and thus the additional component in the mean square error of the naïve forecast is given by the matrix $\mathbf{G}^*(j)$ above.

data. Here we consider the Bank of Italy Quarterly Econometric Model (BIQM) and the quartely national accounts produced by the national statistical agency (ISTAT). The aim is to measure and compare the magnitude of the errors in the preliminary observations and the forecast mean square error of the econometric model *per se*, i.e. when it is run using the definitive data.

The revision process for the Italian quarterly national accounts is thoroughly described in Di Fonzo et al. (1995). In brief, the first estimate for any given quarter is continuously revised for the following three years. In addition, there are occasionally other revisions, say, taking into account data from decennial censuses or improved estimation procedures or changes in the base-year. A major break in the national accounts statistics occurred with the change, in 1999, from the ESA79 to the ESA95 accounting scheme (cf. Eurostat, 1999). As the series following the two schemes are not directly comparable, we have chosen in this paper to use only on the ESA79 data, for which many more observations are available; likewise we do not consider the recently introduced "flash estimates" of Italian real GDP.

Denote by $t.q$ the data vintage that includes the first preliminary observation for quarter q of year t. We consider 35 data vintages, or releases, corresponding to the available data sets between 1988.2 and 1998.3, the latter being the last issued that follows the ESA79 accounting scheme.

As in the previous sections, we denote by $\mathbf{y}_{t,i}$ the i-th preliminar observation for $\mathbf{x}_t$, or more precisely the observation of $\mathbf{x}_t$ available at time $t+i$, and let $\mathbf{e}_{t,i} = \mathbf{y}_{t,i} - \mathbf{x}_t$ be the corresponding release error.

To compute the release error we take as true value $\mathbf{x}_t$ the observation $\mathbf{y}_{t,12}$ ($\mathbf{y}_{t,13}$ if $\mathbf{y}_{t,12}$ corresponds to a vintage that is not available), reflecting the fact that the normal revision process should be terminated after 12 quarters. In principle, one could use the last available observation, i.e. the figure from the vintage 1998.3; however, as noted above, extra revisions in the data do take place occasionally, which implies that the data keep changing even after many years. As an example, Table 1 contains the first 12 vintages for the percentage growth rate of real GDP together with the last available observation[3]. Our view is that, if the goal is to obtain some measure of the noise in the preliminary data, considering the last observation is likely to introduce extra variability. The data for 1989Q4 are a clear example: while the figures of the first 11 releases do not fluctuate much around $\mathbf{y}_{t,12} = 0.545$, the value 1.209 obtained from the vintage 1998.3 is much greater. In any case the results reported in Table 2 below do not change much

[3] The blanks in Table 1 correspond to the vintages that are not available.

when the data from 1998.3 are used as true values.

Table 2 computes mean, standard deviation and root mean square of the release errors $\mathbf{e}_{t,i}$, $i = 1, 2, ..., 11$, for the percentage growth rates of the following series in real terms: Gross Domestic Product (GDP), Final Domestic Consumption (CON), Gross Fixed Capital Formation (INV), Exports of Goods and Services (EXP), Imports of Goods and Services (IMP). The last row of the Table reports the number of observations used to compute those statistics; the time span is from the period $1985Q1$ to $1995Q4$. Note that, by considering percentage growth rates we avoid the problem of data deflated with respect to different base years.

The table indicates that the preliminary observations are approximately unbiased estimators of the true values. As expected, later revisions are, in general, better estimates. A similar exercise was carried out by Di Fonzo et al. (1995, Table 7), using datasets between 1984.4 and 1994.2, with analogous results, except for the investment series which appears noisier in our data.

The figures of Table 2 are broadly in line with those for the other industrialized countries. Faust et al. (2001) analyze the average magnitude of the revisions in the first vintage of real GDP across the G7 countries. For the period 1988-1997 they obtain a value of 0.52 for the root mean square error of Italian GDP, very close to our figure of 0.49, obtained from Table 2. From that study it emerges that the average error for Italy turns out to be larger than those for US, Canada and France, but significantly smaller than for Germany, Japan and the UK.

The correlation between release errors, $corr(e_{t,i}, e_{t,h})$, is shown in Table 3 for the growth rate of real GDP, $i, h = 1, 2..., 11$. The table suggests that successive revisions are positively correlated, which implies that the revision pattern tends to be monotone; on this point see Di Fonzo et al. (1995). The corresponding matrices for the other series are not reported, as the correlation pattern is not qualitatively different from that of GDP.

A formal test of unbiasedness for the i-th release can be obtained from the regressions

$$\mathbf{y}_{t,i} = \beta_0 + \beta_1 \mathbf{x}_t + error, \tag{4.1}$$

by testing the null hypothesis $H_0 : \beta_0 = 0$, $\beta_1 = 1$. The results for this sequence of F-tests, for $i = 1, 2, ..., 8$, are displayed in Table 4 for the percentage growth rates of each of the five series analyzed in this study[4].

[4]This is sometimes called the Mincer-Zarnowitz test of forecast rationality. The regressions are done by Ordinary Least Squares; standard procedures to correct for serial correlation in the residuals will not work, as the sample contains missing observations corresponding to the vintages that are not available. Indeed, Gallo and Marcellino (1999) make the point that, if

It emerges that the preliminary data for exports, imports and GDP appear to be unbiased, unlike the data for consumption and investments. The fit of the regression, as measured by the R^2 and the standard error of regression, is essentially increasing with i, confirming that later releases are more reliable, as from Table 2. As expected, there appears to be a trade-off between the volatility of the preliminary observations and the absence of the bias: for each series, except consumption, lower R^2 essentially correspond to higher p-values for the F-test.

We then compute the forecast errors associated with the Bank of Italy Quarterly Model (BIQM), which, following the framework of Section 3, we want to compare to the errors in the provisional data. The BIQM is a large scale structural model which, in the latest version estimated on the ESA79 data, contains 96 behavioural equations, 885 endogenous and 663 exogenous variables, and a few nonlinearities. A complete description of an older version of the model with the same basic structure is given in Banca d'Italia (1986).

The model has been simulated sequentially with starting points ranging from 1985Q1 to 1994Q4, and the empirical (in-sample) forecast errors for the variables examined, both in logarithms and in first differences of the logarithms, have been calculated; the summary statistics are displayed in Table 5. The data used for both estimation and simulation of the model corresponds to the final release 1998.3; most equations of the BIQM are estimated using observations up to 1996Q4. Note that bias, standard deviation and root mean square error of the forecasts have been computed using a number of observations equal to 40 in all cases.

It emerges from Table 5 that the one-step-ahead forecast error is approximately of the same size as the error of the first vintage of data (taken from Table 2), except for the series of imports where it is larger in the model. For the (log) levels of the series the magnitude of the forecast error increases steadily with the forecast horizon, as expected, while for the percentage growth rates it essentially reaches an upper bound after a few steps of predictions. The fact that the empirical forecast root mean square error for the growth rates is not monotonic can be justified on many grounds, e.g. parameter variation, small sample size, misspecification; see

there is cointegration between provisional and final data, one should consider the augmented regression

$$y_{ti} = \beta_0 + \beta_1 x_t + \beta_2 z_{t-1} + error,$$

where y_{ti} and x_t are first differences (of the logarithms) and z_{t-1} is an error correction term. As the focus of this paper is not on the cointegration properties among the various vintages of data, we do not pursue that approach. Some work in this direction is contained in Di Fonzo et al. (1995).

e.g. Klein (1983, p. 88).

Ideally one would like to compare the noise in preliminary data with the errors of *ex ante* rather than in-sample forecasts. Ex ante forecasts, however, are not necessarily worse: in actual practice, in fact, they are also based on information that cannot be incorporated into an econometric model. This extra information can be provided, for example, by leading indicators, "bridge models" à la Parigi and Schitzler (1995), knowledge of the occurence of institutional changes, and so on.

As an example, the following table gives the root mean square error of the ex ante one-step-ahead forecast for *annual growth rates*. The statistics have been obtained by comparing the actual projections made at Bank of Italy around April-May of each year in the period 1986-1995 with the final values of the series taken from release 1998.3. Note that at the time in which the forecasts were made, they were based on national accounts data up to the last quarter of the previous year; in this sense they are annual one-step-ahead forecasts. Clearly, unlike Table 5, the figures of this table are not not free of the noise arising from the use of provisional data. The table also provides the root mean square error of the in-sample forecasts from the BIQM for the same annual growth rates, when the model is simulated using the final data vintage 1998.3; clearly these are obtained using the true values, as opposed to some projection, of the exogenous variables of the model. As discussed above, it turns out that, except for investment, the magnitude of the ex ante forecast errors is not much greater than that of the in sample errors[5].

