

# 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 macroeconomic model used in Norges Bank (The Central Bank of Norway), which we take as an example of an ECM forecasting model. We develop two dVAR versions of the full RIMINI model and compare ECM and dVAR forecasts for the period 1992.1-1994.4. In addition we compare forecasts from the full scale models with those of univariate dVAR type models. The results seems to confirm the relevance of several important theoretical insights. dVAR forecasts appear to provide some immunity against parameter non-constancies that could seriously bias the ECM forecasts. On the other hand however, for open systems like the RIMINI model, the misspecification resulting from omitting levels information seems to generate substantial biases in the dVAR forecasts. Therefore, the incumbent ECM performs comparatively well over the forecast period investigated in this paper.

**Keywords:** Forecasting, error-correction, differenced VAR models

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# 1 Background and introduction

## 1.1 Two classes of forecasting models

Agencies that build and maintain macroeconomic models often use one and the same model for both policy analysis and forecasts. Critics of macroeconomic 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 lose 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, macroeconomic models 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 new inference procedures for integrated variables. As a result, modern macroeconomic forecasting models are less exposed to Granger and Newbold's critique. At the same time, 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.

Given these developments, macroeconomic model builders and forecasters may be justified in claiming that they finally have at their disposal the concepts and models that enables a successful reconciliation of the conflict between economic interpretability and dynamic specification. In particular, one expects that error-correction models, ECMs, forecast better than models that only use differenced data, so called differenced vector autoregressions, dVARs.

## 1.2 The relative performance of ECM and dVAR models

In a series of recent papers, Michael Clements and David Hendry have re-examined several issues in macroeconomic forecasting, see e.g. Clements and Hendry (1995a), 1995b, 1996. This research reveals the tenancy 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 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.

### 1.3 Forecasting exercises with ECMs and dVARs

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 derived from the full scale 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 macroeconomic 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 Bank 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 ECMs 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

$$\Delta y_t = \pi_0 + \pi_1 \Delta x_t - \alpha [y_{t-1} - \beta x_{t-1}] + \varepsilon_{y,t}, \quad 0 < \alpha < 1, \quad t = 1, \dots, T$$

Given cointegration, the intercept  $\pi_0$  can be rewritten in terms of an “autonomous growth” parameter  $\gamma$ , and the product of the feedback coefficient  $\alpha$ , and a parameter measuring the long-run mean of the cointegration relationship,  $\mu$ , i.e.

$$(2.1) \quad \pi_0 = \gamma + \alpha\mu$$

Using (2.1), the error-correction model can be written as

$$(2.2) \quad \Delta y_t = \gamma + \pi_1 \Delta x_t - \alpha[y_{t-1} - \beta x_{t-1} - \mu] + \varepsilon_{y,t}$$

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

$$(2.3) \quad \Delta x_t = \varepsilon_{x,t}$$

Equations (2.2) and (2.3) 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

$$(2.4) \quad \Delta y_t = \gamma + \pi_1 \Delta x_t + e_{y,t}$$

and (2.3). We further assume that

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

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

## 2.1 Parameters change *after* the forecast is prepared

### Change in the long run mean

We first assume that the long-run mean coefficient changes from its initial level  $\mu$  to a new level  $\mu^*$  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 for the whole of the forecast period.

The 1-period forecast error for the ECM and the dVAR models can be written:

$$(2.5) \quad y_{T+1} - \hat{y}_{T+1, \text{ECM}} = \pi_1 \varepsilon_{x, T+1} - \alpha[\mu - \mu^*] + \varepsilon_{y, T+1}$$

$$(2.6) \quad y_{T+1} - \hat{y}_{T+1, \text{dVAR}} = \pi_1 \varepsilon_{x, T+1} - \alpha[y_T - \beta x_T - \mu^*] + \varepsilon_{y, T+1}$$

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  $\text{bias}_{T+1, \text{ECM}}$  and  $\text{bias}_{T+1, \text{dVAR}}$  respectively:

$$(2.7) \quad \text{bias}_{T+1,\text{ECM}} = -\alpha[\mu - \mu^*]$$

$$(2.8) \quad \text{bias}_{T+1,\text{dVAR}} = -\alpha[y_T - \beta x_T - \mu^*]$$

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, since the bias only contains  $\mu^*$  and not  $\mu$ . 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:

$$(2.9) \quad \text{bias}_{T+2,\text{ECM}} = -\alpha\delta_{(1)}[\mu - \mu^*], \text{ where } \delta_{(1)} = 1 + (1 - \alpha)$$

$$\text{bias}_{T+2,\text{dVAR}} = \gamma(\delta_{(1)} - 2) - \alpha\delta_{(1)}[y_T - \beta x_T - \mu^*]$$

$$(2.10) \quad = -\alpha\gamma - \alpha\delta_{(1)}[y_T - \beta x_T - \mu^*]$$

More generally, for  $h$ -period forecast horizons we derive the following expressions for the forecast errors biases:

$$(2.11) \quad \text{bias}_{T+h,\text{ECM}} = -\alpha\delta_{(h-1)}[\mu - \mu^*]$$

$$(2.12) \quad \text{bias}_{T+h,\text{dVAR}} = -\gamma(\delta_{(h-1)} - h) - \alpha\delta_{(h-1)}[y_T - \beta x_T - \mu^*], \quad h = 2, 3, \dots$$

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

$$(2.13) \quad \delta_{(h-1)} = 1 + \sum_{j=1}^{h-1} (1 - \alpha)^j, \quad h = 2, 3, \dots$$

The 2- and  $h$ -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  $\gamma$ , cf. the term  $\gamma(\delta_{(h-1)} - h) \neq 0$  in equation (2.12). Over longer forecast horizons, that bias may become larger than the ECM forecast bias<sup>1</sup>.

### Change in the equilibrium correction coefficient

Next, we consider the situation where the adjustment coefficient  $\alpha$  changes to a new value,  $\alpha^*$ , after the forecast for  $T+1, T+2, \dots, T+h$  have been prepared. The 1-step forecast error bias for the two models are:

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<sup>1</sup>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  $\gamma\delta_{(h-1)}$  instead of  $\gamma(\delta_{(h-1)} - h)$  as in (2.12).

$$(2.14) \quad \text{bias}_{T+1,\text{ECM}} = -(\alpha^* - \alpha)[y_T - \beta x_T - \mu]$$

$$(2.15) \quad \text{bias}_{T+1,\text{dVAR}} = -\alpha^*[y_T - \beta x_T - \mu]$$

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 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 and dVAR forecast error biases are:

$$(2.16) \quad \text{bias}_{T+h,\text{ECM}} = \gamma(\delta_{(h-1)}^* - \delta_{(h-1)}) \\ - (\alpha^* \delta_{(h-1)}^* - \alpha \delta_{(h-1)})[y_T - \beta x_T - \mu], \quad h=2, 3, \dots$$

$$(2.17) \quad \text{bias}_{T+h,\text{dVAR}} = \gamma(\delta_{(h-1)}^* - h) - \alpha^* \delta_{(h-1)}^*[y_T - \beta x_T - \mu], \quad h=2, 3, \dots$$

where  $\delta_{(h-1)}$  is defined in (2.13) and  $\delta_{(h-1)}^*$  is given in a similar fashion as

$$(2.18) \quad \delta_{(h-1)}^* = 1 + \sum_{j=1}^{h-1} (1 - \alpha^*)^j, \quad h=2, 3, \dots$$

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  $T+2, T+3, \dots, T+h$  are updated conditional on outcomes for period  $T+1$ . Remember that the shift  $\mu \rightarrow \mu^*$  first affects outcomes in period  $T+1$ . When the forecasts for  $T+2, T+3, \dots$  are updated in period  $T+1$ , information about parameter inconstancies will therefore be reflected in the starting value  $y_{T+1}$ . Considering  $\mu \rightarrow \mu^*$  first, the updated forecast for  $y_{T+2}$ , conditional on  $y_{T+1}$  results in the following forecast error bias for the ECM and dVAR respectively:

$$(2.19) \quad \text{bias}_{T+2,\text{ECM}} \mid T+1 = -\alpha[\mu - \mu^*]$$

$$(2.20) \quad \text{bias}_{T+2,\text{dVAR}} \mid T+1 = -\alpha[y_{T+1} - \beta x_{T+1} - \mu^*]$$

Equation (2.19) shows that the ECM forecast error is affected by the parameter change in exactly the same manner as before, cf. (2.9) 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 (2.20). Since the forecast error bias contains both  $y_{T+1}$  and  $\mu^*$ , the forecast incorporates that the change from  $\mu$  to  $\mu^*$

is partly reflected in  $y_{T+1}$ . In this important sense, there is an element of inherent “intercept correction” built into the dVAR forecasts.

