Error-correction versus differencing in macroeconometric forecasting.

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Abstract

Recent work by Clements and Hendry have shown why forecasting systems that are in terms of differences, dVARs, can be more accurate than econometric models that include levels variables, ECMs. For example, dVAR forecasts are insulated from parameter non-constancies in the long run mean of the cointegration relationships. In this paper, the practical relevance of these issues are investigated for RIMINI, the quarterly model of the Central Bank of Norway, which we take as an example of an ECM forecasting model. We develop a dVAR version of the model and compare ECM and dVAR forecasts for the period 1991.1-1994.4. The results confirm the relevance of several theoretical insights. dVAR forecasts appear immune to the parameter non-constancies that bias the ECM forecasts. However, for an open system like RIMINI, the misspecification resulting from the omission of levels information, generates a large bias in the dVAR forecasts. Therefore, the incumbent ECM performs comparatively well over the forecast period investigated in this paper.

Keywords: Forecasting, macroeconomics, error-corection model, VAR model.

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1 Introduction

Agencies that build and maintain macroeconometric models often use one and the same model for both policy analysis and forecasts. Critics of macroeconometric systems have pointed out that in pursuing both objectives, one may end up with models that perform poorly on both scores. For example, Granger and Newbold (1986) argue that theory-driven macro models that largely ignore dynamics and temporal properties of the data, will necessarily produce sub-optimal forecasts, their ability to elucidate important functional relationships in the economy notwithstanding. Forecasting is a time-oriented activity, and a procedure that pays only rudimentary attention to temporal aspects is likely to loose out to rival procedures that put dynamics in the foreground. As is well known, such competing procedures were developed and gained ground in the seventies in the form of Box-Jenkins time series analysis and ARIMA models.

In the eighties, macroeconometric model took advantage of the methodological and conceptual advances within time series econometrics. Genuinely dynamic behavioural equations are now the rule rather than the exception. Extensive testing of misspecification is usually performed. The dangers of spurious regressions has been reduced as a consequence of the adoption of the new inference procedures for integrated variables. As a result, modern macroeconometric forecasting models are less exposed to Granger and Newbold's critique. At the same times, forecasters also focused on other perceived inadequacies of their models, e.g. the overly simplified treatment of supply side factors and of transmission mechanism between the real and financial sectors of the economy, see e.g. Wallis (1989) for an overview.

For applied econometric forecasting, these developments offered some reconciliation of the perceived conflict between theoretical interpretability and data based dynamic specification. Confidence grew that error-correction models (ECMs) would forecast more accurately than models that only use differenced data (dVARs), since ECMs contain "long run" information about economic relationships.

However, in a series of recent paper, Michael Clements and David Hendry have re-examined several issues in macroeconometric forecasting, see e.g. Clements and Hendry (1995a), (1995b), (1996). This research reveals the fragility of a general claim that the econometric ECM outperforms the forecasts from a dVAR. Assuming constant parameters in the forecast period, the dVAR is misspecified relative to a correctly specified ECM, and dVAR forecasts will therefore be suboptimal. However, if the parameters change after the forecast is made, then the ECM is also misspecified in the forecast period. Clements and Hendry have shown that forecasts from a dVAR are *robust* with respect to some well defined classes of parameter changes. Hence, in practice, ECM forecasts may turn out to be less accurate than forecasts derived from a dVAR. Put differently, the "best model" in terms of economic interpretation and econometrics, may not be the best model for forecasts. At first sight, this is paradoxical, since any dVAR can be viewed as a special case of an ECM, since it imposes additional unit root restrictions on the system. However, if the parameters of the levels variables that are excluded from the dVAR change in the forecast period, this in turn makes the ECM misspecified. Hence, the outcome of the horse-race is no longer given, since both forecasting models are misspecified relative to the generating mechanism that prevails in the period we are trying to forecast.

If we take as premises that *a)* cointegration often can be established within sample; but *b)* that parameters are likely to change in the forecast period, practitioners are back to square one, with two competing alternative model classes available for forecasting purposes. In this paper, we demonstrate the relative importance of the two types of misspecification for forecasts of the Norwegian economy in the 1990s. The model that takes the role of the ECM is the macroeconometric forecasting model RIMINI, which is developed and used by the Norwegian Central Bank (the incumbent model). The rival forecasting systems are dVARs that are derived from the full model as well as univariate autoregressive models.

Earlier empirical studies of this issue have investigated small systems, see e.g. Hoffman and Rasche (1996). The attraction of small systems is obvious. They allow a full econometric evaluation of cointegration and of forecast performance. Macroeconometric models used by forecasting agencies are usually large and do not lend themselves easily to complete exposition and evaluation. On the other hand, the successes or failures of these systems have a large impact on the public perception of how useful macroeconometric forecasts are. Hence, it is of interest to investigate whether the new forecasting theory can help us gain new insight into the forecasting properties of the "big" forecasting models that are used in practice.

The rest of this paper is organized as follows. In section 2, we review some analytical results for the forecast errors of simple ECMs and dVARs in the case of parameter changes in the forecast period. In section 3 we give a brief account of the RIMINI model, the incumbent ECM, and the four alternative dVAR forecasting systems that we have developed for comparison. Section 4 contains the results of the forecasting exercise with the different systems. Section 5 concludes and discusses the implications for the role of econometric models in macroeconomic forecasting.

2 Forecast errors of bivariate ECM and dVARs

In this section, we illustrate how the forecast errors of an ECM and the corresponding dVAR might be affected differently by structural breaks. Practical forecasting models are typically open systems, with exogenous variables. Although the open model that we study in this section is of the simplest kind, its properties will prove helpful in interpreting the forecasts errors of the large systems in section 4 below.

The system consists of two cointegrating $I(1)$ variables, x_t and y_t. The error-correction equation for y_t is

$$\begin{aligned} \Delta y_t &= \pi_0 + \pi_1 \Delta x_t - \alpha[y_{t-1} - \beta x_{t-1}] + \varepsilon_{y,t}, \\ 0 &< \alpha < 1, \quad t = 1, \ldots, T. \end{aligned} \tag{1}$$

Given cointegration, the intercept π_0 can be rewritten in terms of an "autonomous growth" parameter γ, and the product of the feedback coefficient α, and a parameter μ, that measure the long-run mean of the cointegration relationship

$$\pi_0 = \gamma + \alpha\mu. \tag{2}$$

Using (2), the error-correction model can be written as

$$\Delta y_t = \gamma + \pi_1 \Delta x_t - \alpha[y_{t-1} - \beta x_{t-1} - \mu] + \varepsilon_{y,t.} \tag{3}$$

In the following, x_t is assumed to be strongly exogenous. To keep the notation as simple as possible, we assume that x_t follows a random-walk

$$\Delta x_t = \varepsilon_{x,t}. \tag{4}$$

Equations (3) and (4) make up the error-correction model, ECM. The disturbances $\varepsilon_{y,t}$ and $\varepsilon_{x,t}$ have zero expectations, constant variances and are uncorrelated. The dVAR model of y_t and x_t imposes one restriction on the model, namely $\alpha = 0$, hence the dVAR consists of

$$\Delta y_t = \gamma + \pi_1 \Delta x_t + e_{y,t}. \tag{5}$$

and (4). We further assume that

- Parameters are known.
- Forecasts for the periods $T+1, T+2, \ldots, T+j$, are made in period T.
- In the forecasts, $\Delta x_{T+i} = 0$ $(i = 1, \ldots, j)$.