	Ex ante	*In sample*
GDP	0.74	0.55
CON	0.86	0.63
INV	3.39	1.20
EXP	2.84	2.14
IMP	3.51	2.39

Overall, the empirical findings on the revision errors and the properties of the BIQM suggest, using the framework of Section 3, that the noise in the data is

[5]Note also that the ex ante forecasts for 1992-1993 are strongly affected by the deep devaluation of the Italian Lira in September 1992 and consequent exit from the European Monetary System.

likely to worsen forecasting performance, and could even make one-step-ahead forecasts less attractive than multistep-ahead forecasts.

Following the articles by Howrey (1978) and Harvey et al. (1983) among others, the optimal way to proceed would be to combine, in an efficient way, the forecasts from the econometric model with the new information embedded in the current and past vintages of data, or in other words to filter out the noise in the data. That approach is reviewed in the following section; the theoretical efficiency gain with respect to the naïve forecasts of Section 3 is computed for the simple AR(1) plus noise model.

5. Optimal forecasts

It is known that for a state space model with Gaussian innovations the Kalman filter provides the minimum mean square error predictor; in absence of Gaussianity the forecasts provided by the Kalman filter are optimal only within the class of linear predictors; see e.g. Anderson and Moore (1979), Harvey (1989) and Koopman et al. (1998).

Consider the following state space representation for a (vector) time series, $\mathbf{x}_t$:

$$\mathbf{x}_t = \mathbf{b}_t + \mathbf{Z}_t\boldsymbol{\alpha}_t + \mathbf{G}_t\mathbf{u}_t, \quad (5.1)$$
$$\boldsymbol{\alpha}_{t+1} = \mathbf{d}_t + \mathbf{T}_t\boldsymbol{\alpha}_t + \mathbf{H}_t\mathbf{u}_t, \quad (5.2)$$
$$\boldsymbol{\alpha}_1 \sim N(\boldsymbol{\alpha}, \mathbf{P}), \quad (5.3)$$
$$\mathbf{u}_t \sim NID(\mathbf{0}, \mathbf{I}), \quad (5.4)$$

where $NID(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ indicates a normally identically distributed variable with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\Sigma}$ and, similarly, $N(.,.)$ a normally distributed variable. In brief, the observable time series $\mathbf{x}_t$ is related to the innovations $\mathbf{u}_t$ via a measurement equation (5.1) and a Markovian transition equation (5.2); $\boldsymbol{\alpha}_t$ is the unobservable state vector, which has some initial condition (5.3). The matrices $\mathbf{Z}_t$, $\mathbf{G}_t$, $\mathbf{T}_t$, $\mathbf{H}_t$ and the vectors $\mathbf{b}_t$, $\mathbf{d}_t$ are deterministic; see Harvey (1989, Chapter 3) for details.

The representation (5.1)-(5.4) is general enough to include the most commonly used time series and econometric models, such as ARIMA models, dynamic linear regressions, time varying regressions and unobserved component models.

Optimal predictions in the model (5.1)-(5.4) are obtained through the Kalman filter. Let $\mathbf{a}_{t+1} = E(\boldsymbol{\alpha}_{t+1}|\,\mathbf{I}_t)$, $\mathbf{P}_{t+1} = Cov(\boldsymbol{\alpha}_{t+1}|\,\mathbf{I}_t)$, where $\mathbf{I}_t$ is the information set given by the observations up to time t: $\mathbf{I}_t = \{\mathbf{x}_t, \mathbf{x}_{t-1}, ...\}$. The Kalman filter is a recursive algorithm for the evaluation of $\mathbf{a}_t$ and $\mathbf{P}_t$. It is given by the following sets of recursions

$$
\begin{aligned}
\mathbf{v}_t &= \mathbf{x}_t - \mathbf{b}_t - \mathbf{Z}_t \mathbf{a}_t, & (5.5)\\
\mathbf{F}_t &= \mathbf{Z}_t \mathbf{P}_t \mathbf{Z}_t' + \mathbf{G}_t \mathbf{G}_t', & (5.6)\\
\mathbf{K}_t &= \left(\mathbf{T}_t \mathbf{P}_t \mathbf{Z}_t' + \mathbf{H}_t \mathbf{G}_t'\right) \mathbf{F}_t^{-1}, & (5.7)\\
\mathbf{a}_{t+1} &= \mathbf{d}_t + \mathbf{T}_t \mathbf{a}_t + \mathbf{K}_t \mathbf{v}_t, & (5.8)\\
\mathbf{P}_{t+1} &= \mathbf{T}_t \mathbf{P}_t \mathbf{T}_t' + \mathbf{H}_t \mathbf{H}_t' - \mathbf{K}_t \mathbf{F}_t \mathbf{K}_t', & (5.9)
\end{aligned}
$$

where $\mathbf{a}_1 = \mathbf{a}$, $\mathbf{P}_1 = \mathbf{P}$. In the previous formulae, $\mathbf{v}_t$ is the innovation, or prediction error, with zero mean and variance equal to $\mathbf{F}_t$, and $\mathbf{K}_t$ is the so-called "Kalman gain".

The optimal j-step-ahead forecast $\widehat{\mathbf{x}}_{t+j|t} = E(\mathbf{x}_{t+j}|\,\mathbf{I}_t)$ is then

$$\widehat{\mathbf{x}}_{t+j|t} = \mathbf{b}_{t+j} + \mathbf{Z}_t \mathbf{a}_{t+j|t}, \qquad (5.10)$$

where $\mathbf{a}_{t+j|t} = E(\boldsymbol{\alpha}_{t+j}|\,\mathbf{I}_t)$. Note that $\mathbf{a}_{t+1|t} = \mathbf{a}_{t+1}$ and, for $j \geq 2$, $\mathbf{a}_{t+j|t}$ is obtained from (5.8) setting the gain $\mathbf{K}_{t+j-1}$ equal to zero. Similarly, setting the gain to zero for $j \geq 2$ in (5.9), one also obtains $\mathbf{P}_{t+j|t} = Var(\boldsymbol{\alpha}_{t+j}|\,\mathbf{I}_t)$, and the forecast mean square error for $\widehat{\mathbf{x}}_{t+j|t}$ thus becomes

$$\mathbf{F}(j) = \mathbf{Z}_{t+j} \mathbf{P}_{t+j|t} \mathbf{Z}_{t+j}' + \mathbf{G}_{t+j} \mathbf{G}_{t+j}'. \qquad (5.11)$$

Compare (5.10)-(5.11) with the corresponding formulae (2.3)-(2.4) for an AR(p) model. Indeed, Koopman and Harvey (1999) obtain a weighting formula analogous to (2.3) valid for any state space model, thus allowing a weight interpretation of the forecasts that can be applied in all generality.

Consider now the measurement error setup of Section 2, where the process generating the true values $\mathbf{x}_t$ (observable only after $d+1$ periods) can be put in a state space form like (5.1)-(5.4) above. Harvey et al. (1983) show how to construct the state space representation for the augmented model made up of the true values $\mathbf{x}_t$, the preliminary data $\mathbf{Y}_t$ and the release errors $\boldsymbol{\varepsilon}_t$ as defined in Section 2; if $\mathbf{x}_t$ is an autoregressive process the representation follows almost immediately (see the example below). Then, applying the formulae (5.5)-(5.9) to the augmented state space form, one can compute the optimal forecasts for $\mathbf{x}_t$, which take into account the noise embedded in the preliminary data, and the resulting (minimum) forecast mean square error.

EXAMPLE: AR(1)+NOISE, d=1. The augmented state space form of the univariate AR(1) plus noise model with $\mathbf{c} = 0$, $\mathbf{A} = 1$, $d = 1$ is the following:

$$\begin{pmatrix} \mathbf{y}_{t,1} \\ \mathbf{x}_{t-1} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \boldsymbol{\alpha}_t + \begin{pmatrix} \sigma_e & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \boldsymbol{\varepsilon}_t \\ \mathbf{u}_t \end{pmatrix},$$

$$\boldsymbol{\alpha}_{t+1} = \begin{pmatrix} \phi & 0 \\ 1 & 0 \end{pmatrix} \boldsymbol{\alpha}_t + \begin{pmatrix} 0 & \sigma_u \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \boldsymbol{\varepsilon}_t \\ \mathbf{u}_t \end{pmatrix},$$

where $\boldsymbol{\alpha}_t = (\mathbf{x}_t, \mathbf{x}_{t-1})$, $\mathbf{a}_1 = (0, 0)$ and

$$P_1 = \frac{\sigma_u^2}{1-\phi^2} \begin{pmatrix} 1 & \phi \\ \phi & 1 \end{pmatrix}.$$

Using (5.5)-(5.9), it is not difficult to show that, for $j = 1, 2, ...,$

$$E\left(\mathbf{x}_{t+j} | \mathbf{I}_t^*\right) = \phi^j \left(\frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \mathbf{y}_{t1} + \phi \frac{\sigma_e^2}{\sigma_u^2 + \sigma_e^2} \mathbf{x}_{t-1} \right), \tag{5.12}$$

$$MSE\left(\mathbf{x}_{t+j} | \mathbf{I}_t^*\right) = \sigma_u^2 \sum_{h=1}^{j} \phi^{2(h-1)} + \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \sigma_e^2 \phi^{2j}, \tag{5.13}$$

where $\mathbf{I}_t^*$ is the information set $\{\mathbf{y}_{t1}, \mathbf{x}_{t-1}, \mathbf{y}_{t-1,2}, \mathbf{x}_{t-2}, ...\}$. The gain with respect to the naïve forecast of Section 3 is then determined by the factor $\sigma_u^2/(\sigma_u^2 + \sigma_e^2)$. Note that (5.13) is an increasing function of σ_e^2, the upper bound being, for $\sigma_e^2 \to \infty$, the mean square error of the $j+1$-step-ahead forecast from the model, $MSE\left(E(\mathbf{x}_{t+j+1} | \mathbf{I}_t)\right)$.