The analysis of changes in the adjustment coefficient is very similar. The ECM does not adjust automatically to  $\alpha \rightarrow \alpha^*$  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 dVAR type forecasting systems based on differenced data

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  $\alpha$  and the long-run mean  $\mu$ , 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 Norges Bank<sup>2</sup>, 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.

#### 3.1 The incumbent ECM model - eRIM

Norges 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 (with no feedback 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

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<sup>2</sup>RIMINI was originally an acronym for a model for the Real economy and Income accounts - a MINI-version. The model version used in this paper has 205 endogenous variables, although a large fraction of these are accounting identities or technical relationships creating links between variables.

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 likewise the level of real-activity feeds back on to wage-price 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.

### 3.2 Two full scale dVAR models - dRIM and dRIMc

Because all the behavioural equations of RIMINI are in error-correction form, a simple dVAR version of the model, dRIM, can be obtained by simply 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 big 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 (2.4) is autocorrelated provided that there is some autocorrelation in the disequilibrium term in (2.1). 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. This constitutes the backbone of the dRIMc model.

### 3.3 The consumer price equations in eRIM and dRIMc

To illustrate our approach, we consider the estimated “consumer price equation” in eRIM, reported in equation (3.1) 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 ( $\Delta pb_t$ ), wage costs per hour ( $\Delta wcf_t$ ) and an acceleration term ( $\Delta^2 wcf_{t-3}$ ). The next two variables are *real* GDP output growth ( $\Delta yf$ ), 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 ( $\Delta cpi_{t-4}$ ). Finally, there are three seasonal dummies  $S_{i,t}$  ( $i = 1, 2, 3$ ), a VAT dummy, and a dummy for income policy ( $IP_t$ ). 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 (3.1) 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 et al. (1992)<sup>3</sup>.

$$\begin{aligned}
(3.1) \quad \widehat{\Delta cpi}_t = & 0.009 + 0.054 \Delta pb_t + 0.182 \Delta wcf_t \\
& (0.003) \quad (0.016) \quad (0.027) \\
& + 0.064 \Delta \Delta wcf_{t-3} + 0.022 (0.5 \Delta yf_{t-1} + \Delta yf_{t-2}) \\
& (0.019) \quad (0.016) \\
& - 0.065 \Delta_4 zyf_t + 0.176 \Delta cpi_{t-4} \\
& (0.019) \quad (0.046) \\
& - 0.076 (cpi - pb - T3)_{t-1} + 0.047 (wcf - pb - zyf)_{t-1} \\
& (0.011) \quad (0.010) \\
& - 0.0144 IP1_t + 0.044 VAT_t - 0.001 S1_t \\
& (0.0014) \quad (0.004) \quad (0.0018) \\
& - 0.004 S2_t - 0.002 S3_t \\
& (0.002) \quad (0.002) \\
T = & 91[1969.2-1991.4], \hat{\sigma} = 0.36\% \\
\chi_F^2(12) = & 14.44[0.27], F_{Chow}(12, 77) = 1.06[0.41]
\end{aligned}$$

Turning to parameter constancy, the  $F_{Chow}$  and  $\chi_F^2$  tests reported with equation (3.1) 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 3.1, the estimated standard error of (3.1) 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%, thus the inflation equation in **eRIM** seems to be well specified. The second column in table 3.1 reveals that the corresponding equation in the first of our rival models, **dRIM** which is obtained by merely omitting the levels terms from (3.1), 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 in the inflation equation in the second rival model, **dRIMc** which is a re-modelled version of **dRIM** and obeys the restriction that it contains no level terms, but still seems to pass as a well designed equation.

Equation (3.2) shows the details of the **dRIMc**-equation referred to in the third column of table 3.1. Apparently, the extra autoregressive term  $\Delta cpi_{t-2}$ , 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 (3.1) 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 **dRIM** equation. Indeed, the

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<sup>3</sup>MacKinnon’s 1991 Dickey-Fuller 1% critical value for the null hypothesis that  $(cpi - pb - T3)_t$  and  $(wcf - pb - zyf)_t$  do not cointegrate, is  $-4.02$ .

Table 3.1: 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 $\chi^2$	[0.641]	[0.477]	[0.856]
HET $F$	[0.124]	[0.004]	[0.880]
RESET $F$	[0.850]	[0.907]	[0.740]
Forecast $\chi^2$	[0.273]	[0.030]	[0.103]
Chow $F$	[0.405]	[0.188]	[0.353]
<b>Notes</b>			
Estimated by OLS. Estimation period is 1969.2-1991.4. Forecast period is 1992.1-1994.4. Left hand side variable is $\Delta cpi_t$ in all equations. Numbers in brackets are p-values of the test statistics in the first column.			

p-values of  $\chi_F^2(12)$  and  $F_{Chow}(12, 79)$  are only marginally different from those we found for the incumbent ECM price equation.

$$\begin{aligned}
 (3.2) \quad \widehat{\Delta cpi}_t = & \quad 0.007 + 0.206 (\Delta cpi_{t-2} + \Delta cpi_{t-4}) \\
 & \quad (0.004) \quad (0.030) \\
 & \quad - 0.0264 \Delta (wcf - pb - zyf)_{t-5} \\
 & \quad \quad (0.013) \\
 & \quad - 0.064 (\Delta zyf_{t-1} + \Delta zyf_{t-2}) \\
 & \quad \quad (0.021) \\
 & \quad + 0.20632 \Delta wcf_t + 0.059 \Delta pb_t + 0.040 \Delta yf_{t-4} \\
 & \quad \quad (0.030) \quad (0.019) \quad (0.016) \\
 & \quad - 0.017 IP1_t + 0.043 VAT_t + 0.008 S1_t \\
 & \quad \quad (0.0015) \quad (0.004) \quad (0.004) \\
 & \quad - 0.011 S2_t - 0.005 S3_t \\
 & \quad \quad (0.007) \quad (0.004) \\
 T = & \quad 91[1969.2-1991.4], \hat{\sigma} = 0.41\% \\
 \chi_F^2(12) = & \quad 18.44[0.103], F_{Chow}(12, 79) = 1.124[0.35].
 \end{aligned}$$

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 3.1. Special attention was paid to constant terms, as their inclusion bias dVAR forecast, as shown in section 2.1. 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 analysis.

### 3.4 Two univariate models - dAR and dARr

All three model versions considered so far are true “system of equations” forecasting models. For comparison, we have also prepared single equation forecasts 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.

### 3.5 Five different forecasting models - a summary

Table 3.2 summarizes the five models in terms of the incumbent “baseline” ECM model and the four “rival” dVAR type models.

*Table 3.2: The models used in the 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	71 equations modelled as 4.order AR models
4.Rival	dARr	71 equations modelled as restricted 4.order AR models

## 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 4.1 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 was recovering. The most vigorous movements

are found in the row for annual growth in the housing price index and the interest rate level.

Table 4.1: Some macroeconomic indicators of the Norwegian economy 1991-1994

	1991	1992	1993	1994
<i>Annual growth-rate(%)</i>				
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
<i>Level (%)</i>				
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.

In this section we first use graphs to illustrate how the eRIM forecast the interest rate level ( $RLB$ ), housing price growth ( $\Delta_4ph$ ), the rate of inflation ( $\Delta_4cpi$ ) and the level of unemployment ( $UTOT$ ) compared to the four dVARs: dRIM, dRIMc, dAR and dARr. We evaluate three dynamic forecasts, 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.