Although all coefficients may change in the forecast period, the most relevant coefficients in our context is α, β and μ, i.e. the coefficients that are present in the ECM but not in the dVAR. Among these, we concentrate on α and μ, since β represents partial structure by virtue of being a cointegration parameter.

2.1 Parameters change *after* the forecast is prepared

2.1.1 Change in the long run mean

We first assume that the long-run mean coefficient changes form its initial level μ to a new level μ^* after the forecast is made in period T. Hence all forecast errors from $T+1$ and onwards are affected by the parameter change. All other coefficients are assumed constant throughout the forecast period.

The 1-period forecast error for the ECM can be written

$$y_{T+1} - \hat{y}_{T+1,\text{ECM}} = \pi_1 \varepsilon_{x,T+1} - \alpha[\mu - \mu^*] + \varepsilon_{y,T+1}. \tag{6}$$

For the dVAR, the corresponding forecast error is

$$y_{T+1} - \hat{y}_{T+1,\text{dVAR}} = \pi_1 \varepsilon_{x,T+1} - \alpha[y_T - \beta x_T - \mu^*] + \varepsilon_{y,T+1}. \tag{7}$$

In the following we focus on the bias of the forecast errors. The 1-step biases are defined by the conditional expectation of the forecast errors and are denoted $\mathsf{bias}_{T+1,\text{ECM}}$ and $\mathsf{bias}_{T+1,\text{dVAR}}$ respectively:

$$\begin{aligned} \mathsf{bias}_{T+1,\text{ECM}} &= -\alpha[\mu - \mu^*], && (8)\\ \mathsf{bias}_{T+1,\text{dVAR}} &= -\alpha[y_T - \beta x_T - \mu^*]. && (9) \end{aligned}$$

The following points are worth noting: First, the ECM bias is directly proportional to the parameter change. The dVAR forecast too is biased, unless it happens that y_T is exactly equal to its new attractor $\beta x_T + \mu^*$. Second, the dVAR error is robust to the parameter non-constancy as such, i.e., the bias only contains μ^* and not μ.

Third, even in this simple case, there is no ranking of the two biases. Which of the two is bigger (in absolute terms) depends on the initial conditions and the size of parameter change.

For comparison with section 2.2 below, we also write down the biases of the 2-period forecast errors.

$$\mathsf{bias}_{T+2,\mathrm{ECM}} = -\alpha\delta_{(1)}[\mu - \mu^*], \tag{10}$$

where $\delta_{(1)} = 1 + (1-\alpha)$ and

$$\begin{aligned} \mathsf{bias}_{T+2,\mathrm{dVAR}} &= \gamma(\delta_{(1)} - 2) - \alpha\delta_{(1)}[y_T - \beta x_T - \mu^*]. \\ &= -\alpha\gamma - \alpha\delta_{(1)}[y_T - \beta x_T - \mu^*]. \end{aligned} \tag{11}$$

Finally, for the $j-$periods ECM forecasts:

$$\mathsf{bias}_{T+j,\mathrm{ECM}} = -\alpha\delta_{(j-1)}[\mu - \mu^*], \tag{12}$$

where $\delta_{(j-1)}$ is defined as

$$\delta_{(j-1)} = 1 + \sum_{i=1}^{j-1}(1-\alpha)^i,\ j = 2, 3, ... \tag{13}$$

The corresponding $j-$period bias of the dVAR forecast becomes

$$\mathsf{bias}_{T+j,\mathrm{dVAR}} = -\gamma(\delta_{(j-1)} - j) - \alpha\delta_{(j-1)}[y_T - \beta x_T - \mu^*],\ j = 2, 3, ... \tag{14}$$

The $2-$ and $j-$period ahead forecast errors show how the parameter change affects the ECM forecast adversely even for long forecast horizons. The parameter shift in itself does not harm the dVAR forecasts. However, starting from the second forecast period, the dVAR forecasts errors are biased as long as the dVAR contains a non-zero autonomous growth component γ, cf. the term $\gamma(\delta_{(j-1)} - j) \neq 0$ in equation (14). Over longer forecast horizons, that bias may become larger that the ECM forecast bias.[1]

2.1.2 Change in the equilibrium correction coefficient

Next, we consider the situation where the adjustment coefficient α changes to a new value, α^*, after the forecast for $T+1$, $T+2$,. . .,$T+j$ have been prepared. The 1-step errors for the two types of forecasts for the two models are:

$$\mathsf{bias}_{T+1,\mathrm{ECM}} = -(\alpha^* - \alpha)[y_T - \beta x_T - \mu], \tag{15}$$

and

$$\mathsf{bias}_{T+1,\mathrm{dVAR}} = -\alpha^*[y_T - \beta x_T - \mu]. \tag{16}$$

The ECM bias is proportional to the size of the shift, while the dVAR bias is proportional to the magnitude of the new coefficient itself. Hence, if the parameter

[1]Note that to avoid an intercept related component in the dVAR bias, $\gamma = 0$ in the data generating process. If $\gamma \neq 0$, but the dVAR used for forecasting is without an intercept term, the intercept-bias becomes $\gamma\delta_{(j-1)}$ instead of $\gamma(\delta_{(j-1)} - j)$ as in (14)

change is small relative to the (new) level of the coefficient, the dVAR bias will be larger than the ECM bias.

For the multi-period forecasts, the ECM bias is

$$(17)\qquad \mathsf{bias}_{T+j,\mathrm{ECM}} = \gamma(\delta^*_{(j-1)} - \delta_{(j-1)}) \\ -(\alpha^*\delta^*_{(j-1)} - \alpha\delta_{(j-1)})[y_T - \beta x_T - \mu],\ j = 2, 3, ...,$$

where $\delta_{(j-1)}$ is defined in (13) and $\delta^*_{(j-1)}$ is given in a similar fashion as

$$(18)\qquad \delta^*_{(j-1)} = 1 + \sum_{i=1}^{j-1}(1-\alpha^*)^i,\ j = 2, 3, ...$$

For the dVAR, the j-period ahead forecast error bias is given by

$$(19)\qquad \mathsf{bias}_{T+j,\mathrm{dVAR}} = \gamma(\delta^*_{(j-1)} - j) - \alpha^*\delta^*_{(j-1)}[y_T - \beta x_T - \mu],\ j = 2, 3, ...$$

Hence, even though the dVAR bias is unaffected by the parameter instability as such, the size of the dVAR bias is likely to be larger than the ECM bias, even for short forecast horizons.