For the AR(1)+NOISE example above, the same result of optimal prediction can be obtained by modifying the initial conditions in the naïve forecasting formula (3.1) by weighting the preliminary observations with the model forecasts via regression methods and by using appropriate intercept corrections; this is explained in the next two sections.

6. Suboptimal forecasts by regression methods: weighted preliminary data

In many cases, the state space framework of the previous section may be difficult to implement due to the complexity of the models at hand. For instance, it is certainly no easy task to put such a large model as the BIQM into state space form and apply the Kalman filter machinery.

For these large models, a more practical approach could be to try to combine (suboptimally) the two sources of information using regression methods. In particular, we may want to reduce the noise in the preliminary data, by weighting them with the model forecasts, since, as we saw in Sections 2-3, the forecasts can even outperform the new data.

The strategy we propose is to regress the true data on the preliminary ones and the model predictions, and use the regression coefficients (weights) to obtain what we may call *weighted preliminary data*. If both the preliminary observations and the model forecasts are unbiased estimators of the true values, then, in principle, the weights should sum to one. The weighted preliminary data, then, can be used to obtain modified initial conditions for the model forecasts. Clearly, these forecasts will have better properties -to some extent- than the standard naïve forecasts of Section 3, though they will be suboptimal if compared with those from the augmented state space representation described in the previous section.

Notice that if we regard a preliminary observation as a forecast of the underlying true value, our construction of the weighted preliminary data corresponds to the idea of combining forecasts advanced in Bates and Granger (1969).

EXAMPLE: AR(1)+NOISE, d=1. The weighted preliminary data, denoted $\mathbf{x}_t^*$, can be expressed as

$$\mathbf{x}_t^* = \beta \mathbf{y}_{t1} + (1-\beta)\widehat{\mathbf{x}}_{t|t-1}, \tag{6.1}$$

where $\widehat{\mathbf{x}}_{t|t-1} = \phi \mathbf{x}_{t-1}$ is the one-step-ahead forecast from the AR(1) model and $\beta = \sigma_u^2/(\sigma_u^2 + \sigma_e^2)$ is the population regression coefficient. The j-step-ahead forecast of $\mathbf{x}_t$ constructed using the weighted preliminary data is then $\phi^j \mathbf{x}_{t-j}^*$. This is exactly the Minimum Mean Square Error forecast obtained from the state space representation of the previous section, that is, in this simple case the two forecasting procedures, optimal and suboptimal, are equivalent.

In general, there are a number of ways to obtain the weights to assign to preliminary observations and model forecasts to construct the weighted preliminary data. In Table 6, we report the results of a set of ordinary least squares regressions, labelled R1 to R4, and the implied weights. In each case the dependent variable is the true value, taken from release 1998.3, and the explanatory variables correspond to the columns selected among those labelled constant, $\mathbf{y}_{t,1}$, $\widehat{\mathbf{x}}_{t|t-1}$, $\widehat{\mathbf{x}}_{t|t-2}$.[6] For example, R2 correspond to the regression (6.1) above; for the cases R2 to R4 we impose the restrictions that weights must sum up to unity and that there be

[6] In this exercise the one and two-step-ahead forecasts used among the regressors are obtained projecting the BIQM with the dataset 1998.3. In the simulation experiments S5, S8 in the next section, by contrast, the weighted preliminary data will be constructed by weighting the preliminary observations with the naive forecasts from the BIQM.

no intercept. The sample period is 1988Q1-1994Q4. The R^2, the Durbin-Watson statistics and the p-value for the F-test of the restrictions are reported. The last column contains the percentage reduction in the mean square error obtained from using the weighted preliminary data as opposed to treating the preliminary observations $\mathbf{y}_{t,1}$ as true values. The figures are constructed from the formula $100(1 - SSE_R/SSE_0)$, where $SSE_0 = \sum(\mathbf{x}_t - \mathbf{y}_{t1})^2$ and $SSE_R = \sum e_t^2$, e_t being the regression residuals from which of the regressions R1,...,R4 apply in each case.

Table 6 suggests that the BIQM forecasts offer a significant contribution towards more reliable estimates of the true values. The weights associated with the forecasts can be as high as 0.6 and are highly significant most of the time. The mean square error of these estimates is also appreciably reduced, e.g. by 21% for GDP and up to 44% for exports. The simple regression R2 appears to be adequate. As expected, if the one-step-ahead forecast is included among the regressors, adding the two-step-ahead forecast does not improve the outcome significantly. As mentioned, many alternative options for the obtaining the weights are possible, such as correcting for serial correlation in the residuals and using system estimates to account for cross correlations among revisions (for the latter, results are available from the author on request).

7. Forecasting with intercept corrections

Another simple method of reducing the forecast error due to preliminary data is using intercept corrections (or addfactors), i.e. adjusting the constant term of certain behavioural equations of the model. Reasons for employing addfactors in the practice of forecasting from structural models are given in Hendry and Clements (1994) and Siviero and Terlizzese (2001). For example, when a behavioural relation is thought to be subject to a structural break and thus the static one-step-ahead forecasts systematically overestimate, or underestimate, the realized values, it may be appropriate, for the purpose of multistep-ahead forecasting, to include a constant adjustment to that equation reflecting the average static prediction error of the recent past.

For what can be viewed as a general principle, Siviero and Terlizzese (2001, page 26) argue that it is "undesirable to let the latest data impact on all the coefficients of a given equation: an adjustment of the sole constant term may in fact suffice to guarantee that the model is *in line* with the latest observations ...".

Hendry and Clements (1994) explicitly consider the case of data measurement errors to justify the use of intercept corrections in macroeconomic forecasting. For a simple AR(1) model they also obtain the expression for the optimal addfactor, i.e. that which permits to achieve the minimum prediction mean square error.

EXAMPLE: AR(1)+NOISE, d=1. The one-step-ahead forecast of $\mathbf{x}_{t+1}$ with an intercept correction, say d_t, is given by $\phi\mathbf{y}_{t1} + d_t$. Equating this with the minimum mean square error forecast $\phi\mathbf{x}_t^*$ as defined in (6.1), we obtain the expression of the optimal addfactor,

$$\widetilde{d}_t = -\phi(1-\beta)(\mathbf{y}_{t1} - \phi\mathbf{x}_{t-1}),$$

where, as in (6.1), $\beta = \sigma_u^2/(\sigma_u^2 + \sigma_e^2)$.

In the practice of forecasting, addfactors are often set equal to some average of past static simulation errors. Though these will not in general be optimal in the above sense, they may nevertheless help reduce the forecast mean square error in the presence of preliminary data. The following section will show this to be so for the Bank of Italy Quarterly Model.

8. The effect of weighted preliminary data and intercept corrections in the Bank of Italy Quarterly Model

This section compares the BIQM forecasts using final data with those incorporating the noise of the preliminary observations (naïve forecasts). Two types of correction are then applied to mitigate the effect of the noise: modifying the initial conditions by weighting the preliminary data as in Section 6 and using addfactors as in Section 7. Both methods prove to be effective.

The main problem in carrying out this exercise is incorporating the noise of the various vintages of data in our forecasts. The difficulty is that it is not appropriate to simply simulate the model using the series of provisional data while leaving all the other variables unchanged at their final figures. This is because those series are related to hundreds of endogenous variables, which should change accordingly. The strategy we adopt is thus to use the model itself to modify these other variables, by a so-called *renormalization* procedure. The idea of the procedure is to target the values of the preliminary observations through the use of either certain exogenous variables or the residuals of certain behavioural equations; the simultaneous structure of the model will then take care of changing the other endogenous variables in a coherent way. The procedure is described in detail in Appendix B; similar ideas can be found in Whitley (1994, pp. 200-208).

In the experiments described below, the targets are the five series of preliminary data from the national accounts: these have been achieved through the residuals of five equations, each strongly related to one target.