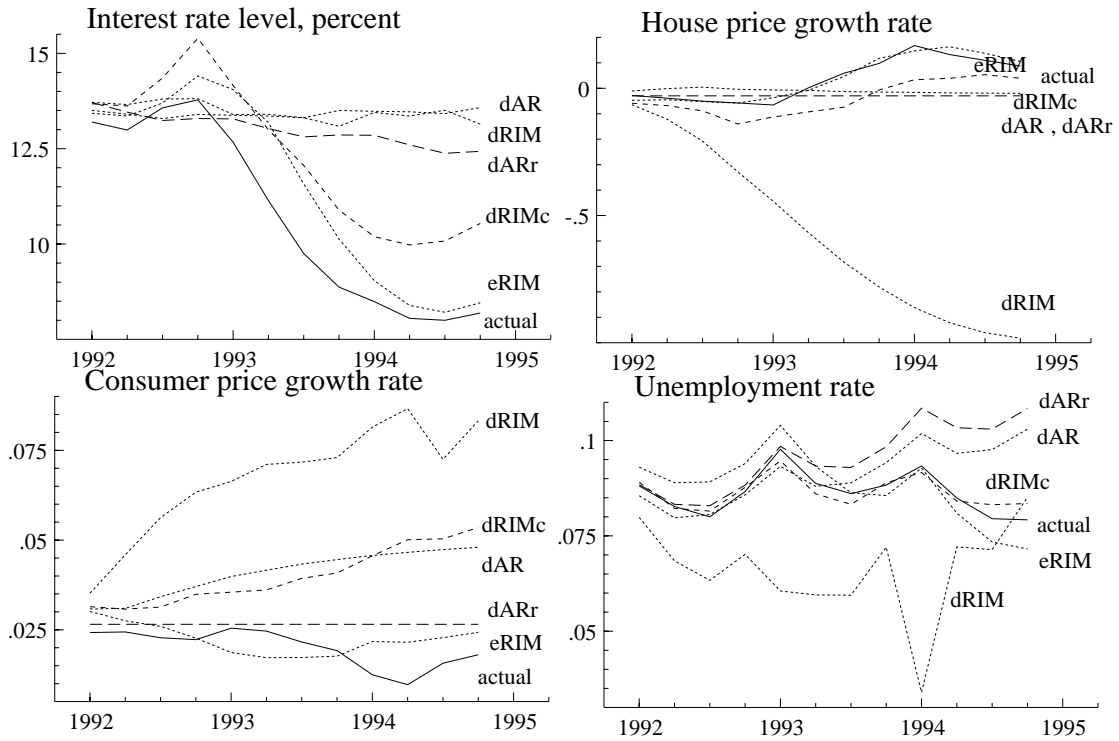


Figure 4.1: 1992.1-1994.4 forecasts and actual values for the interest rate level ( $RLB$ ), housing price growth ( $\Delta_4ph$ ), the rate of inflation ( $\Delta_4cpi$ ) and the level of unemployment ( $UTOT$ ).

The results are summarized in figure 4.1-4.3 below. Figure 4.1 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 4.1. 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 4.1, the incumbent error-correction model seems 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.

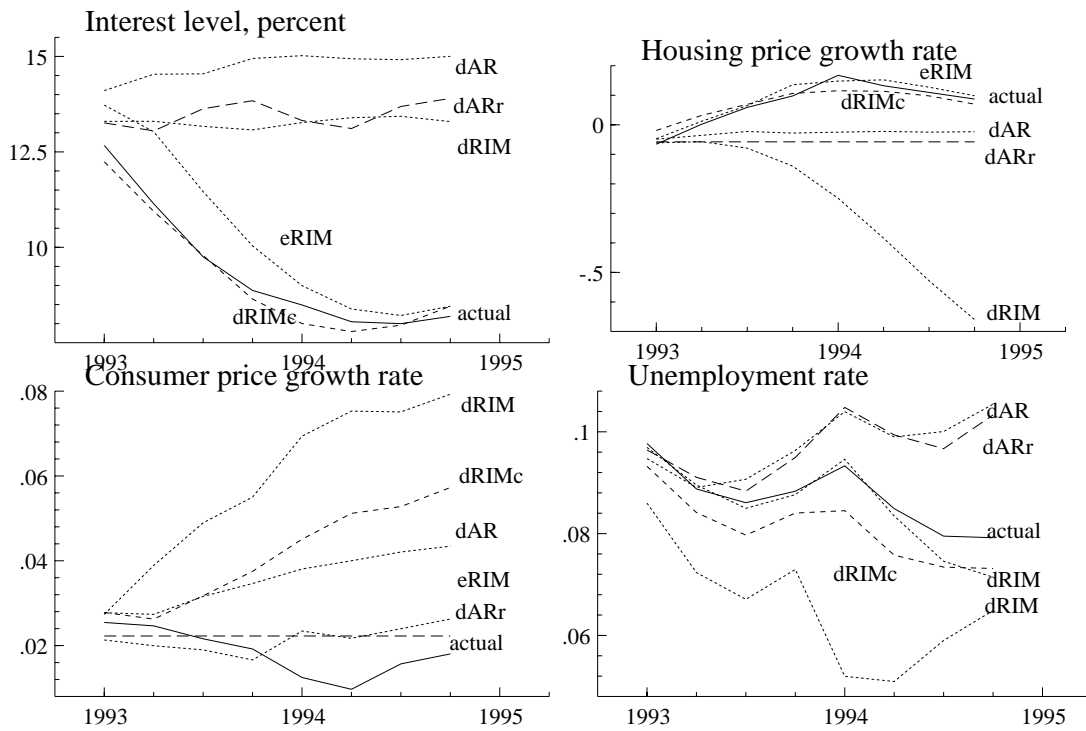


Figure 4.2: 1993.1-1994.4 forecasts and actual values for the interest rate level ( $RLB$ ), housing price growth ( $\Delta_4ph$ ), the rate of inflation ( $\Delta_4cpi$ ) and the level of unemployment ( $UTOT$ ).

One might wonder how it is possible for **dRIMc** to be accurate about unemployment in spite of the poor inflation forecasts. The explanation is found by considering **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 confirm 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 the mark for the interest rate and for the 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 4.1. Figure 4.2 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 4.1: 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 eRIM. The result is a good example of the intercept-correction provided by the differencing. Equations (2.19) and (2.20) 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 4.1. 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.

The 4-period forecasts are shown in figure 4.3, 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 target. 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.

The relative accuracy of the eRIM forecasts, might be confined to the four variables covered by figures 4.1-4.3. We therefore compare the forecasting properties of the five different models on a larger (sub)set of 43 macroeconomic variables (cf. table A.1 in appendix A for details). The list includes most of the variables that are regularly forecasted, such as e.g. GDP growth, the trade balance, wages and productivity.

The figures B.1–B.18 (appendix B) show the forecasts for 36 the variables based on dynamic simulation of the five different models across the three forecast horizons, starting in 1992.1 (top), 1993.1 (middle) and 1994.1 (bottom).

The graphs reveal that, as a rule dARr (i.e.,  $\Delta_4 \Delta x_t = 0$ ) yields forecasts that are too smooth and “conservative”. This is particularly evident for 8 and 12 quarter

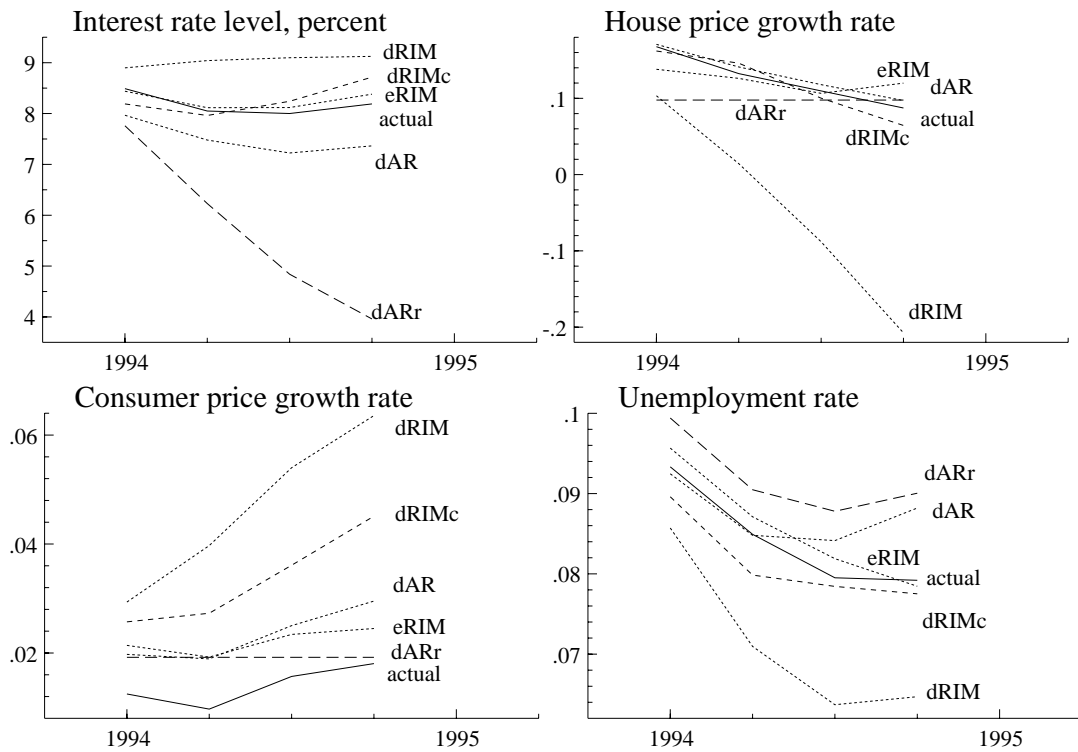


Figure 4.3: 1994.1-1994.4 forecasts and actual values for the interest rate level ( $RLB$ ), housing price growth ( $\Delta_{4ph}$ ), the rate of inflation ( $\Delta_{4cpi}$ ) and the level of unemployment ( $UTOT$ ).

horizons. For the 4-quarter horizon the  $dARr$  is sometimes quite accurate, total imports in the first panel provides one example: In 1994, the average growth rate in imports was close to zero, which is well captured by the  $dARr$  prediction. The 1994 forecasts show other examples of quite accurate  $dARr$  forecast, e.g., the annual growth rate in consumer prices (figure B.2), consumer expenditure (figure B.2) and wage growth (figure B.12). However, several variables show varying growth rates also within the year 1994, and for these variables the  $dARr$  forecasts are inaccurate, see e.g., housing completions and starts (figure B.3 and B.4) and money demand (figure B.7).