2.2 Parameter change *before* the forecast is made

This situation is illustrated by considering how the forecasts for $T+2, T+3, ..., T+j$ is updated conditional on outcomes for period $T+1$. The shift $\mu \to \mu^*$ first affects outcomes in period $T+1$. When the forecasts for $T+2, T+3$...are updated in period $T+1$, information about parameter inconstancies are therefore present in the starting value y_{T+1}. Considering $\mu \to \mu^*$ first, the updated forecast for y_{T+2}, conditional on y_{T+1} yields

$$(20)\qquad \mathsf{bias}_{T+2,\mathrm{ECM}} \mid T+1 = -\alpha[\mu - \mu^*],$$

for the ECM and

$$(21)\qquad \mathsf{bias}_{T+2,\mathrm{dVAR}} \mid T+1 = -\alpha[y_{T+1} - \beta x_{T+1} - \mu^*].$$

for the dVAR.

Equation (20) shows that the ECM forecast error is affected by the parameter change in exactly the same manner as before, cf. (10) above, despite the fact that in this case the effect of the shift is incorporated in the initial value y_{T+1}. In this important sense, the ECM forecasts do not error-correct to events that have occurred prior to the preparation of the forecast. Instead, unless the forecasters detect the parameter change and take appropriate action by intercept correction, the effect of a parameter shift prior to the forecast period will bias the forecasts "forever". The situation is different for the dVAR, see equation (21). Since the forecast-error contains both y_{T+1} and μ^*, the forecast incorporates that the change from μ to μ^* is partly reflected in y_{T+1}. In this important sense, there is an element of inherent "intercept correction" built into the dVAR forecasts period.

The analysis of changes in the adjustment coefficient is very similar. The ECM does not adjust automatically to $\alpha \to \alpha^*$ occurring prior to the preparation of the forecast, whereas the dVAR partly adjusts to such parameter inconstancies.

3 A large scale ECM model and four forecasting systems based on differenced data (dVARs)

Section 2 brought out that even for very simple systems, it is in general difficult to predict which version of the model is going to have the smallest forecast error, the ECM or the dVAR. While the forecast errors of the dVAR are robust to changes in the adjustment coefficient α and the long-run mean μ, the dVAR forecast error may still turn out to be larger than the ECM forecast error. Typically, this is the case if the parameter change (included in the ECM) is small relative to the contribution of the error-correction term (which is omitted in the dVAR) at the start of the forecast period.

In section 4 below, we generate multi-period forecasts from the econometric model RIMINI used by the Central Bank of Norway, and compare these to the forecasts from models based on differenced data. In order to provide some background to those simulations, this section first describes the main features of the incumbent ECM and then explains how we have designed the dVAR forecasting systems.

The Norwegian Central Bank uses the quarterly macroeconomic model RIMINI as a primary instrument in the process of forecast preparation. The typical forecast horizon is four to eight quarters in the Bank's Inflation report, but forecasts for up to five years ahead are also published regularly as part of the assessment of the medium term outlook of the Norwegian economy. The 205 equations of RIMINI (version 2.9) fall into three categories

- 146 definitional equations, e.g. national accounting identities, composition of the work-force etc.
- 33 estimated "technical " equations, e.g. price indices with different base years and equations that serve special reporting purposes (there is no feed-back to the rest of the model).
- 26 estimated "behavioural" equations.

The two first groups of equations are identical in RIMINI and the dVAR versions of the model. It is the specification of 26 econometric equations that distinguish the models. Together they contain quantitative knowledge about behaviour relating to aggregate outcome, e.g. consumption, savings and household wealth; labour demand and unemployment; wage and price interactions (inflation); capital formation; foreign trade. Seasonally unadjusted data are used for the estimation of the equations. To a large extent, macroeconomic interdependencies are contained in the dynamics of the model. For example, prices and wages are Granger-causing output, trade and employment and the level of real-activity feeds back on to wage-prices inflation. The model is an open system: Examples of important non-modelled variables are the level of economic activity by trading partners, as well as inflation and wage-costs in those countries. Indicators of economic policy (the level of government expenditure, the short-term interest rate and the exchange rate), are also non-modelled and the forecasts are therefore conditional on a particular scenario for these variables. In the following, we refer to the incumbent version of RIMINI as eRIM.

Because all the behavioural equations of RIMINI are in error-correction form, a simple dVAR version of the model can be obtained by just omitting the error-correction terms from the equation and re-estimating the coefficients of the remaining (differenced variables). Omission of significant error-correction terms means that the resulting differenced equations become misspecified, with autocorrelated and heteroscedastic residuals. From one perspective this is not a problem: The main thrust of the theoretical discussion is that the dVAR is indeed misspecified within sample, cf. that the error-term $e_{y,t}$ in the dVAR equation (5) is autocorrelated provided that there is some autocorrelation in the disequilibrium term in (1). The dVAR might still forecast better than the ECM, if the coefficients relating to the error-correction terms change in the forecast period. That said, having a misspecified dVAR does put that model at a disadvantage compared to the ECM. Hence we decided to re-model all the affected equations, in terms of differences alone, in order to make the residuals of the dVAR-equations empirically white-noise.

To illustrate our approach, we consider the estimated "consumption price equation" in eRIM, reported in equation (22) below. Lower case Latin letters denote logs, hence the estimated coefficients are elasticities. OLS standard errors are reported below the estimates. The first three terms on the right hand side give the impact on inflation of import price growth (Δpb_t), wage costs per hour (Δwcf_t) and an acceleration term ($\Delta^2 wcf_{t-3}$). The next two variables are *real* GDP output growth (Δyf), a weighted average over two quarters, and productivity growth, an average over four quarters ($\Delta_4 zyf_t$). The last growth rate term is the fourth quarter lag of inflation (Δcpi_{t-4}). Finally, there are three seasonal dummies $S_{i,t}$ ($i = 1, 2, 3$), a VAT dummy and an incomes policy dummy (IP_t). It might be noted that the explanatory variables pb_t, wcf_t, yf_t and zyf_t are all model-endogenous variables.

The two levels terms in (22) are $(cpi - pb - T3)_{t-1}$ and $(wcf - pb - zyf)_{t-1}$. Together they impose the following set of restrictions:

- Nominal long-run homogeneity.
- Labour cost and productivity are restricted to enter the long run part of the model in the form of unit labour costs ($wcf - zyf$).
- A long run coefficient of unity is imposed for the indirect tax-rate, $T3$.

The estimated adjustment coefficient of $(cpi - pb - T3)_{t-1}$ is low (0.076), indicating relatively slow adjustment of consumer prices to increases in wage costs or in import prices. However, the t-value of the adjustment coefficient is -6.90 which suggests that $(cpi - pb - T3)_t$ cointegrates with $(wcf - pb - zyf)_t$, although a formal test requires weak exogeneity of wcf_t, pb_t and zyf_t, see Kremers, Ericsson, and Dolado (1992).[2]

[2]MacKinnon's (1991)Dickey-Fuller 1% critical value for the null hypohesis that $(cpi - pb - T3)_t$ and $(wcf - pb - zyf)_t$ do not cointegrate, is -4.02.