Table 7 gives the results of eight forecasting experiments, S1 to S8, with the BIQM. In all cases the BIQM has been simulated sequentially, with starting periods ranging from 1988Q2 to 1994Q4. The bias and the root mean square error of the resulting j-step ahead forecasts are reported for our variables of interests, $j = 1, ..., 8$. The differences among the simulations is in the data used and the presence or absence of addfactors.

The basic simulation, where the final data are used and there are no addfactors, is S1. As expected, this achieves the lowest forecast RMSE.

In S2 we incorporate the noise corresponding to the latest observation of the latest released data prior to each simulation period, 1988Q2 to 1994Q4: this is done by applying the growth rates of the latest observation to the levels of the final figures[7] and renormalizing the model as described in Appendix B. For example, for the simulation over the horizon 1990Q1-1991Q4 we take as initial conditions the final data up to period 1989Q3 and modify the observations of GDP, CON, INV, EXP, IMP for 1989Q4 by taking the growth rates at period 1989Q4 from the vintage 1989.4 and applying them to the final levels at time 1989Q3; the modified levels for 1989Q4 obtained in this way are then used as target variables for the renormalization procedure, by which in principle all the endogenous variables will turn out to be modified, at time 1989Q4, according to the reconstructed levels (incorporating the noise) of our five series from the national accounts.

In S3 we replace the artificially constructed noisy observations of S2 with the weighted preliminary data as initial conditions. The weighted preliminary data are obtained by using the weights corresponding to the regression R2 of the previous section to compute the modified growth rates and then applying the latter to the final levels as above.

The noise of the whole set of 11 preliminary observations corresponding to the latest released data prior to the simulation horizon is embedded in the initial conditions of S4: this is done by applying the 11 growth rates to the final levels (of 12 periods before) and renormalizing. Note that in this experiment the initial conditions are different from those of S1 for 11 quarters prior to the simulation, reflecting the fact that the revision process should be terminated after three years.

The noise embedded in the initial conditions of S4 is mitigated in S5 by

[7] Simply sticking in the levels of the latest released data is not correct as in general the base-year of the final figures is different from that of the preliminary data.

weighted preliminary data regressions, in S6-S7 by the use of addfactors and in S8 in both ways. The difference between S6 and S7 consists in the computation of the addfactors: in the former it is the average of the four most recent residuals, in the latter that of the eight most recent. Four residuals are also used in the addfactor of S8.

The following Table summarizes the characteristics of the eight experiments; the column labelled *Periods* shows the number of quarters, prior to the beginning of the simulations, with initial conditions differing from those of S1.

Experiment	*Initial Conditions*	*Periods*	*Addfactors*
S1:	Final data	–	NO
S2:	Preliminary data	1	NO
S3:	Weighted preliminary data	1	NO
S4:	Preliminary data	11	NO
S5:	Weighted preliminary data	11	NO
S6:	Preliminary data	11	YES: 4 residuals
S7:	Preliminary data	11	YES: 8 residuals
S8:	Weighted preliminary data	11	YES: 4 residuals

Consider first experiments S2 and S4, which essentially correspond to the definition of naïve forecasts of Section 3. Introducing the preliminary data noise considerably amplifies the forecast error. For the series of consumption, the one-step-ahead RMSE doubles, from 0.35% when the final data are used to 0.7% when all 11 preliminary observations are considered. For the other series, the deterioration in forecasting performance is less dramatic but still sizeable. Note that much of the extra volatility seems to be attributable to the first release, as the difference between S2 and S4 is not as great as that between S1 and S2.

As predicted by the theoretical arguments of Section 3, we find that the erratic nature of the preliminary data often makes the 1- and 2-step-ahead forecasts less reliable than those at larger horizons. For example, the 2-step-ahead RMSE of GDP in S4 is 0.99%, against 0.69% of the 4-step-ahead one.

In general, modifying the initial conditions by the use of weighted preliminary data (S3 and S5) improves performance by comparison with the naïve forecasts, especially at shorter horizons. The correction turns out to be especially effective for GDP. Two exceptions seem to be investment and consumption in experiment S5: the former appears even more volatile while the latter remains virtually unchanged. Notice that in the construction of the weighted preliminary data for S5 we have regressed the final figures on the first-release data and the one-step-ahead forecasts from S4 (naïve forecasts). Alternatively one could use as regressors the one step ahead forecasts from S1 in place of S4: this was not done since in actual forecasting the final data are almost never available. Moreover, in S5 only the most recent noisy observation is replaced by the corresponding weighted preliminary datum; clearly one could try to adjust the initial conditions in a similar way also for the previous periods and obtain even better results.

The use of addfactors also appears very effective, particularly in reducing the extra bias of the naïve forecasts S4. A notable example is imports, where the estimated bias of S6 is -0.12% as opposed to -1.94% for S4; for this series the estimated bias in the simulations S6 to S8 is even lower than that in S1. Combining the two methods of weighted preliminary data and addfactors in general permits to achieve extra gains in terms of bias and RMSE: the results of experiment S8 are generally better than those of S5, S6 and S7.

In summary, Table 7 provides quite strong evidence that the strategies outlined for reducing the extra noise due to the presence of preliminary data can be successful. However, the results are not only model-dependent but are also based on somewhat arbitrary decisions about the construction of the weighted preliminary data and the choice of instruments in the renormalization procedure. As a check for robustness, alternative options for the sets of instruments and regressions have been adopted, providing in all cases results qualitatively similar to those reported in Table 7. There is therefore good reason for confidence that the outcome of these experiments sustains the effectiveness of the suggested modifications to the naïve forecasts.

9. Concluding remarks

The paper has considered the impact of provisional data on econometric forecasts. Two simple methods alternative to the state space framework adopted in much of the literature have been proposed to reduce the extra volatility of the forecasts due the presence of preliminary observations. The methods are particularly appealing for large-scale macroeconometric models. A series of simulation experiments with the Bank of Italy Quarterly Model suggest that the methods work well in practice. Substantiation of these results, e.g. by considering alternative models and datasets, is a direction for future research.

Appendix A: Mean square error of naïve forecasts

Let $p^* = max(d, p)$. By the Markov representation of an autoregressive model, the system (2.1)-(2.2) can be rewritten as

$$\begin{aligned} \overline{\mathbf{Y}}_t &= \overline{\mathbf{c}} + \overline{\mathbf{A}}\overline{\mathbf{X}}_t + \overline{\boldsymbol{\varepsilon}}_t, & (9.1) \\ \overline{\mathbf{X}}_t &= \overline{\boldsymbol{\Phi}}\overline{\mathbf{X}}_{t-1} + \overline{\mathbf{U}}_t, & (9.2) \end{aligned}$$

where, if $d < p$, $\overline{\mathbf{Y}}_t = \left(\mathbf{Y}_t', \mathbf{x}_{t-d}', ..., \mathbf{x}_{t-p+1}'\right)'$, $\overline{\boldsymbol{\varepsilon}}_t = (\boldsymbol{\varepsilon}_t', 0, ..., 0)'$, $\overline{\mathbf{c}} = (\mathbf{c}, \mathbf{0})'$, $\overline{\mathbf{X}}_t = \mathbf{X}_t$,

$$\overline{\boldsymbol{\Phi}} = \begin{pmatrix} \boldsymbol{\Phi}_1 & \boldsymbol{\Phi}_2 & ... & \boldsymbol{\Phi}_{p^*-1} & \boldsymbol{\Phi}_{p^*} \\ \mathbf{I} & \mathbf{0} & ... & \mathbf{0} & \mathbf{0} \\ ... & ... & ... & ... & ... \\ \mathbf{0} & \mathbf{0} & ... & \mathbf{I} & \mathbf{0} \end{pmatrix}, \ \overline{\mathbf{U}}_t = \begin{pmatrix} \mathbf{u}_t \\ \mathbf{0} \\ ... \\ \mathbf{0} \end{pmatrix},$$

whereas, if $d \geq p$, $\overline{\mathbf{Y}}_t = \mathbf{Y}_t$, $\overline{\boldsymbol{\varepsilon}}_t = \boldsymbol{\varepsilon}_t$, $\overline{\mathbf{c}} = \mathbf{c}$, $\overline{\mathbf{X}}_t = \left(\mathbf{X}_t, \mathbf{x}_{t-p}', ...\mathbf{x}_{t-d}'\right)'$, $\overline{\boldsymbol{\Phi}}$ is given by the previous expression after setting $\boldsymbol{\Phi}_{d+1}, ..., \boldsymbol{\Phi}_{p^*}$ equal to $\mathbf{0}$, and $\overline{\mathbf{U}}_t$ is as before.