The  $dRIM$  forecasts are usually way off the mark, which confirms our previous results for interest rates, housing prices, inflation and unemployment. As a rule,  $dRIM$  is outperformed by both the unrestricted and restricted univariate autoregression,  $dAR$  and  $dARr$ . Hence, the high degree of misspecification present in  $dRIM$  introduces a dominant bias, eventhough  $dRIM$  is put at an advantage relative to  $dAR$  and  $dARr$  by the conditioning on correct values on the non-modelled variables in  $dRIM$ .

The two large scale models  $eRIM$  and  $dRIMc$  are able to make better use of the information present in the non-modelled variables. In fact, the overall impression from the graphs is that these two systems are the two real contenders. However, the graphs represents a plethora of information which makes it difficult to obtain a clear picture of each model's overall performance. Therefore, Table 4.2 summarizes the information from calculated RMSFEs (the tables C.1-C.3 (appendix C), compare the RMSFEs for 43 variables for all five models).

## A horse-race summary of the results

A simple way to summarize the information in Table C.1, is to assemble the number of first places (lowest RMSFE), second places and so on, that each model attain. Part a) of Table 4.2 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 loser, 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 4.2 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 4.1-4.3 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 4.2. 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 4.2: 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.

<b>a) 12 period forecasts, 1992.1—1994.4</b>					
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>b) 4 period forecasts, 1992.1—1992.4</b>					
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

<b>c) 4 period forecasts, 1993.1—1993.4</b>					
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

<b>d) 4 period forecasts, 1994.1—1994.4</b>					
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

## 5 Discussion

The dominance of error-correction models (ECMs) over systems consisting of relationships between differenced variables (dVARs) can be shown 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, 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.

To illustrate the empirical relevance of these claims, we used a model that is currently being used 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 demonstrated the 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.

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# A Variable symbols and definitions

Symbol	Definition
$A_t$	Total exports, fixed 1991-prices. Mill. NOK.
$B_t$	Total imports, fixed 1991-prices. Mill. NOK.
$CP_t$	Private consumption expenditure, fixed 1991-prices. Mill. NOK.
$CPI_t$	Consumer price index. 1991 = 1.
$D_4CPI_t$	Annual inflation rate (CPI based).
$D_4M2M_t$	Annual growth in M2 (quarterly averaged).
$D_4WCF_t$	Annual growth in wage costs, mainland sectors.
$D_4WCIBA_t$	Annual growth in wage costs, manufacturing and construction.
$FYHP_t$	Real disposable income for households, fixed 1991-prices. Mill. NOK.
$HC_t$	Completions of new housing capital. Mill. square meters.
$HIP_t$	Stock of housing capital in progress. Mill. square meters.
$HS_t$	Starts of new housing capital. Mill. square meters.
$HUSBOL_t$	Stipulated value of household sector stock of housing capital. Mill. NOK.
$HUSHL_t$	Total loans by households. Mill. NOK.
$J_t$	Total gross investments in fixed capital, fixed 1991-prices. Mill. NOK.
$JBOL_t$	Gross investments in housing capital, fixed 1991-prices. Mill. NOK.
$JIBA_t$	Gross investments in fixed capital, manufacturing and construction, fixed 1991-prices.
$JTV_t$	Gross investments in fixed capital, private service production, fixed 1991-prices.
$LX_t$	Trade balance. Mill. NOK.
$M2M_t$	Broad money $M2$ corrected for underreporting of bank deposits during the period 1984-1988 (see Klovland (1990)). Average of the end-of-month observations.
$NW_t$	Employed wage earners. 1000 persons.
$NWIBA_t$	Employed wage earners in manufacturing and construction. 1000 persons.
$NWTV_t$	Employed wage earners in private service production. 1000 persons.
$PA_t$	Deflator of exports ( $A_t$ ). 1991=1.
$PB_t$	Deflator of total imports ( $B_t$ ). 1991=1.
$PH_t$	Housing price index, used housing capital. 1991=1.
$PHN_t$	Housing price index, new housing capital, identical with $PJBOL_t$ before 1989. 1991=1.
$PJBOL_t$	Deflator of gross investments in residential housing ( $JBOL_t$ ). 1991=1.
$PY_t$	Deflator of GDP ( $Y_t$ ). 1991=1.
$R.BS_t$	Yield on 6 years government bonds, quarterly average.
$RLB_t$	Average interest rate on bank loans.
$RMB_t$	Average interest rate on bank deposits.
$UTOT_t$	“Total” unemployment (registered and participant on programmes) as a fraction of labour force (excluding self employed).
$WCF_t$	Hourly wage cost, mainland production sectors, NOK/hour.
$WCIBA_t$	Hourly wage cost, manufacturing and construction, NOK/hour.
$WCO_t$	Hourly wage costs in government sectors, NOK/hour.
$WCTVJ_t$	Hourly wage costs in private service production, NOK/hour.
$Y_t$	GDP, fixed 1991-prices. Mill. NOK.
$YIBA_t$	Value added at factor costs, manufacturing and construction, fixed 1991-prices. Mill. NOK.
$YTV_t$	Value added at factor costs, private service production, fixed 1991 prices. Mill. NOK.
$ZYF_t$	Value added labour productivity, mainland production sectors. Mill. NOK.
$ZYIBA_t$	Value-added labour productivity, manufacturing and construction. Mill. NOK.
$ZYTV_t$	Value added per man-hour in service production, Mill. NOK.

Table A.1: Variable symbols and definitions

## B Figures with forecast comparisons

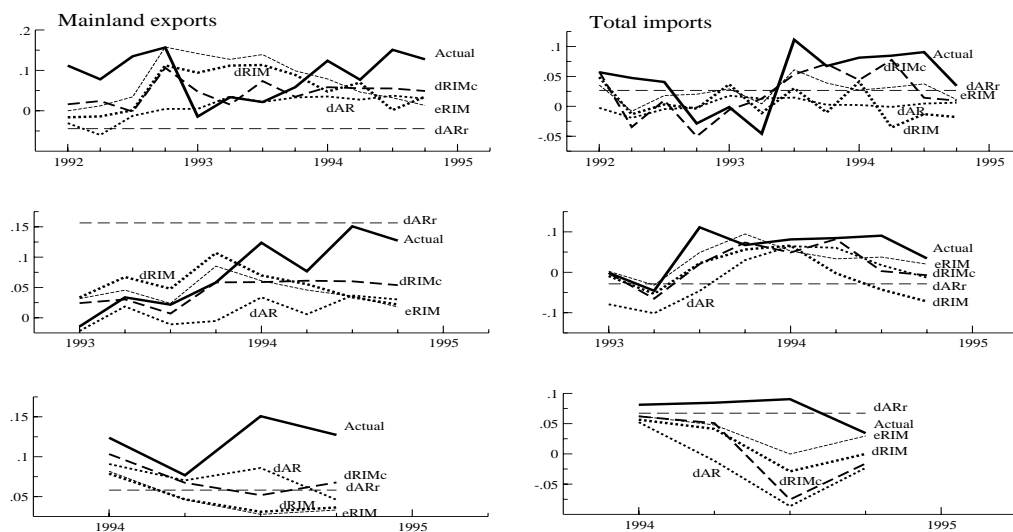


Figure B.1: Annual growth rates for mainland exports ( $A_t$ ) and total imports ( $B_t$ ) top) 1992.1–1994.4; middle) 1993.1–1994.4; bottom) 1994.1–1994.4.