$$
\begin{aligned}
(22)\quad \widehat{\Delta cpi_t} = \; & \underset{(0.003)}{0.009} + \underset{(0.016)}{0.054}\ \Delta pb_t + \underset{(0.027)}{0.182}\ \Delta wcf_t \\
& + \underset{(0.019)}{0.064}\ \Delta\Delta wcf_{t-3} + \underset{(0.016)}{0.022}\ (0.5\Delta yf_{t-1} + \Delta yf_{t-2}) \\
& - \underset{(0.019)}{0.065}\ \Delta_4 zyf_t + \underset{(0.046)}{0.176}\ \Delta cpi_{t-4} \\
& - \underset{(0.011)}{0.076}\ (cpi - pb - T3)_{t-1} + \underset{(0.010)}{0.047}\ (wcf - pb - zyf)_{t-1} \\
& - \underset{(0.0014)}{0.0144}\ IP1_t + \underset{(0.004)}{0.044}\ VAT_t - \underset{(0.0018)}{0.001}\ S1_t \\
& - \underset{(0.002)}{0.004}\ S2_t - \underset{(0.002)}{0.002}\ S3_t
\end{aligned}
$$

$$T = 91\ [1969.2 - 1991.4]\ \hat{\sigma} = 0.36\%$$
$$\chi^2_F(12) = 14.44\ [0.27]\ F_{Chow}(12, 77) = 1.06\ [0.41]$$

Turning to parameter constancy, the F_{Chow} and χ^2_F tests reported with equation (22) show no sign of "breakdown" in the forecast period 1992.1—1994.4, i.e. any non-constancies in the forecast period are not significant compared with the estimated uncertainty of the equation. In Table 1, the estimated standard error of (22) is repeated in the first column together with p-values of several other diagnostic tests. None of the tests are even close to significance at 5% or 10%. The inflation equation in eRIM seems to be well specified. The second column in Table 1 reveals that the corresponding dRIM equation, which is obtained by merely omitting the levels terms from (22), indeed does produce a misspecified inflation equation: There are signs of autocorrelation (even by the joint test of fifth order autocorrelation), heteroscedastisity and parameter non-constancy. Finally, we note that the third column shows no significant misspecification for the re-modelled version of the inflation equation used in dRIMc.

[Table 1 about here.]

Equation (23) shows the details of the dVAR-version referred to in the third column of Table 1. Apparently, the extra autoregressive term Δcpi_{t-2}, together with longer lags on wage-costs, import prices and (in particular) productivity growth, are enough to render the residuals empirically white noise, even though the level terms in (22) have been omitted. The estimated residual standard error ($\hat{\sigma}$) is a little higher than in the ECM version. Importantly, there are no signs of the inconstancies that stand out so strongly for the simple dVAR equation. Indeed, the p-values of $\chi^2_F(12)$ and $F_{Chow}(12, 79)$ are only marginally different from those we found for the incumbent ECM price equation.

$$
\begin{aligned}
\widehat{\Delta cpi_t} = \; & \underset{(0.004)}{0.007} + \underset{(0.030)}{0.206} \, (\Delta cpi_{t-2} + \Delta cpi_{t-4}) \\
& - \underset{(0.013)}{0.0264} \, \Delta\left(wcf - pb - zyf\right)_{t-5} - \underset{(0.021)}{0.064} \, (\Delta zyf_{t-1} + \Delta zyf_{t-2}) \\
& + \underset{(0.030)}{0.20632} \, \Delta wcf_t + \underset{(0.019)}{0.059} \, \Delta pb_t + \underset{(0.016)}{0.040} \, \Delta yf_{t-4} \\
& - \underset{(0.0015)}{0.017} \, IP1_t + \underset{(0.004)}{0.043} \, VAT_t + \underset{(0.004)}{0.008} \, S1_t \\
& - \underset{(0.007)}{0.011} \, S2_t - \underset{(0.004)}{0.005} \, S3_t
\end{aligned} \tag{23}
$$

$T = 91$ $[1969.2 - 1991.4]$ $\hat{\sigma} = 0.41\%$

$\chi^2_F(12) = 18.44$ $[0.103]$ $F_{Chow}(12, 79) = 1.124$ $[0.35]$.

In order to complete dRIMc, the 26 econometric equations in eRIM were all carefully re-modelled in terms of differences alone. All dRIMc equations contain empirical white noise residuals, when residual properties are evaluated using the same test statistics as in Table 1. Special attention was paid to constant terms, as their inclusion bias dVAR forecast, as shown in section 2.1.1. Hence, for a number of equations, the constant was constrained to zero. For example in the equations for average bank interest rates, household loans, and housing prices. However, constant terms were included in the price and wage equations in dRIMc: Over the sample mean wage and price inflation is positive. With collective wage-bargaining, a sustained fall in nominal wage levels is unlikely to be observed, see Holden (1997)for an theoretical analysis.

All three model versions considered so far are true "system of equations" forecasting models. For comparison, we have also prepared single equation forecast for each variable. The first set of single equation forecasts is dubbed dAR, and is based on unrestricted estimation of AR(4) models. Finally, we generate forecasts from a completely restricted fourth order autoregressive model, hence forecasts are generated from $\Delta_4 \Delta \ln X_t = 0$, for a variable X_t that is among the endogenous variables in the original model. This set of forecasts is called dARr, where the r is a reminder that the forecasts are based on (heavily) restricted AR(4) processes. Thus, we will compare forecast errors from 5 forecasting systems.
Table 2 summarizes the 5 models in terms of one "baseline" model and four "rivals".

[Table 2 about here.]

4 Relative forecast performance 1992.1-1994.4.

All models that enter this exercise were estimated on a sample ending in 1991.4. The period 1992.1-1994.4 is used for forecast comparisons. That period saw the start of a marked upswing in the Norwegian economy. Hence, several of the model-endogenous variables change substantially over the 12 quarter forecast period. This is illustrated in Table 3 which shows the annual growth rates for non-oil GDP-output, the consumer price index (CPI) and the annual percentage increase in housing prices. In addition, the table includes the average level of the unemployment rate and the average interest rate on bank loans.

In terms of GDP growth, the upswing was well under way already in 1992, following a fall in "mainland" GDP in 1991. Despite the positive and increasing growth rates, inflation declined throughout the period, reflecting partly that nominal wage growth was also modest (cf., the historical high level of unemployment shown in the table) and that productivity growth is recovering. The most vigorous movements are found in the row for annual growth in the housing price index and the interest rate level.

[Table 3 about here.]

4.1 Forecast errors for a selection of "headline" variables

The variables included in Table 3 are among the "headline" variables that are regularly forecasted with the aid of the Bank's model, eRIM in our notation. In this section we use graphs to illustrate how the eRIM forecasts compare to the four dVARs: dRIM, dRIMc, dAR and dARr. We compare three dynamic forecast, distinguished by the start period: The first forecast is for the whole 12 quarter horizon, so the first period being forecasted is 1992.1. The second simulation starts in 1993.1 and the third in 1994.1. Furthermore, all forecast are conditional on the actual values of the models' exogenous variables and the initial conditions, which of course change accordingly when we initialize the forecasts in different start periods. The use of correct values of the non-modelled variables of course bias the comparison of the multi-variate forecasts (eRIM, dRIM, dRIMc) with the univariate forecasts (dAR and dARr), since in practice, the non-modelled variables also have to be forecasted. However the main issue here is the effect of "over differencing" in a multi-equation context. Since both dRIM and dRIMc make use of the same non-modelled variables as eRIM, that comparison is not biased by the use of correct "exogenous" information.