The naïve forecast for $\mathbf{x}_t$ (3.1) can also be expressed by taking the first n components of the np^* dimensional vector $\overline{\mathbf{X}}_{t+j|t}^N$, defined as

$$\overline{\mathbf{X}}_{t+j|t}^N = \overline{\boldsymbol{\Phi}}^j \overline{\mathbf{Y}}_t.$$

Then

$$\overline{\mathbf{X}}_{t+j} - \overline{\mathbf{X}}_{t+j|t}^N = \left(\overline{\mathbf{X}}_{t+j} - \overline{\boldsymbol{\Phi}}^j \overline{\mathbf{X}}_t\right) - \overline{\boldsymbol{\Phi}}^j \overline{\boldsymbol{\varepsilon}}_t - \overline{\boldsymbol{\Phi}}^j \left(\overline{\mathbf{c}} + \left(\overline{\mathbf{A}} - \mathbf{I}\right) \overline{\mathbf{X}}_t\right),$$

and

$$E\left(\overline{\mathbf{X}}_{t+j} - \overline{\mathbf{X}}_{t+j|t}^N\right)\left(\overline{\mathbf{X}}_{t+j} - \overline{\mathbf{X}}_{t+j|t}^N\right)' = \overline{\mathbf{F}}(j) + \overline{\mathbf{G}}(j) + \overline{\mathbf{H}}(j), \qquad (9.3)$$

where

$$\begin{aligned} \overline{\mathbf{F}}(j) &= E\left(\overline{\mathbf{X}}_{t+j} - \overline{\boldsymbol{\Phi}}^j \overline{\mathbf{X}}_t\right)\left(\overline{\mathbf{X}}_{t+j} - \overline{\boldsymbol{\Phi}}^j \overline{\mathbf{X}}_t\right)' = MSE\left(\widehat{\overline{\mathbf{X}}}_{t+j|t}\right), \\ \overline{\mathbf{G}}(j) &= \overline{\boldsymbol{\Phi}}^j E\left(\overline{\boldsymbol{\varepsilon}}_t \overline{\boldsymbol{\varepsilon}}_t'\right) \overline{\boldsymbol{\Phi}}^{j\prime}, \\ \overline{\mathbf{H}}(j) &= \overline{\boldsymbol{\Phi}}^j \left(\overline{\mathbf{A}} - \mathbf{I}\right) E\left(\overline{\mathbf{X}}_t \overline{\mathbf{X}}_t'\right)\left(\overline{\mathbf{A}} - \mathbf{I}\right)' \overline{\boldsymbol{\Phi}}^{j\prime}. \end{aligned}$$

From the previous expressions it is clear that $\overline{\mathbf{F}}(j+1) - \overline{\mathbf{F}}(j)$ is a positive definite matrix, whereas both $\overline{\mathbf{G}}(j+1) - \overline{\mathbf{G}}(j)$ and $\overline{\mathbf{H}}(j+1) - \overline{\mathbf{H}}(j)$ are negative semidefinite, as the eigenvalues of $\overline{\mathbf{\Phi}}$ are inside the unit circle.

The mean square error of the naïve j-step ahead forecast is the $n \times n$ top left block of (9.3), i.e. $\overline{\mathbf{F}}_{11}(j) + \overline{\mathbf{G}}_{11}(j) + \overline{\mathbf{H}}_{11}(j)$, where for $\mathbf{M}(\cdot)$=$\overline{\mathbf{F}}(\cdot)$,$\overline{\mathbf{G}}(\cdot)$,$\overline{\mathbf{H}}(\cdot)$ we partition the $np^* \times np^*$ matrix $\mathbf{M}(\cdot)$ as

$$\mathbf{M}(\cdot) = \begin{pmatrix} \mathbf{M}_{11}(\cdot) & \mathbf{M}_{12}(\cdot) \\ \mathbf{M}_{21}(\cdot) & \mathbf{M}_{22}(\cdot) \end{pmatrix},$$

with $\mathbf{M}_{11}(\cdot)$ being $n \times n$. Using the result of Rao (1973, p.32), it follows that if $\mathbf{M}(j+1) - \mathbf{M}(j)$ is positive (negative) semidefinite, so is $\mathbf{M}_{11}(j+1) - \mathbf{M}_{11}(j)$. This proves the claim of Section 3 that the mean square error of the naïve forecasts can be written as the sum of a negative semidefinite matrix and a positive semidefinite one.

Appendix B: Renormalization

Consider the simple model

$$\begin{aligned} C &= \beta Y + e, \\ Y &= C + I, \end{aligned}$$

where C, Y are the endogenous variables, I, e are the exogenous variables and β is a fixed coefficient. Let $C' = C + \Delta C$ be a preliminary observation, which we want to target: in this context we may think of ΔC as a revision error which makes the preliminary value C' different from the final figure C.

The renormalization procedure consists in obtaining a solution of the model in terms of C'. The solution can be achieved by using e as instrument, i.e. by exchanging the roles between the endogenous variable C and the exogenous variable e. By doing so, one easily obtains $e' = e + (1 - \beta)\Delta C$ and $Y' = Y + \Delta C$. Thus C', Y' is a solution of the model in terms of e', I.

In general, consider a nonlinear model in reduced form

$$Y = f(X; \theta),$$

where Y and X are the endogenous and exogenous variables, θ are coefficients and f is a "well-behaving" nonlinear map. Partition $Y = (Y_1, Y_2)$, $X = (X_1, X_2)$, with Y_1 and X_1 having the same number of elements, say k, and let

$$f_i = \frac{\partial Y_i}{\partial X_1}, \quad i = 1, 2,$$

with f_1 being a $k \times k$ full rank matrix. If the target is $Y_1' = Y_1 + \Delta Y_1$, the model has the solution $Y' = f(X'; \theta)$, where $X' = (X_1 + f_1^{-1}\Delta Y_1, X_2)$ and $Y' \simeq (Y_1', Y_2 + f_2 f_1^{-1}\Delta Y_1)$.

The procedure then consists in putting a (possibly nonlinear) structural model such as the BIQM in reduced form and computing the jacobians f_1, f_2. In practice, though, one can obtain the jacobians without having to derive the reduced form analytically, but by applying small shocks to X_1 from a current solution of the model and computing the resulting values for the endogenous variables. Then, only f_1 needs to be determined: through f_1 one in fact obtains the X_1' to plug into the structural or reduced form of the model for achieving Y'.

If the model is dynamic, in general it can be written as $A(L)Y = f(X; \theta)$, where

$$A(L) = \begin{pmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{pmatrix}$$

is a polynomial in the lag operator L, partitioned comformably with Y. Then the solution Y', X' obtained above still holds, with $f_i = \partial(A^*_{ii}(L)f(X_i))/\partial X_1$, $i = 1, 2$, and $A^*(L) \equiv A(L)^{-1}$ has the same partitioned structure as $A(L)$.

This renormalization procedure is frequently adopted in the forecasting exercises with the BIQM, for example when only part of the overall data can be updated by the new observations produced by the statistical agencies. A more detailed treatment of these methods and their use in policy analysis can be found in Whitley (1994, pp. 200-208).

The experiments of Section 8 use the full BIQM, the targets being the preliminary observations for the five series of GDP, consumption, investment, exports, imports, all in real terms. Instruments were the residuals of five behavioural equations relating to the series of inventories, consumption, investment, exports and imports.

References

[1] Anderson, B.D.O and J.B. Moore (1979), Optimal Filtering, Prentice-Hall, Englewood Cliffs.

[2] Bates, J.M. and C.W.J. Granger (1969), The combination of forecasts, Operational Research Quarterly 20, 133-167.

[3] Banca d'Italia (1986), Modello trimestrale dell'economia italiana, Banca d'Italia, Temi di discussione, n. 80.

[4] Bordignon, S. and U. Trivellato (1989), The optimal use of provisional data in forecasting with dynamic models, Journal of Business and Economic Statistics 7, 275-286.

[5] Cole, R. (1969), Errors in provisional estimates of Gross National Product, NBER, New York.

[6] Conrad, W. and C. Corrado (1979), Application of the Kalman filter to revisions in monthly sales estimates, Journal of Economic Dynamics and Control 1, 177-198.

[7] Eurostat (1999), Handbook on Quarterly National Accounts.

[8] Faust, J., Rogers, J.H. and J.H. Wright (2001), News and noise in G-7 GDP announcements, mimeo, Board of Governors of the Federal Reserve System.

[9] Di Fonzo, T., Pisani S. and G. Savio (1995), Revisions to italian quarterly national accounts aggregates: some empirical results, Università di Brescia, Rapporti di Ricerca del Dipartimento Metodi Quantitativi 86.

[10] Gallo, G.M. and M. Marcellino (1999), Ex post and ex ante analysis of provisional data, Journal of Forecasting 18, 421-434.

[11] Hamilton, J.D. (1994), Time series analysis, Princeton, Princeton University Press.