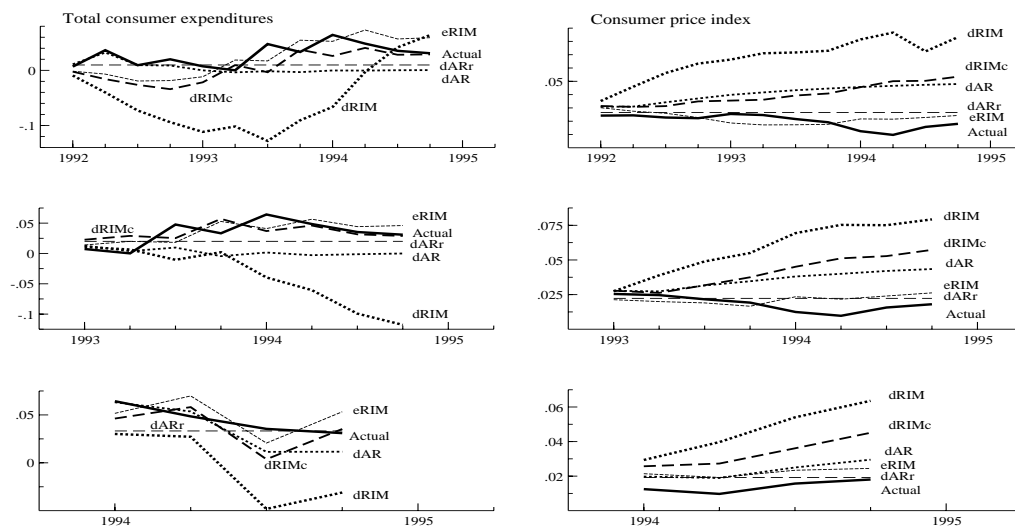


Figure B.2: Annual growth rates for total consumer expenditures ( $CP_t$ ) and the consumer price index ( $CPI_t$ ) top) 1992.1–1994.4; middle) 1993.1–1994.4; bottom) 1994.1–1994.4.

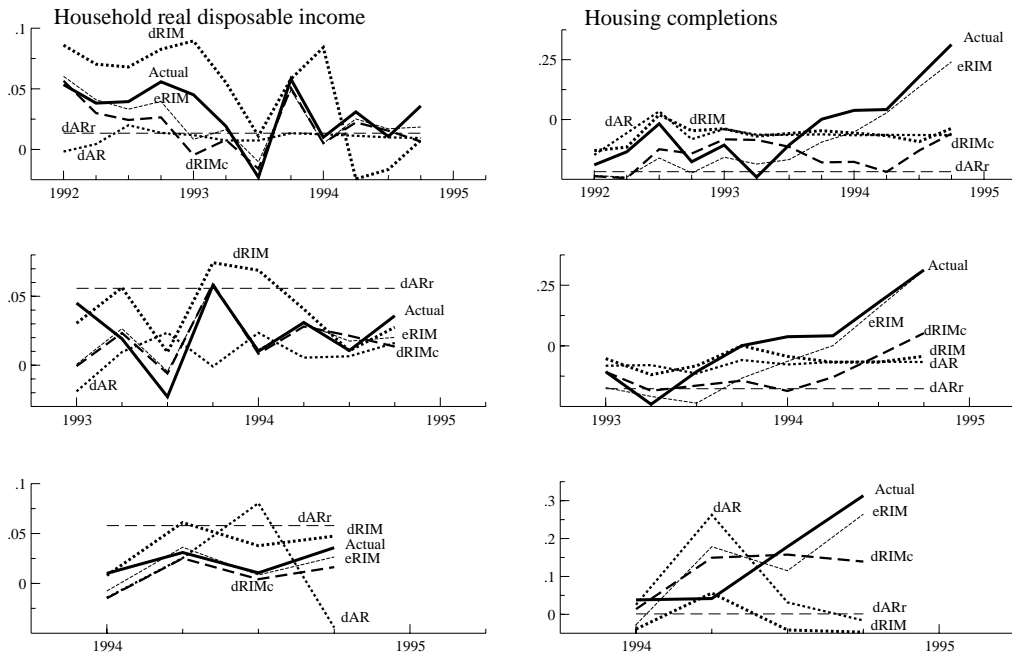


Figure B.3: Annual growth rates for household real disposable income ( $FYHP_t$ ) and the number of housing completions ( $HC_t$ )  
top) 1992.1–1994.4; middle) 1993.1–1994.4; bottom) 1994.1–1994.4.

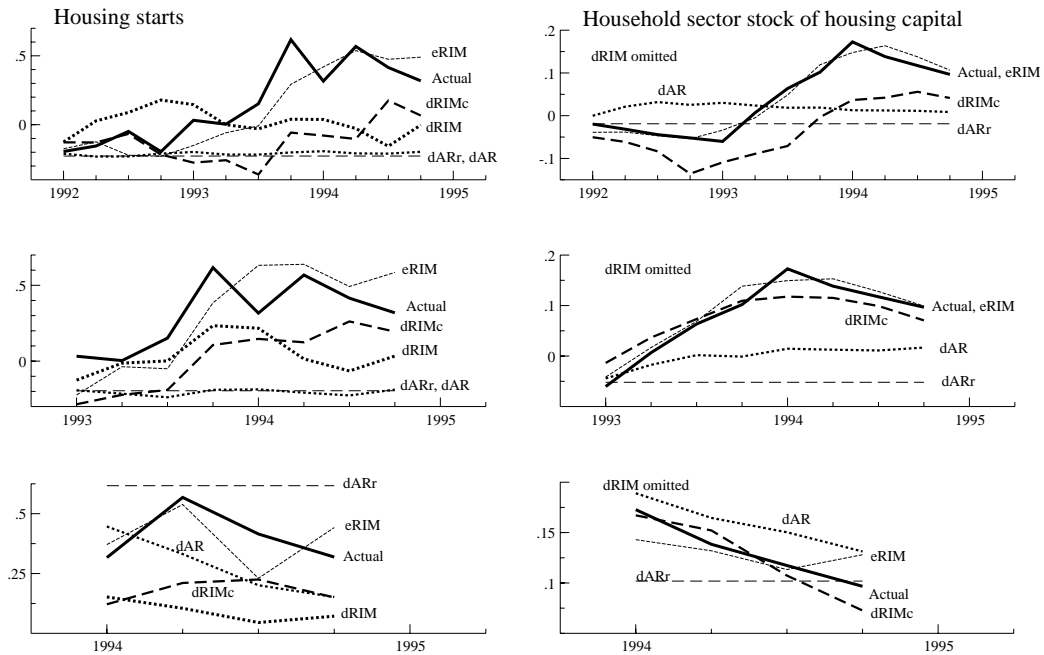


Figure B.4: Annual growth rates in the number of housing starts ( $HS_t$ ) and the value of the household sector stock of housing capital ( $HUSBOL_t$ )  
top) 1992.1–1994.4; middle) 1993.1–1994.4; bottom) 1994.1–1994.4.

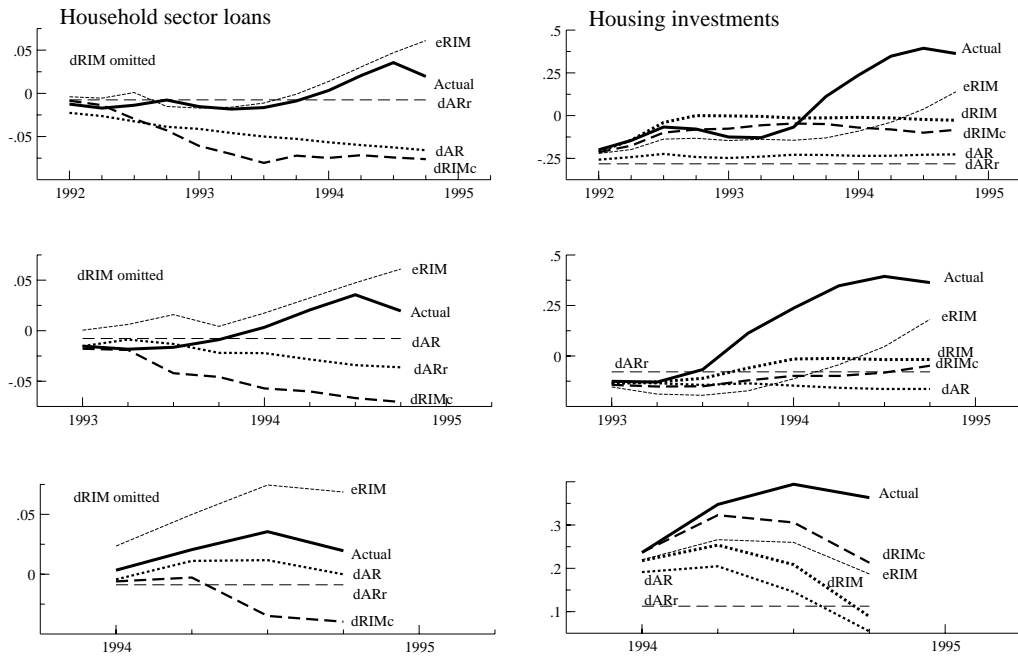


Figure B.5: Annual growth rates in household sector loans ( $HUSHL_t$ ) and housing investments ( $JBOL_t$ )  
top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