[Figure 1 about here.]

The results are summarized in Figure 1-3 below. Figure 1 shows actual and forecasted values from the 12-quarter dynamic simulation. Looking at the graph for the interest rate first, the poor forecast from the dRIM model is immediately evident. Remember that this model was set up by deleting all the levels term in the individual ECM equations, and then re-estimating these misspecified equations on the same sample as in eRIM. Hence, dRIM imposes a large number of units roots, and there is no attempt to patch-up the resulting misspecification. Not surprisingly, dRIM is a clear loser on all the four variables in Figure 1. This turns out to be typical, it is very seldom that a variable is forecasted more accurately with dRIM than with dRIMc, the re-modelled dVAR version of eRIM.

Turning to dRIMc versus eRIM, one sees that for the 12-quarter dynamic forecasts in Figure 1, the incumbent error-correction model seem to outperform dRIMc for interest rates, growth in housing prices and the inflation rate. However, dRIMc beats the ECM when it comes to forecasting the rate of unemployment.

[Figure 2 about here.]

One might wonder how it is possible for dRIMc to be accurate about unemployment when the inflation forecasts are off so badly. The explanation is found in eRIM, where the level of unemployment affects inflation, but where there is very little feedback from inflation per se on economic activity. In eRIM, the level of unemployment only reacts to inflation to the extent that inflation accrues to changes in level variables, such as the effective real exchange rates or real household wealth. Hence, if eRIM generated inflation forecast errors of the same size that we observe for dRIMc, that would be quite damaging for the unemployment forecasts of that model as well. However, this mechanism is not present in dRIMc, since all levels terms have been omitted. Hence, the unemployment forecasts of the dVAR versions of RIMINI are effectively insulated from the errors in the inflation forecast. In fact, the figures supports the empirical relevance of Hendry's (1996)claim that when the data generating mechanism is unknown and non-constant, models with less causal content (dRIMc) may still outperform the model that contains a closer representation of the underlying mechanism (eRIM).

The univariate forecasts, dAR and dARr, are also way off for the interest rate and for unemployment rate. However, the forecast rule $\Delta_4 \Delta cpi_t = 0$, in dARc, predicts a constant annual inflation rate that yields a quite good forecast for inflation in this period, see Figure 1.

Figure 2 shows the dynamics forecast for the same selection of variables, but now the first forecast period is 1993.1. For the interest rate, the ranking of dRIMc and eRIM forecasts is reversed from Figure 1: dRIMc is spot on for most of the forecast-horizon, while eRIM consistently over-predicts. Evidently, dRIMc uses the information embodied in the actual development in 1992 much more efficiently than RIM. The result is a good example of the inherent intercept-correction provided by the differencing. Equations (20) and (21) show that if the parameters of ECM change prior to the start of the forecast (i.e., in 1992 in the present case), then the dVAR might constitute the better forecasting model. Since the loan interest rate is a major explanatory variable for housing price growth (in both eRIM and dRIMc) it is not surprising that the housing price forecasts of the dRIMc are much better than in Figure 1. That said, we note that, with the exception of 1993.4 and 1994.2, eRIM forecasts housing prices better than dRIMc, which is evidence of countervailing forces in the forecasts for housing prices. The impression of the inflation forecasts are virtually the same as in the previous figure, while the graph of actual and forecasted unemployment shows that the eRIM wins on this forecast horizon.

[Figure 3 about here.]

The 4-period forecasts are shown in Figure 3, where simulation starts in 1994.1. Interestingly, also the eRIM interest rate forecasts have now adjusted. This indicates that the parameter instability that damaged the forecasts that started in 1993.1 turned out to be a transitory shift. dRIMc now outperforms the housing price forecasts of eRIM. The improved accuracy of dARr as the forecast period is moved forward in time is very clear. It is only for the interest rate that the dARr is still very badly off. The explanation is probably that using $\Delta_4 \Delta x_t = 0$ to generate forecasts works reasonably well for series with a clear seasonal pattern, but not for interest rates. This is supported by noting the better interest rate forecast of dAR, the unrestricted AR(4) model.

4.2 Comparison of forecasts for a larger set of variables

The relative accuracy of the eRIM forecasts might be confined to the four variables covered by Figures 1-3. We therefore compare the forecasting properties of the five different models on a larger set of 43 macroeconomic variables. In addition to the headline variables, the extended data set includes

- Exports and imports (volumes and prices) and trade balance.
- Domestic expenditures (private consumption and capital formation).
- Housing starts, under construction and completions.
- Money stock (M2) and growth in money stock
- Employment.
- Output and productivity (total GDP and by manufacturing and private service sector)
- Wage rates and wage growth.

In preparing the forecasts, these variables usually receive just as much attention as the final headline variables. A detailed list with definitions is given in the appendix.

Table 5 in the appendix contains the root mean square forecast errors (RMSFEs) for all 43 variables, based on dynamic simulation of the different models and gives the result of the same 12-quarter forecast period as in Figure 1. A simple way to summarize the information in Table 5, is to assemble the number of first places (lowest RMSFE), second places and so on, that each model attain. Part a) of Table 4 shows the placements of the five models in the 43 horse-races. The incumbent model has the lowest RMSFE for 24 out of the 43 variables, and also has 13 second places. Hence eRIM comes out best or second best for 86% of the horse-races, and seems to be a clear winner on this score. The two "difference" versions of the large econometric model (dRIMc and dRIM) have very different fates. dRIMc, the version where each behavioural equation is carefully re-modelled in terms of differences is a clear second best, while dRIM is just as clear a looser, with 27 bottom positions. Comparing the two sets of univariate forecasts, it seems like the restricted version ($\Delta_4 \Delta x_t$) behaves better than the unrestricted AR model. Finding that the very simple forecasting rule in dARr outperforms the full model in 6 instances (and is runner-up in another 8), in itself suggests that it can be useful as a baseline and yardstick for the modelbased forecasts.

Part b)-d) in Table 4 collect the result of three 4-quarter forecast contest. Interestingly, several facets of the picture drawn from the 12-quarter forecasts and the graphs in Figures 1-3 appear to be modified. Although the incumbent eRIM model collects a majority of first and second places, it is beaten by the double difference model $\Delta_4 \Delta x_t = 0$, dARr, in terms of first places in two of the three contest. This shows that the impression from the "headline" graphs, namely that dARr works much better for the 1994.1-1994.4 forecast, than for the forecast that starts in 1992, carries over to the larger set of variables covered by Table 4. In this way, our result shows in practice what the theoretical discussion foreshadowed, namely that forecasting systems that are blatantly misspecified econometrically, nevertheless can forecast better than the econometric model with a higher causal content.

[Table 4 about here.]