[12] Harrison, R., Kapetanios, G. and T. Yates (2003), Forecasting with measurement errors in dynamic models, mimeo, Bank of England.

[13] Harvey, A.C. (1989), Forecasting, structural time series models and the Kalman filter, Cambridge, Cambridge University Press.

[14] Harvey, A.C., McKenzie, C.R., Blake, D.P.C. and M.J. Desai (1983), Irregular data revisions, in: A. Zellner (ed.), Applied Time Series Analisys of Economic Data, US Bureau of the Census, Washington, DC.

[15] Hendry, D.F. and M.P. Clements (1994), On a theory of intercept corrections in macroeconomic forecasting, in: S. Holly (ed.), Money, inflation and employment: essays in honour of James Ball, Aldershot, Edward Elgar, 160-182.

[16] Howrey, E.P. (1978), The use of preliminary data in econometric forecasting, Review of Economics and Statistics 60, 193-200.

[17] Howrey, E.P. (1984), Data revisions, reconstruction and prediction: an application to inventory investment, Review of Economics and Statistics 66, 386-393.

[18] Johansen, S. (1995), Likelihood-based inference in cointegrated vector autoregressive models, Oxford University Press, Oxford.

[19] Klein, L.R. (1983), Lectures in Econometrics, Elsevier Science Publishers, Amsterdam.

[20] Koopman, S.J. and A.C. Harvey (1999), Computing observation weights for signal extraction and filtering, mimeo.

[21] Koopman, S.J., Shepard, N. and J.A. Doornik (1998), Statistical algorithms for models in state space using SsfPack 2.2, Econometrics Journal 1, 1-55.

[22] Mankiw, N.G. and M.D. Shapiro (1986), News or noise? An analysis of GNP revisions, NBER Working Paper 1939.

[23] Mariano, R.S. and H. Tanizaki (1995), Prediction of final data with use of preliminary and/or revised data, Journal of Forecasting 14, 351-380.

[24] Parigi, G. and G. Schlitzer (1995), Quarterly forecasts of the italian business cycle by means of monthly economic indicators, Journal of Forecasting 14, 117-141.

[25] Patterson, K.D. (1995a), A state space approach to forecasting the final vintage of revised data with an application to the index of industrial production, Journal of Forecasting 14, 337-350.

[26] Patterson, K.D. (1995b), Forecasting the final vintage of real disposable income: a state space approach, International Journal of Forecasting 11, 395-405.

[27] Patterson, K.D. (2000), Which vintage of data to use when there are multiple vintages of data? Cointegration, Weak exogeneity and common factors, Economics Letters 69, 115-121.

[28] Rao, C.R. (1973), Linear statistical inference and its applications, 2nd ed., Wiley, New York.

[29] Siviero, S. and D. Terlizzese (2001), Macroeconomic forecasting: debunking a few old wives' tales, Banca d'Italia, Temi di Discussione, n. 395.

[30] Trivellato, U. and E. Rettore (1986), Preliminary data errors and their impact on the forecast error of simultaneous equation models, Journal of Business and Economic Statistics 4, 445-453.

[31] Whitley, J.D. (1994), A course in macroeconomic modelling and forecasting, Harvester Wheatsheaf, NY.

[32] Zellner, A. (1958), A statistical analysis of provisional estimates of Gross National Product and its components, of selected national income components, and of personal savings, Journal of the American Statistical Association 53, 54-65.

Table 1

First 12 vintages and final value for percentage growth rate of real GDP

Observation	$y_{t,1}$	$y_{t,2}$	$y_{t,3}$	$y_{t,4}$	$y_{t,5}$	$y_{t,6}$	$y_{t,7}$	$y_{t,8}$	$y_{t,9}$	$y_{t,10}$	$y_{t,11}$	$y_{t,12}$	1998.3
1988 Q1		1.251		1.446	0.999			1.101	1.100	1.102	1.250		1.194
1988 Q2	0.636		0.777	0.542			0.680	0.622	0.644	0.567		**0.897**	0.512
1988 Q3		1.063	0.729			1.064	1.059	1.018	0.808		0.703		0.697
1988 Q4	1.013	1.044			0.641	0.832	0.838	0.904		0.760		**0.803**	0.961
1989 Q1	0.735			0.991	0.678	0.604	0.814		0.580		0.638	**0.698**	0.604
1989 Q2			0.660	0.799	0.871	0.767		0.934		0.859	0.935	**0.935**	0.538
1989 Q3		0.699	0.826	0.783	0.678		0.971		0.859	0.862	0.862	**0.772**	0.688
1989 Q4	0.436	0.517	0.719	0.702		0.355		0.386	0.426	0.426	0.545	**0.545**	1.209
1990 Q1	0.939	0.624	0.820		0.839		0.744	0.750	0.739	0.744	0.754	**0.739**	0.629
1990 Q2	-0.202	-0.383		-0.201		0.119	0.088	0.071	0.015	-0.023	-0.077		0.035
1990 Q3	0.662		0.502		0.397	0.886	0.992	0.932	0.977	1.071		**1.071**	0.413
1990 Q4		0.086		-0.090	-0.105	-0.223	-0.113	-0.129	-0.428		-0.428	**-0.428**	-0.372
1991 Q1	0.349		0.603	0.523	0.339	0.395	0.415	0.415		0.497	0.415	**0.246**	0.528
1991 Q2		0.420	0.466	0.623	0.550	0.526	0.477		0.474	0.535	0.383	**0.383**	0.309
1991 Q3	0.053	0.204	0.335	0.260	0.181	0.332		0.124	0.231	0.500	0.500	**0.500**	0.687
1991 Q4	0.289	0.445	0.436	0.587	0.466		0.565	0.493	0.640	0.640	0.640	**0.640**	0.381
1992 Q1	0.583	0.552	0.569	0.537		0.632	0.473	0.244	0.414	0.313	0.419	**0.607**	0.196
1992 Q2	0.216	0.248	0.168		0.234	0.315	0.146	0.016	0.100	-0.081	-0.100		0.075
1992 Q3	-0.610	-0.452		-0.716	-0.544	-0.762	-0.961	-0.880	-0.860	-1.052		**-1.052**	-0.483
1992 Q4	-0.571		-0.494	-0.510	-0.190	-0.075	-0.088	-0.010	0.003		0.003	**0.003**	-0.601
1993 Q1		-0.142	-0.204	-0.460	-0.238	-0.329	-0.329	-0.473		-0.545	-0.510	**-0.764**	-0.622
1993 Q2	0.762	0.707	0.399	0.257	0.242	0.230	0.003		0.169	0.132	0.267	**0.149**	0.064
1993 Q3	-0.475	-0.427	-0.636	-0.581	-0.688	-0.873		-0.960	-0.992	-0.858	-0.733	**-0.297**	-0.261
1993 Q4	0.800	0.947	1.034	1.191	1.117		1.081	1.116	1.059	1.041	0.819	**0.819**	0.883
1994 Q1	0.070	0.411	0.289	0.358		0.310	0.212	0.268	0.289	0.139	0.165	**0.241**	0.407
1994 Q2	1.402	1.135	0.986		0.841	1.033	0.977	0.916	1.331	1.260	1.169	**1.170**	1.075
1994 Q3	0.989	1.318		1.506	1.595	1.374	1.382	0.785	0.800	0.756	0.756	**0.756**	0.567
1994 Q4	0.024		0.387	0.033	-0.021	-0.023	0.279	0.359	0.473	0.473	0.473	**0.473**	0.441
1995 Q1		1.347	1.524	1.378	1.240	1.530	1.550	1.405	1.501	1.609	1.616	**1.705**	1.705
1995 Q2	-0.385	-0.090	-0.047	0.064	0.210	0.133	0.127	0.160	-0.066	-0.029	-0.095	**-0.095**	-0.095
1995 Q3	1.951	1.844	2.052	0.606	0.598	0.634	0.490	0.555	0.409	0.616	0.616	**0.616**	0.616
1995 Q4	-0.916	-1.060	0.083	0.050	0.290	0.100	0.221	0.373	0.378	0.378	0.378	**0.378**	0.378