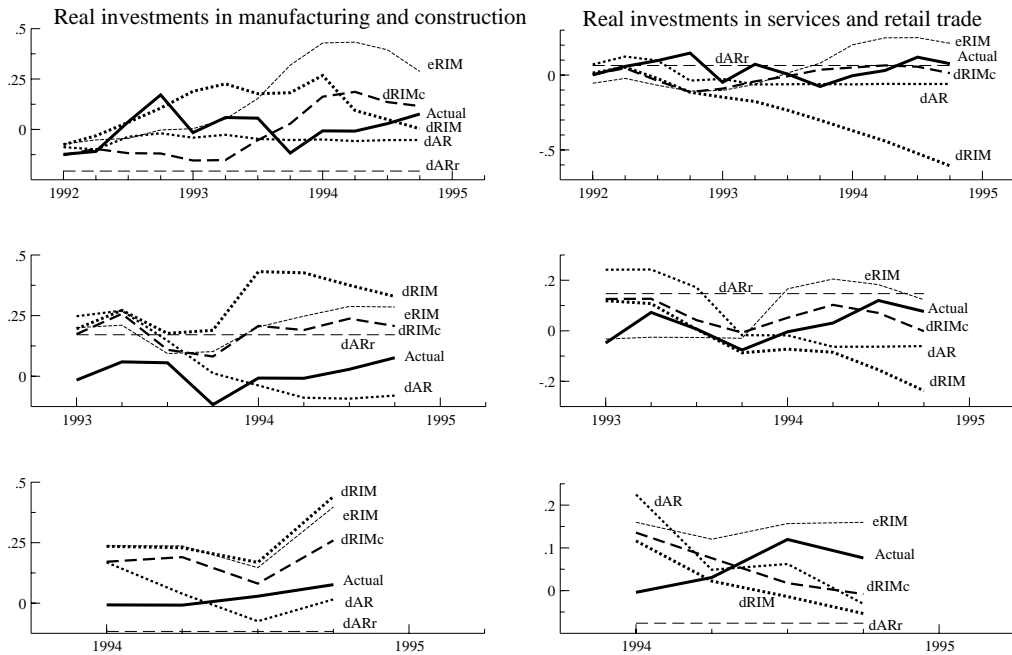


Figure B.6: Annual growth rates for real investments in the manufacturing industry/construction ( $JIBA_t$ ) and services/retail trade sectors ( $JTV_t$ )  
top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

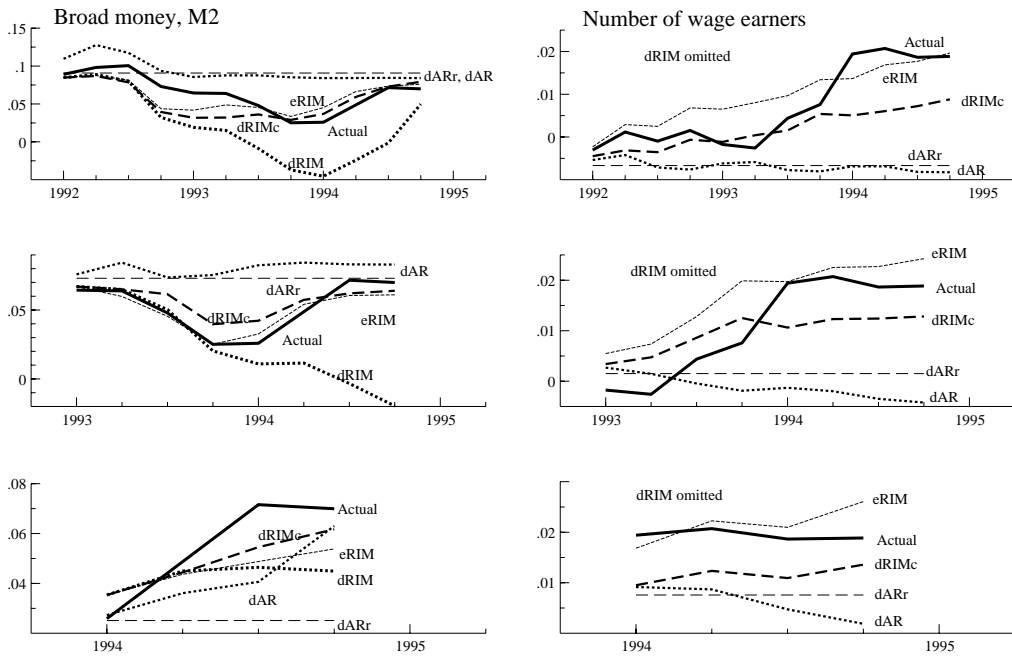


Figure B.7: Annual growth rates for  $M2$  ( $M2M_t$ ) and the total number of wage earners ( $NW_t$ ) (top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

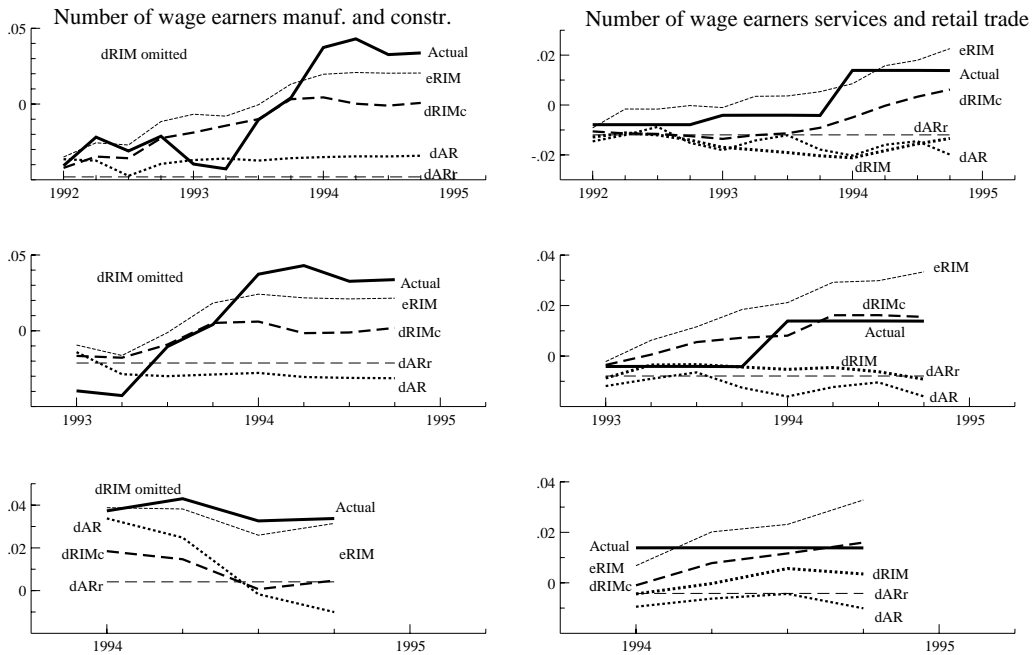


Figure B.8: Annual growth rates for the number of wage earners in the manufacturing industry/construction ( $NWIBA_t$ ) and services/retail trade ( $NWTV_t$ ) sectors (top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.



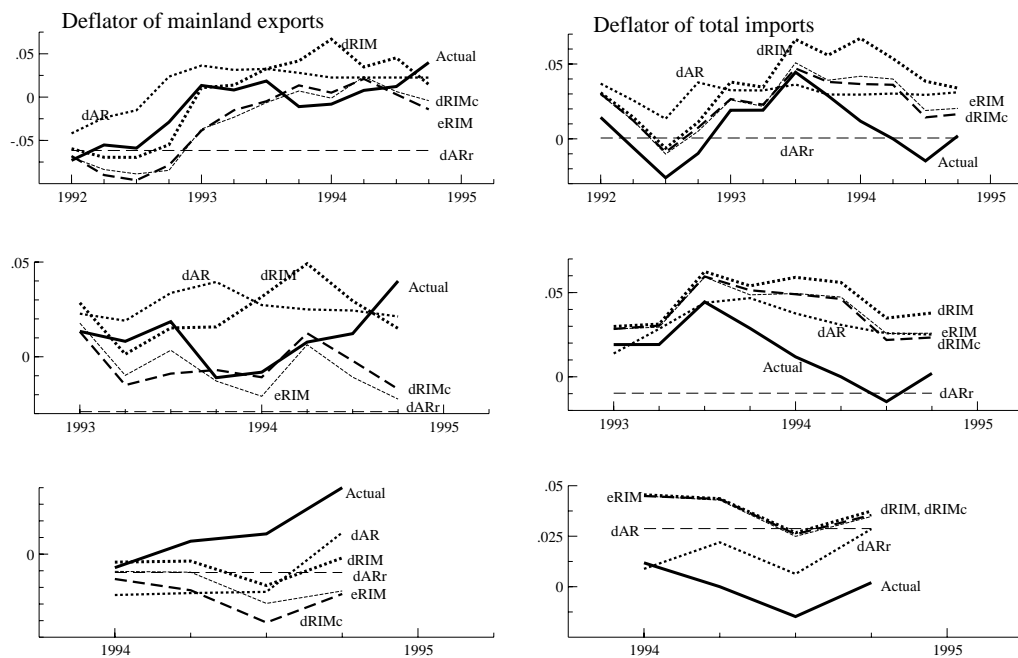


Figure B.9: Annual growth rates for the deflators of mainland exports ( $PA_t$ ) and total imports ( $PB_t$ )  
top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