5 Discussion

The dominance of error-correction models (ECMs) over systems consisting of relationships between differenced variables (dVARs) is evident if one assume that the ECM model coincides with the underlying data generating mechanism. However, that assumption is too strong to form the basis of practical forecasting. First, some form of parameter non-constancies, somewhere in the system, is almost certain to arise in the forecast period. The simple algebraic example of an open system in section 2 demonstrated how non-constancies in the long-run mean of the cointegrating relations, or in the adjustment coefficients, make it impossible to assert the dominance of the ECM over a dVAR which omits cointegrating terms. Second, the forecasts of a simple ECM were shown to be incapable of correcting for parameter changes that happened *prior to* the start of the forecast, whereas the dVAR was capable of utilizing the information about the parameter shift embodied in the initial conditions. Third, one must expect that large scale macro econometric models that are used for practical forecasting purposes are themselves misspecified in unknown ways, their ability to capture partial structure in the form of long-run cointegration equations notwithstanding. The joint existence of misspecification and structural breaks, opens for the possibility that models with less causal content may turn out as the winner in a forecasting contest.

In this paper, we have illustrated the practical relevance of these claims, by use of the model that is currently being used by Norges Bank (the Norwegian Central Bank) for forecasting the Norwegian economy. Forecasts for the period 1992.1-1994.4 were calculated both for the incumbent ECM version of the Bank model and the dVAR version of that model. Although the large scale model holds its ground in this experiment, several of the theoretical points that have been made about the dVAR-approach seem to have considerable practical relevance. Hence we have seen examples of automatic intercept correction of the dVAR forecasts (parameter change prior to forecast), and there were instances when the lower causal-content of the dVAR insulated forecast errors in one part of that system from contaminating the forecasts of other variables. The overall impression is that the automatic intercept correction of the dVAR systems is most helpful for short forecast horizons. For longer horizons, the bias in the dVAR forecasts that are due to misspecification tends to dominate, and the ECM model performs relatively better.

Given that operational ECMs are multi-purpose models that are used both for policy analysis and forecasting, while the dVAR is only suitable for forecasting, one would perhaps be reluctant to give up the ECM, even in a situation where its forecasts are consistently less accurate than dVAR forecast. We do not find evidence of such dominance, overall the ECM forecasts stand up well compared to the dVAR forecasts. Moreover, in an actual forecasting situation, intercept corrections are used to correct ECM forecast for parameter changes occurring before the start of the forecast. From the viewpoint of practical forecast preparation, one interesting development would be to automatize intercept correction based on simple dVAR forecast.

A Forecasts for a larger set of variables, detailed results and definitions

[Table 5 about here.]

Definitions of variables in the RMSFE tables

A	Total exports, fixed Baseyear-prices. Mill. NOK.
B	Total imports, fixed Baseyear-prices. Mill. NOK.
CP	Private consumption expenditure, fixed Baseyear-prices. Mill. NOK.
D4CPI	Annual inflation rate (CPI based).
D4M2M	Annual growth in M2 (quarterly averaged).
D4PH	Annual growth in housing prices.
D4WCF	Annual growth in wage costs, mainland sectors.
D4WCIBA	Annual growth in wage costs, manufacturing and construction.
FYHP	Real disposable income for households, fixed Baseyear-prices. Mill. NOK.
HC	Completions of new housing capital. Mill. square meters-
HIP	Stock of housing capital in progress. Mill. square meters.
HS	Starts of new housing capital. Mill. square meters.
HUSBOL	Stipulated value of household sector stock of housing capital, . Mill. NOK.
HUSHL	Total loans by households. Mill. NOK.
J	Total gross investments in fixed capital, fixed Baseyear-prices. Mill. NOK.
JBOL	Gross investments in housing capital, fixed Baseyear-prices. Mill. NOK.
JIBA	Gross investments in fixed capital, manufacturing and construction, fixed Baseyear-prices. Mill. NOK.
JTV	Gross investments in fixed capital in private service production, fixed Baseyear-prices. Mill. NOK.
LX	Trade balance. Mill. NOK.
M2M	Broad money aggregate corrected for the underreporting of bank deposits during the period 1984-1988 (see Klovland(1990)), including notes and coins, demand deposits, time deposits and unused overdraft facilities in banks and postal institutions. Average of the end-of- month observations in each quarter.
NW	Employed wage earners. 1000 persons.
NWIBA	Employed wage earners in manufacturing and construction. 1000 persons.
NWTV	Employed wage earners in private service production. 1000 persons.
PA	Deflator of exports (A). Baseyear=1.
PB	Deflator of total imports (B). Baseyear=1.
PH	Housing price index, used housing capital. Baseyear=1.

PHN	Housing price index, new housing capital, identical with PJBOL before 1989. Baseyear=1.
PJBOL	Deflator of gross investments in residential housing (JBOL). Baseyear=1.
R.BS	Yield on 6 years government bonds, quarterly average.
RLB	Average interest rate on bank loans.
RMB	Average interest rate on bank deposits.
UTOT	"Total" unemployment (registered and participant on programmes) as a fraction of labour force (excluding self employed).
WCF	Hourly wage cost. Total economy less oil and gas production and shipping. NOK.
WCIBA	Hourly wage cost in manufacturing and construction. NOK.
WCO	Hourly wage costs in government sectors. NOK.
WCTVJ	Hourly wage costs in private service production. NOK.
Y	GDP, fixed Baseyear-prices. Mill. NOK.
YIBA	Value added at factor costs in manufacturing and construction, fixed Baseyear prices. Mill. NOK.
YTV	Value added at factor costs in private service production, fixed Baseyear prices. Mill. NOK.
ZYF	Value added labour productivity, fixed Baseyear-prices. Mill. NOK.
ZYIBA	Value-added labour productivity in manufacturing and construction, fixed Baseyear-prices. Mill. NOK.
ZYTV	Value added per man-hour in service production, fixed Baseyear-prices. NOK.

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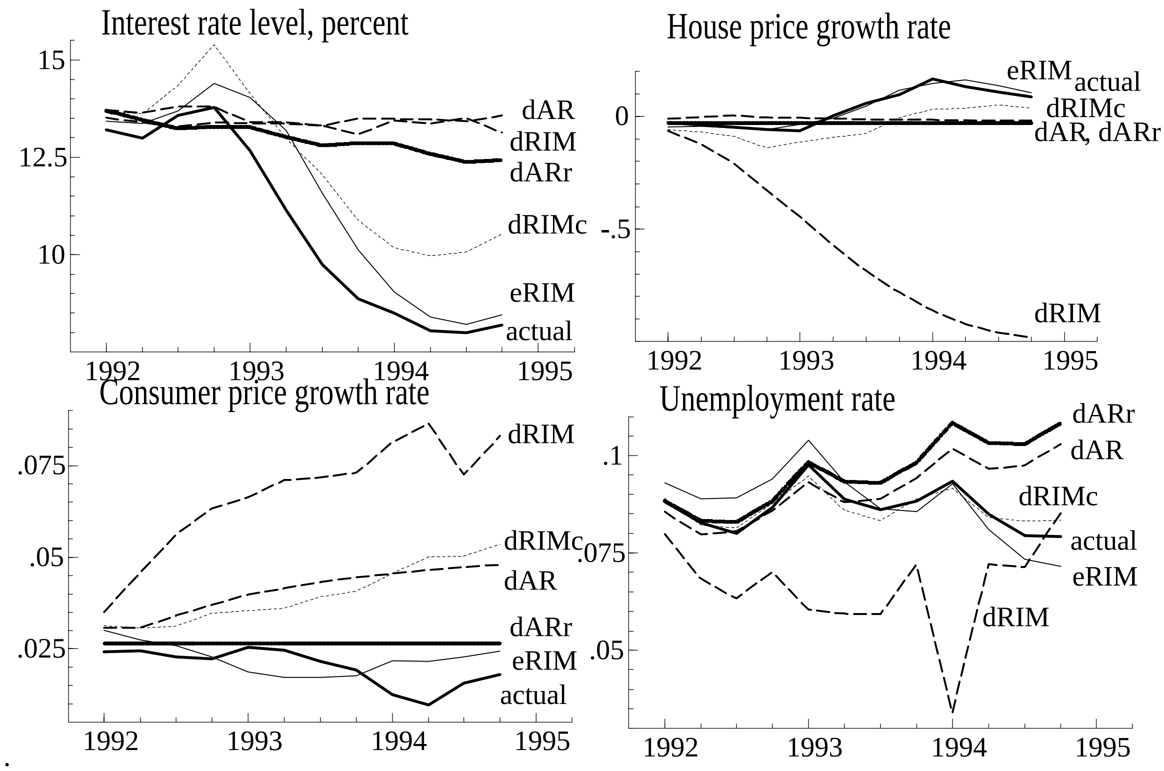