Table 2

Preliminary data errors for Italian quarterly national accounts

		Vintage										
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
	mean	-0.04	0.10	-0.03	0.05	-0.04	0.05	0.03	0.01	-0.02	0.02	0.02
GDP	**s.dev.**	0.49	0.49	0.47	0.31	0.41	0.27	0.23	0.26	0.26	0.19	0.17
	rmse	0.48	0.49	0.46	0.31	0.40	0.27	0.23	0.26	0.25	0.19	0.17
	mean	0.05	0.08	0.05	-0.01	-0.04	0.02	0.08	-0.02	0.00	-0.04	-0.01
CON	**s.dev.**	0.37	0.38	0.38	0.30	0.33	0.25	0.23	0.19	0.17	0.15	0.08
	rmse	0.36	0.38	0.38	0.39	0.33	0.25	0.24	0.19	0.17	0.16	0.08
	mean	0.25	-0.02	0.15	-0.03	0.14	-0.05	0.12	0.15	0.06	0.00	-0.01
INV	**s.dev.**	1.13	1.20	1.13	1.17	1.15	0.90	0.97	0.71	0.62	0.57	0.42
	rmse	1.13	1.18	1.12	1.14	1.14	0.88	0.96	0.72	0.61	0.57	0.42
	mean	-0.16	0.23	0.08	0.53	-0.48	0.36	-0.22	0.22	0.02	-0.03	0.18
EXP	**s.dev.**	2.25	1.79	2.28	2.03	1.78	1.59	1.66	1.21	1.33	0.69	1.05
	rmse	2.21	1.77	2.23	2.06	1.81	1.60	1.64	1.21	1.31	0.68	1.05
	mean	0.14	0.06	0.16	0.06	0.33	-0.04	-0.14	0.46	-0.28	0.14	-0.15
IMP	**s.dev.**	1.33	1.15	1.16	1.45	0.95	1.77	1.65	1.78	1.85	1.23	1.17
	rmse	1.31	1.33	1.15	1.42	0.99	1.74	1.63	1.81	1.84	1.22	1.17
	N	24	25	26	27	28	29	30	31	32	33	34

Table 3

Correlations among revision errors

	1	2	3	4	5	6	7	8	9	10	11
1	1										
2	0.94	1									
3	0.81	0.80	1								
4	0.50	0.61	0.55	1							
5	0.38	0.49	0.71	0.85	1						
6	0.44	0.55	0.31	0.80	0.69	1					
7	0.17	0.35	0.29	0.77	0.82	0.79	1				
8	0.16	0.34	0.36	0.60	0.70	0.73	0.74	1			
9	0.09	0.13	0.06	0.48	0.40	0.61	0.61	0.78	1		
10	0.12	0.16	0.26	0.51	0.34	0.52	0.36	0.85	0.61	1	
11	0.14	0.25	0.30	0.40	0.32	0.49	0.33	0.52	0.87	0.62	1

Table 4

Test of unbiasedness of preliminary data

		Release							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
GDP	**F prob.**	0.90	0.28	0.11	0.54	0.00	0.27	0.06	0.21
	s.e.	0.50	0.48	0.44	0.31	0.33	0.27	0.22	0.25
	R^2	0.49	0.52	0.42	0.75	0.62	0.81	0.84	0.81
CON	**F prob.**	0.00	0.07	0.06	0.20	0.12	0.33	0.20	0.19
	s.e.	0.26	0.35	0.35	0.28	0.31	0.25	0.23	0.19
	R^2	0.58	0.56	0.58	0.77	0.73	0.84	0.89	0.89
INV	**F prob.**	0.00	0.00	0.00	0.01	0.02	0.00	0.09	0.02
	s.e.	0.75	0.83	0.81	0.99	1.01	0.73	0.91	0.65
	R^2	0.61	0.74	0.78	0.74	0.75	0.84	0.79	0.88
EXP	**F prob.**	0.51	0.42	0.17	0.43	0.17	0.48	0.15	0.22
	s.e.	2.23	1.77	2.16	2.07	1.76	1.62	1.59	1.19
	R^2	0.71	0.71	0.79	0.75	0.69	0.75	0.85	0.90
IMP	**F prob.**	0.87	0.93	0.25	0.97	0.06	0.98	0.90	0.37
	s.e.	1.36	1.18	1.13	1.48	0.92	1.80	1.68	1.81
	R^2	0.68	0.80	0.85	0.73	0.89	0.58	0.66	0.64
	N	24	25	26	27	28	29	30	31

Table 5

Forecast errors of the BIQM - Rolling simulations 1985Q1-1994Q4

		Forecast Horizon							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
log(GDP)	**bias**	-0.04	-0.08	-0.13	-0.19	-0.25	-0.30	-0.38	-0.47
	s.dev.	0.59	0.79	0.96	1.11	1.22	1.35	1.42	1.48
	RMSE	0.58	0.78	0.95	1.11	1.23	1.36	1.45	1.53
Δlog(GDP)	**bias**	-0.04	-0.04	-0.05	-0.06	-0.06	-0.05	-0.08	-0.09
	s.dev.	0.59	0.68	0.64	0.67	0.66	0.63	0.66	0.66
	RMSE	0.58	0.67	0.64	0.66	0.66	0.63	0.66	0.65
log(CON)	**bias**	-0.11	-0.17	-0.22	-0.25	-0.32	-0.38	-0.45	-0.52
	s.dev.	0.35	0.68	0.94	1.08	1.21	1.33	1.44	1.50
	RMSE	0.36	0.69	0.95	1.09	1.24	1.37	1.49	1.57
Δlog(CON)	**bias**	-0.11	-0.06	-0.05	-0.03	-0.07	-0.06	-0.07	-0.07
	s.dev.	0.35	0.41	0.39	0.39	0.40	0.40	0.41	0.41
	RMSE	1.36	0.41	0.39	0.39	0.40	0.40	0.41	0.41
log(INV)	**bias**	-0.06	-0.02	0.00	0.06	0.15	0.19	0.19	0.10
	s.dev.	1.02	1.72	2.15	2.56	2.82	3.11	3.46	3.98
	RMSE	1.01	1.70	2.13	2.53	2.78	3.07	3.42	3.93
Δlog(INV)	**bias**	-0.06	0.04	0.03	0.06	0.09	0.04	0.00	-0.08
	s.dev.	1.02	1.12	1.14	1.14	1.09	1.22	1.23	1.27
	RMSE	1.01	1.10	1.13	1.12	1.08	1.20	1.22	1.26
log(EXP)	**bias**	-0.13	-0.11	-0.14	-0.23	-0.39	-0.64	-0.75	-0.87
	s.dev.	2.46	2.55	2.63	2.75	2.92	2.88	3.14	3.21
	RMSE	2.43	2.52	2.60	2.73	2.90	2.91	3.19	3.28
Δlog(EXP)	**bias**	-0.13	0.03	-0.03	-0.09	-0.16	-0.25	-0.12	-0.12
	s.dev.	2.46	3.03	3.09	3.23	3.31	3.26	3.17	3.19
	RMSE	2.43	2.99	3.05	3.19	3.27	3.23	3.14	3.15
log(IMP)	**bias**	-0.32	-0.45	-0.63	-0.73	-0.88	-0.97	-0.12	-1.42
	s.dev.	2.28	2.69	3.02	3.41	3.88	4.14	4.52	4.90
	RMSE	2.27	2.70	3.05	3.44	3.93	4.20	4.63	5.04
Δlog(IMP)	**bias**	-0.32	-0.13	-0.19	-0.10	-0.15	-0.09	-0.26	-0.19
	s.dev.	2.28	2.58	2.58	2.65	2.66	2.66	2.84	2.85
	RMSE	2.27	2.56	2.56	2.62	2.63	2.62	2.82	2.82

Table 6

Weighted preliminary data regressions

		constant	$y_{t,1}$	$x_{t\|t-1}$	$x_{t\|t-2}$	R^2	DW	F-prob	Δsse (%)
GDP	R1	0.06 (0.77)	0.75 (6.55)			0.62	1.65		17.68
	R2		0.77 (9.15)	0.23 (2.74)		0.67	1.58	35.19	21.12
	R3		0.88 (8.95)		0.12 (1.21)	0.62	2.03	16.36	4.84
	R4		0.74 (6.87)	0.22 (2.40)	0.04 (0.46)	0.67	1.54	39.78	21.43
CON	R1	-0.12 (1.17)	0.98 (7.22)			0.67	1.42		11.80
	R2		0.40 (2.28)	0.60 (3.36)		0.74	1.40	69.12	28.83
	R3		0.60 (4.37)		0.40 (2.86)	0.73	1.18	36.59	22.48
	R4		0.36 (1.97)	0.44 (2.03)	0.21 (1.27)	0.75	1.23	64.07	32.90
INV	R1	-0.23 (1.15)	1.24 (8.92)			0.75	2.06		12.74
	R2		0.44 (2.98)	0.56 (3.74)		0.85	1.30	5.02	34.02
	R3		0.76 (4.64)		0.24 (1.43)	0.79	1.20	6.08	6.98
	R4		0.43 (2.43)	0.54 (3.28)	0.03 (0.19)	0.85	1.26	3.43	34.11
EXP	R1	0.59 (1.38)	0.59 (6.26)			0.60	2.07		42.49
	R2		0.46 (3.80)	0.54 (4.40)		0.63	1.21	26.16	41.48
	R3		0.67 (7.22)		0.33 (3.59)	0.56	2.11	11.69	32.21
	R4		0.47 (3.83)	0.41 (2.30)	0.12 (0.99)	0.62	1.41	38.13	43.60
IMP	R1	0.15 (0.37)	0.87 (6.53)			0.62	2.42		3.45
	R2		0.69 (4.47)	0.31 (1.98)		0.66	2.07	66.17	12.44
	R3		0.92 (6.84)		0.08 (0.58)	0.62	2.39	68.12	1.22
	R4		0.72 (4.46)	0.38 (1.98)	-0.10 (0.67)	0.67	1.97	65.10	13.89