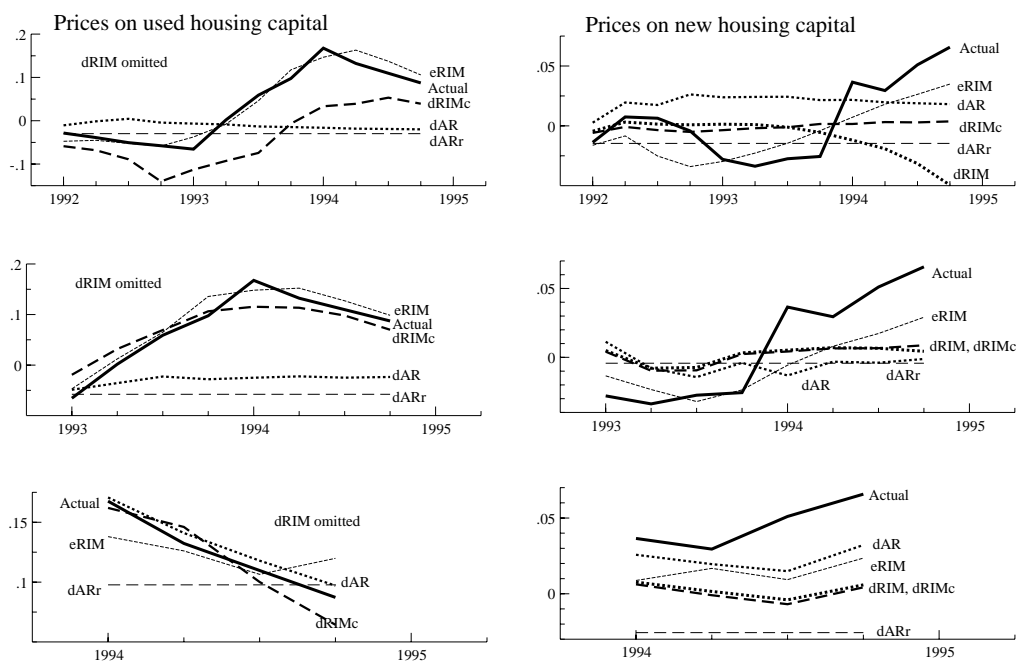


Figure B.10: Annual growth rates for prices on used ( $PH_t$ ) and new ( $PHN_t$ ) housing capital  
top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

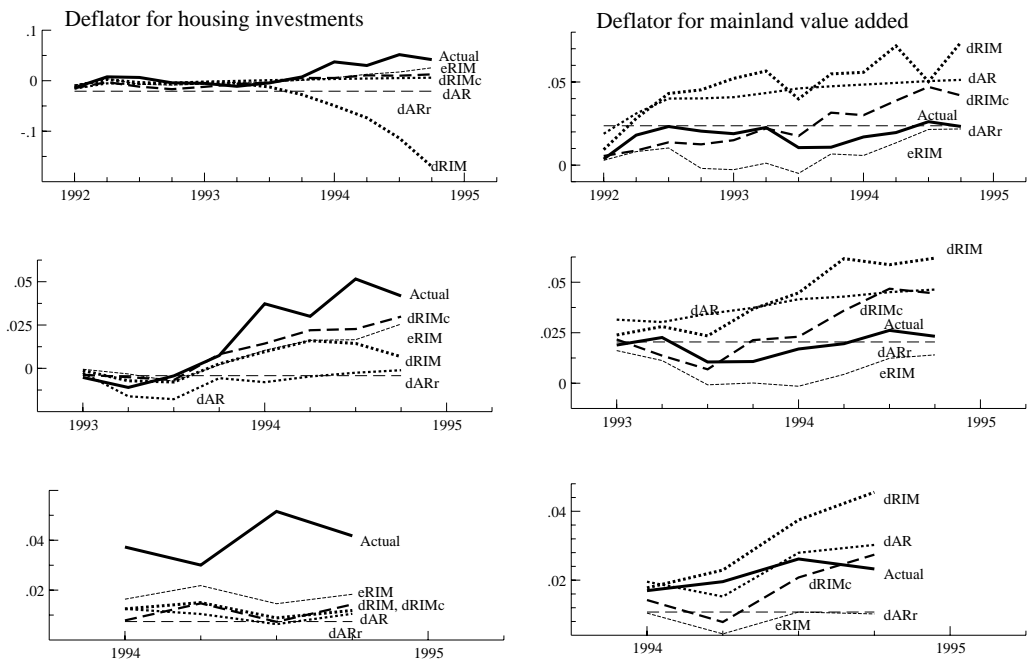


Figure B.11: Annual growth rates for the deflators for housing investment ( $PJBOL_t$ ) and mainland value added ( $PYF_t$ )  
top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

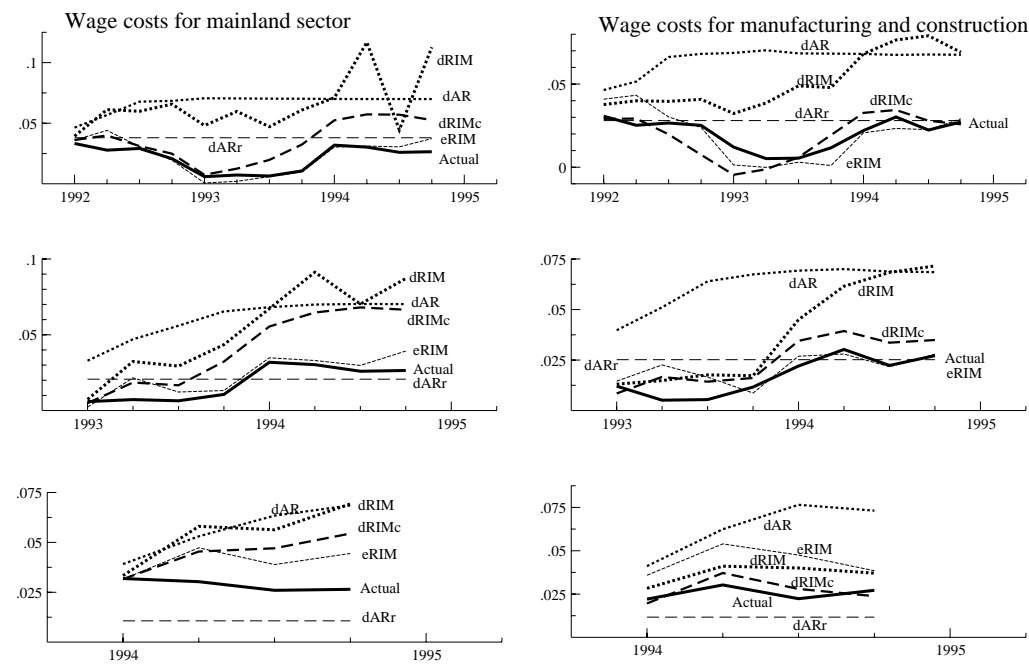


Figure B.12: Annual growth rates for wage costs for the mainland sector ( $WCF_t$ ) and manufacturing industry/construction ( $WCIBA_t$ )  
top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