Figure 1: 1992.1-1994.4 forecasts and actual values for the interest rate level (RLB), housing price growth ($\Delta_4 ph$), the rate of inflation ($\Delta_4 cpi$) and the level of unemployment ($UTOT$).

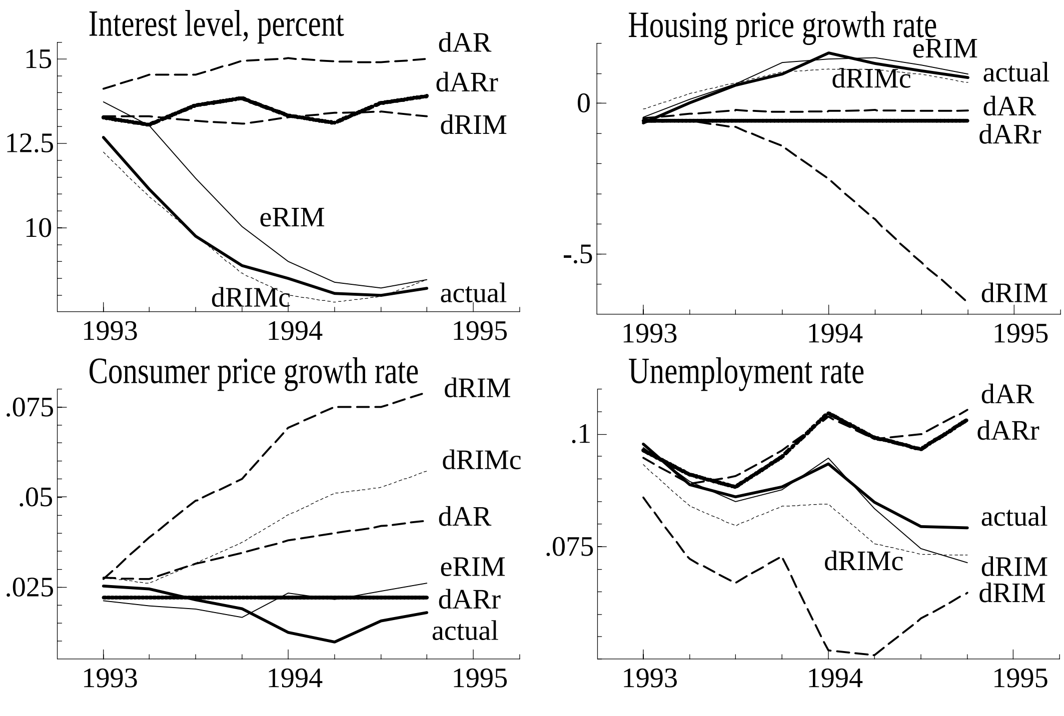

Figure 2: 1993.1-1994.4 forecasts and actual values for the interest rate level (RLB), housing price growth ($\Delta_4 ph$), the rate of inflation ($\Delta_4 cpi$) and the level of unemployment ($UTOT$).

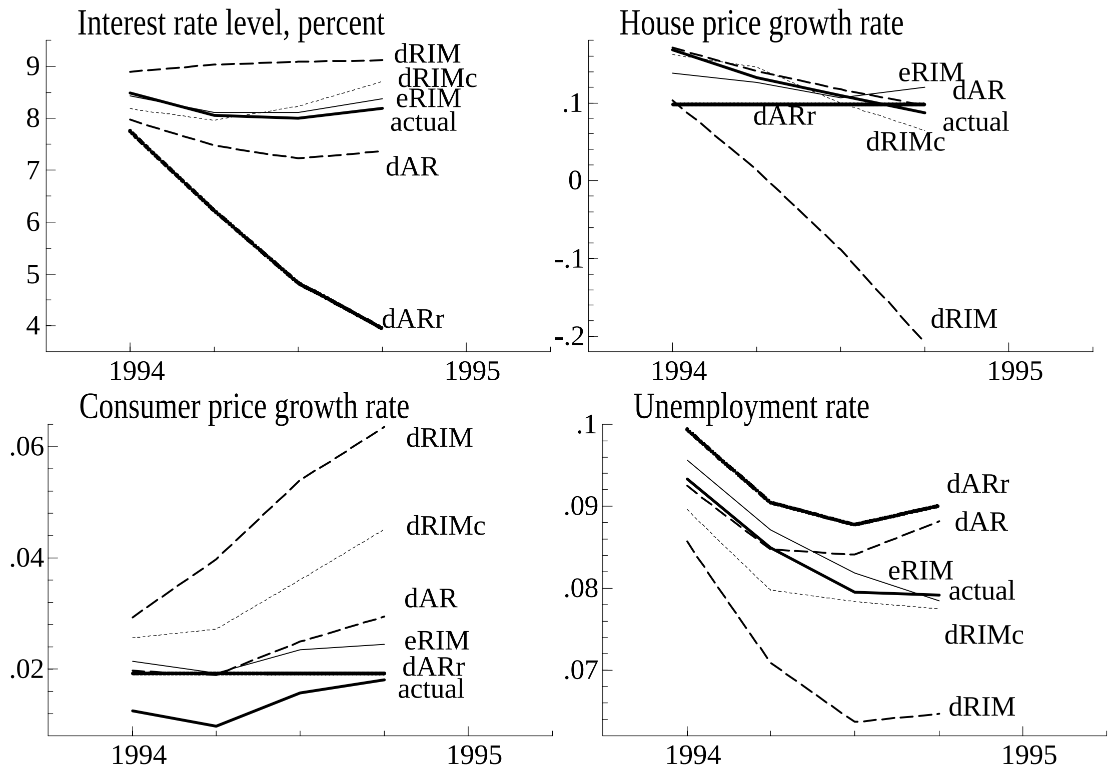

Figure 3: 1994.1-1994.4 forecasts and actual values for the interest rate level (RLB), housing price growth ($\Delta_4 ph$), the rate of inflation ($\Delta_4 cpi$) and the level of unemployment ($UTOT$).