Comparison of forecasts from the BIQM - Rolling simulations 1988Q2-1994Q4

			1	2	3	4	5	6	7	8
GDP	S1	bias	-0.14	-0.09	-0.01	-0.01	-0.02	-0.04	-0.11	-0.14
		rmse	0.60	0.71	0.67	0.70	0.69	0.68	0.72	0.70
	S2	bias	-0.19	-0.14	-0.06	-0.04	-0.04	-0.05	-0.11	-0.15
		rmse	0.77	0.76	0.67	0.67	0.73	0.65	0.72	0.71
	S3	bias	-0.13	-0.10	-0.08	-0.07	-0.07	-0.05	-0.11	-0.14
		rmse	0.75	0.71	0.68	0.71	0.72	0.67	0.72	0.71
	S4	bias	-0.38	-0.49	-0.31	-0.20	-0.09	-0.08	-0.13	-0.18
		rmse	0.85	0.99	0.73	0.69	0.68	0.68	0.73	0.72
	S5	bias	-0.36	-0.39	-0.30	-0.22	-0.13	-0.08	-0.13	-0.18
		rmse	0.81	0.87	0.72	0.72	0.70	0.68	0.73	0.72
	S6	bias	-0.21	-0.12	-0.15	-0.13	-0.13	-0.12	-0.18	-0.22
		rmse	0.72	0.78	0.76	0.72	0.75	0.75	0.74	0.76
	S7	bias	-0.29	-0.18	-0.14	-0.10	-0.11	-0.11	-0.19	-0.23
		rmse	0.74	0.85	0.72	0.71	0.73	0.72	0.73	0.74
	S8	bias	-0.22	-0.11	-0.13	-0.13	-0.14	-0.12	-0.18	-0.22
		rmse	0.73	0.75	0.73	0.73	0.75	0.75	0.74	0.75
CON	S1	bias	0.01	0.03	0.01	0.00	-0.03	-0.04	-0.06	-0.08
		rmse	0.35	0.44	0.43	0.45	0.46	0.47	0.47	0.48
	S2	bias	-0.05	-0.08	-0.10	-0.07	-0.06	-0.05	-0.06	-0.09
		rmse	0.64	0.53	0.55	0.60	0.59	0.51	0.50	0.53
	S3	bias	-0.05	-0.09	-0.12	-0.08	-0.06	-0.04	-0.06	-0.10
		rmse	0.59	0.54	0.56	0.57	0.56	0.50	0.50	0.52
	S4	bias	-0.45	-0.68	-0.64	-0.40	-0.18	-0.06	-0.08	-0.15
		rmse	0.70	0.86	0.85	0.69	0.53	0.48	0.50	0.53
	S5	bias	-0.45	-0.68	-0.64	-0.41	-0.18	-0.06	-0.08	-0.15
		rmse	0.70	0.86	0.85	0.69	0.52	0.48	0.50	0.53
	S6	bias	-0.13	-0.08	-0.07	-0.07	-0.10	-0.12	-0.13	-0.15
		rmse	0.61	0.61	0.60	0.60	0.61	0.63	0.65	0.61
	S7	bias	-0.12	-0.06	-0.05	-0.06	-0.10	-0.12	-0.13	-0.14
		rmse	0.58	0.59	0.61	0.62	0.59	0.57	0.57	0.57
	S8	bias	-0.13	-0.08	-0.07	-0.07	-0.11	-0.12	-0.13	-0.15
		rmse	0.61	0.61	0.59	0.59	0.60	0.62	0.64	0.61
INV	S1	bias	-0.06	0.00	0.02	0.09	0.14	0.06	-0.11	-0.33
		rmse	0.88	1.08	1.13	1.16	1.13	1.24	1.26	1.29
	S2	bias	-0.09	-0.07	-0.05	0.02	0.08	0.01	-0.17	-0.38
		rmse	0.97	1.12	1.18	1.18	1.14	1.25	1.27	1.30
	S3	bias	-0.11	-0.03	0.00	0.03	0.07	-0.02	-0.18	-0.38
		rmse	0.94	1.14	1.15	1.18	1.14	1.27	1.27	1.29
	S4	bias	-0.22	-0.27	-0.36	-0.31	-0.21	-0.22	-0.37	-0.58
		rmse	1.01	1.20	1.31	1.31	1.16	1.28	1.35	1.42
	S5	bias	-0.27	-0.26	-0.29	-0.25	-0.19	-0.23	-0.37	-0.57
		rmse	1.12	1.24	1.26	1.27	1.12	1.28	1.34	1.41
	S6	bias	-0.26	-0.30	-0.28	-0.27	-0.24	-0.32	-0.47	-0.68
		rmse	1.07	1.32	1.42	1.48	1.34	1.42	1.34	1.48
	S7	bias	-0.28	-0.35	-0.35	-0.33	-0.27	-0.36	-0.53	-0.77
		rmse	1.05	1.27	1.35	1.46	1.38	1.41	1.40	1.45
	S8	bias	-0.33	-0.35	-0.31	-0.27	-0.24	-0.32	-0.48	-0.68
		rmse	1.22	1.31	1.32	1.35	1.24	1.41	1.36	1.48
EXP	S1	bias	-0.06	0.09	-0.05	-0.06	-0.11	-0.17	-0.13	-0.08
		rmse	2.10	2.55	2.52	2.59	2.68	2.57	2.59	2.62
	S2	bias	0.20	0.18	-0.01	-0.04	-0.08	-0.16	-0.11	-0.06
		rmse	2.24	2.97	2.62	2.63	2.57	2.49	2.53	2.63
	S3	bias	0.05	0.18	0.10	0.01	-0.07	-0.17	-0.12	-0.06
		rmse	2.27	2.90	2.67	2.64	2.65	2.53	2.59	2.61
	S4	bias	0.76	0.73	0.01	0.04	-0.08	-0.14	-0.07	0.04
		rmse	2.64	2.84	2.77	2.61	2.67	2.54	2.57	2.64
	S5	bias	0.39	0.47	0.14	0.04	-0.07	-0.14	-0.07	0.03
		rmse	2.74	2.62	2.66	2.58	2.64	2.54	2.62	2.64
	S6	bias	0.41	0.27	0.23	0.04	-0.03	-0.14	-0.05	-0.03
		rmse	2.48	2.82	2.67	2.68	2.72	2.62	2.75	2.59
	S7	bias	0.67	0.31	0.20	0.07	0.01	-0.05	0.02	0.04
		rmse	2.26	2.88	2.68	2.63	2.66	2.60	2.67	2.67
	S8	bias	0.21	0.21	0.23	0.07	-0.04	-0.13	-0.08	-0.03
		rmse	2.47	2.74	2.63	2.68	2.70	2.62	2.79	2.61
IMP	S1	bias	-0.69	-0.21	-0.08	0.21	0.12	-0.02	-0.29	-0.31
		rmse	1.97	2.34	2.42	2.40	2.39	2.45	2.71	2.76
	S2	bias	-0.81	-0.37	-0.13	0.16	0.07	-0.06	-0.32	-0.32
		rmse	3.00	2.61	2.41	2.20	2.27	2.51	2.64	2.75
	S3	bias	-0.50	-0.14	-0.07	0.09	0.01	-0.08	-0.30	-0.31
		rmse	2.50	2.57	2.41	2.30	2.40	2.53	2.68	2.75
	S4	bias	-1.94	-1.12	-0.82	-0.17	-0.21	-0.21	-0.38	-0.30
		rmse	3.80	2.71	2.80	2.32	2.29	2.46	2.69	2.77
	S5	bias	-1.74	-1.04	-0.70	-0.32	-0.30	-0.26	-0.37	-0.29
		rmse	3.34	2.73	2.71	2.43	2.40	2.48	2.71	2.76
	S6	bias	-0.12	-0.31	-0.15	-0.09	-0.12	-0.24	-0.48	-0.55
		rmse	2.85	2.62	2.60	2.57	2.54	2.68	2.84	2.85
	S7	bias	-0.34	-0.51	-0.19	-0.01	-0.06	-0.25	-0.52	-0.58
		rmse	3.10	2.50	2.66	2.51	2.50	2.59	2.72	2.79
	S8	bias	-0.12	-0.13	-0.11	-0.11	-0.18	-0.29	-0.52	-0.54
		rmse	2.41	2.72	2.67	2.59	2.59	2.70	2.88	2.83