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Table 1: Diagnostics for the consumer price equation in eRIM and the corresponding inflation equations in dRIM and dRIMc.

Diagnostic	**Model**		
	eRIM	**dRIM**	**dRIMc**
$\hat{\sigma}\%$	0.36%	0.46%	0.41%
AR 1-5 F	[0.918]	[0.030]	[0.497]
ARCH 1-4 F	[0.435]	[0.853]	[0.805]
Norm χ^2	[0.641]	[0.477]	[0.856]
HET F	[0.124]	[0.004]	[0.880]
RESET F	[0.850]	[0.907]	[0.740]
Forecast χ^2	[0.273]	[0.030]	[0.103]
Chow F	[0.405]	[0.188]	[0.353]

Notes

Estimation is by OLS. Estimation period is 1969.2-1991.4. Forecast period is 1992.1-1994.4. Left hand side variable is Δcpi_tin all equations. The numbers in brackets are p-values of the test statistics in the first column.

Table 2: The models used inthe forecasts.

Model	**Name**	**Description**
Baseline	eRIM	26 Behavioural equations, error-correction equations 33+146 Technical and definitional equations
1.Rival	dRIM	26 Behavioural equations, reestimated after omitting level terms 33+146 Technical and definitional equations
2.Rival	dRIMc	26 Behavioural equations, remodelled without levels-information 33+146 Technical and definitional equations
3.Rival	dAR	43 Behavioural and technical equations modelled as 4.order AR
4.Rival	dARr	43 Behavioural and technical equations modelled as restricted 4.order AR

Table 3: Some macroeconomic indicators of the Norwegian economy 1991-1994

	1991	1992	1993	1994
Annual growth-rate(%)				
GDP	-0.51	2.04	2.08	3.05
CPI	3.43	2.34	2.27	1.39
Housing price	-6.40	-4.39	2.33	12.4
Level (%)				
Unemployment	7.57	8.44	9.02	8.42
Loan interest-rate	13.86	13.39	10.61	8.18

Notes: GDP is in fixed 1991 prices. CPI and Housing price are indices (1991=1).
Unemployment is including programmes, Interest rate is the average rate on bank loans.

Table 4: Results of 43 RMSFE forecast contests a) 1992.1—1994.4; b) 1992.1—1992.4; c) 1993.1—1993.4; d) 1994.1—1994.4.

a) 12 period forecasts. 1992.1—1994.4					
place #	**eRIM**	**dRIMc**	**dRIM**	**dAR**	**dARr**
1	24	13	1	1	6
2	13	11	4	5	8
3	2	8	5	14	13
4	2	10	6	15	10
5	2	1	27	8	6

b) 4 period forecasts. 1992.1—1992.4					
place #	**eRIM**	**dRIMc**	**dRIM**	**dAR**	**dARr**
1	7	8	10	6	12
2	17	13	3	4	6
3	13	7	8	10	7
4	3	11	2	17	9
5	3	4	20	6	9

c) 4 period forecasts. 1993.1—1993.4					
place #	**eRIM**	**dRIMc**	**dRIM**	**dAR**	**dARr**
1	17	9	7	1	11
2	16	13	7	2	3
3	3	12	11	12	5
4	3	9	2	17	12
5	4	0	16	11	12

d) 4 period forecasts. 1994.1—1994.4					
place #	**eRIM**	**dRIMc**	**dRIM**	**dAR**	**dARr**
1	13	4	5	5	16
2	11	17	1	9	6
3	7	8	11	9	7
4	7	8	13	9	6
5	5	6	13	11	8

Table 5: 12 quarter dynamic forecasts. RMSFEs of annual growth rates and levels.

Variable	**p/q/v**	**eRIM92**	**dRIMc92**	**dRIM92**	**dAR92**	**dARr92**
		RMSFE of annual growth rates:				
A	**q**uantity	0.0340	0.0201	0.0321	0.0472	0.0473
B	q	0.0376	0.0369	0.0490	0.0475	0.0452
CP	q	0.0249	0.0241	0.0653	0.0215	0.0185
CPI	**p**rice	0.0058	0.0146	0.0192	0.0098	0.0048
FYHP	**v**olume	0.0124	0.0164	0.0356	0.0223	0.0221
HC	q	0.0978	0.1565	0.1449	0.1493	0.1537
HIP	q	0.0945	0.1453	0.1356	0.1667	0.1499
HS	q	0.1590	0.2214	0.2435	0.2340	0.2414
HUSBOL	v	0.0154	0.0316	1.4039	0.0815	0.0764
HUSHL	v	0.0100	0.0337	1.3646	0.0295	0.0173
J	q	0.0450	0.0346	0.0577	0.0824	0.0817
JBOL	q	0.1861	0.1906	0.1837	0.1899	0.1973
JIBA	q	0.1783	0.1578	0.1048	0.0675	0.0845
JTV	q	0.1415	0.0953	0.3324	0.0844	0.0624
M2M	v	0.0139	0.0183	0.0248	0.0147	0.0224
NW	q	0.0047	0.0054	0.0571	0.0098	0.0091
NWIBA	q	0.0178	0.0219	0.2227	0.0303	0.0320
NWTV	q	0.0043	0.0041	0.0109	0.0116	0.0095
PA	p	0.0088	0.0088	0.0100	0.0444	0.0502
PB	p	0.0109	0.0107	0.0170	0.0161	0.0189
PH	p	0.0169	0.0329	1.4022	0.0833	0.0769
PHN	p	0.0183	0.0291	0.0470	0.0331	0.0318
PJBOL	p	0.0128	0.0117	0.0785	0.0173	0.0211
PY	p	0.0066	0.0151	0.0130	0.0228	0.0184
WCF	p	0.0057	0.0192	0.0236	0.0144	0.0100
WCIBA	p	0.0079	0.0155	0.0219	0.0134	0.0087
WCO	p	0.0132	0.0243	0.0252	0.0134	0.0116
WCTVJ	p	0.0063	0.0182	0.0313	0.0140	0.0105
Y	q	0.0112	0.0144	0.0308	0.0188	0.0175
YIBA	q	0.0177	0.0153	0.1855	0.0264	0.0214
YTV	q	0.0093	0.0172	0.0185	0.0132	0.0167
ZYF	q	0.0073	0.0091	0.0257	0.0202	0.0142
ZYIBA	q	0.0215	0.0155	0.0484	0.0230	0.0198
ZYTV	q	0.0095	0.0176	0.0237	0.0273	0.0236
		RMSFE of levels:				
LX	v	0.2510	0.2806	0.2981	0.2851	-
D4CPI	p	0.0059	0.0152	0.0203	0.0101	0.0049
D4M2M	p	0.0147	0.0193	0.0247	0.0154	0.0237
D4WCF	p	0.0059	0.0205	0.0257	0.0149	0.0102
D4WCIBA	p	0.0081	0.0162	0.0236	0.0139	0.0089
R.BS	p	0.0208	0.0136	0.0162	0.0144	0.0136
RLB	p	0.6477	0.6148	2.2803	2.3322	1.9386
RMB	p	0.6159	0.5481	0.9718	2.0672	1.8623
UTOT	q	0.0050	0.0022	0.0158	0.0086	0.0094