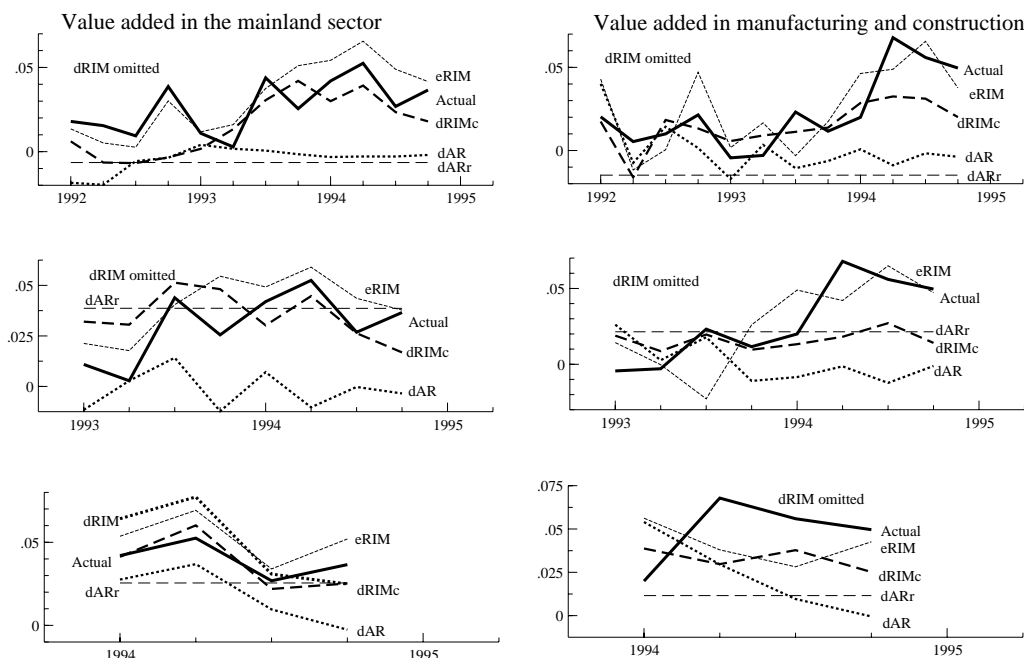


Figure B.13: Annual growth rates for value added in the mainland sector ( $YF_t$ ) and manufacturing industry/construction ( $YIBA_t$ )  
top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

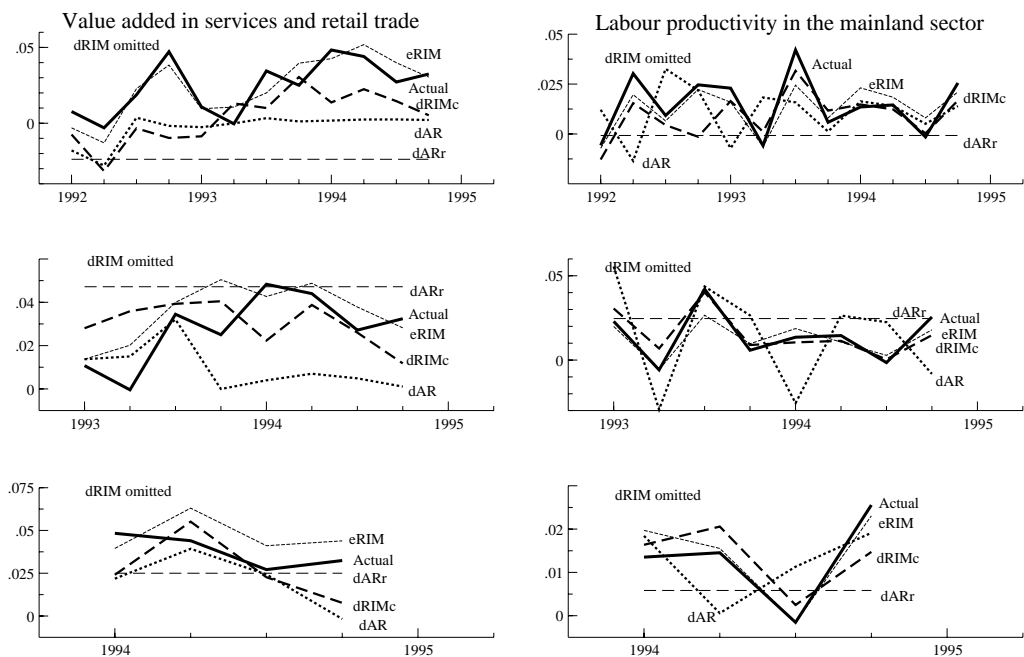


Figure B.14: Annual growth rates for value added in services/retail trade ( $YTV_t$ ) and mainland sector labour productivity ( $ZYF_t$ )  
top) 1992.1—1994.4; middle) 1993.1—1994.4; bottom) 1994.1—1994.4.

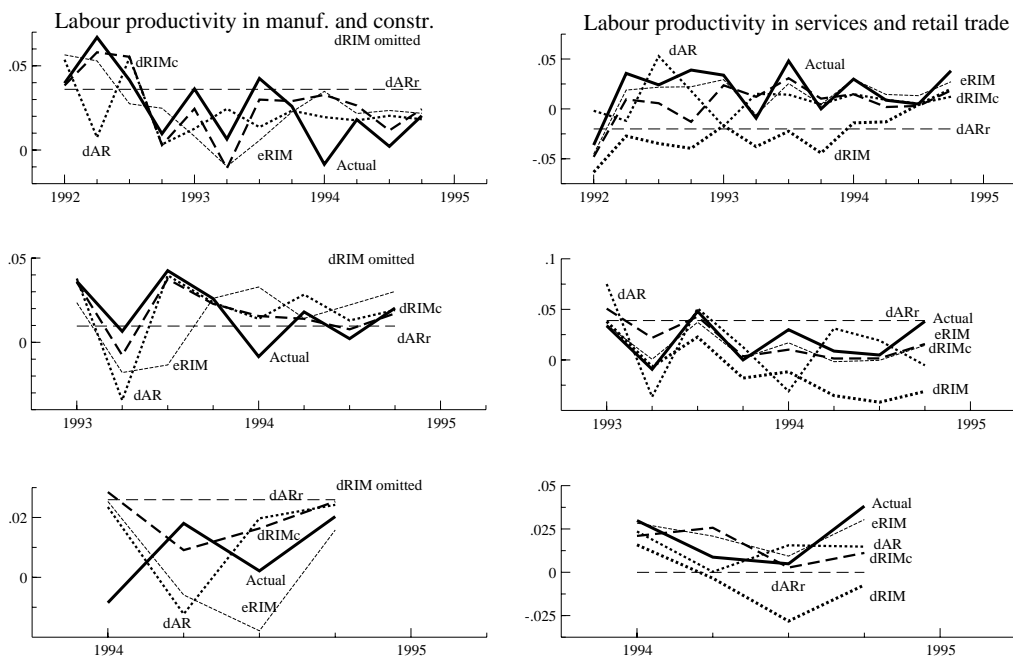


Figure B.15: Annual growth rates for labour productivity in manufacturing industry/construction ( $ZYIBA_t$ ) and services/retail trade ( $ZYTV_t$ ) sectors (top) 1992.1–1994.4; middle) 1993.1–1994.4; bottom) 1994.1–1994.4.

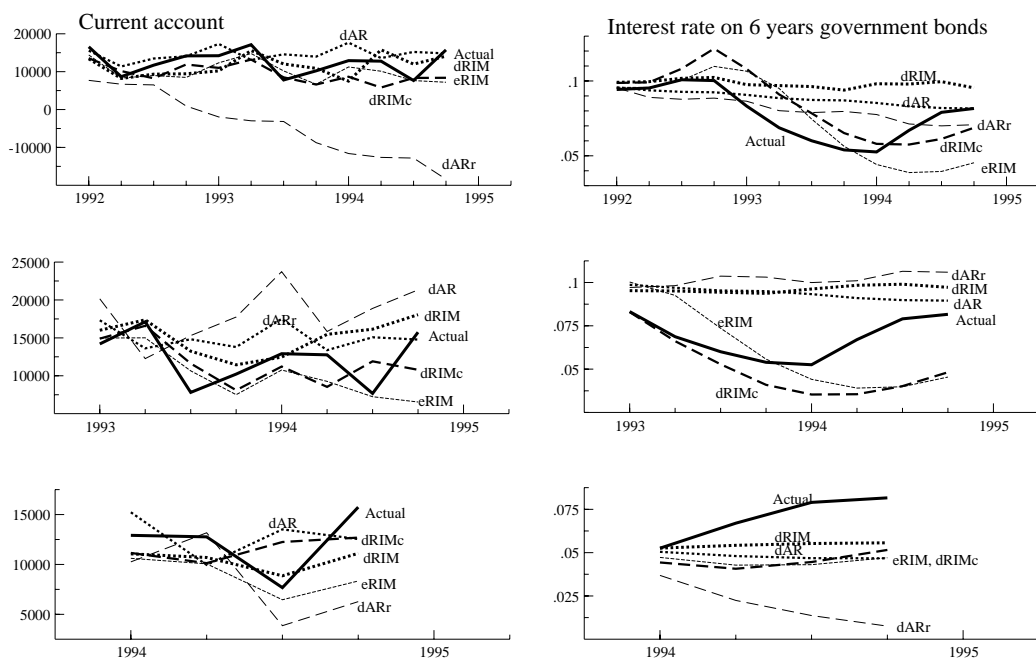


Figure B.16: Current account ( $LX_t$ ) and the interest rate on government bonds ( $R.BS_t$ ) (top) 1992.1–1994.4; middle) 1993.1–1994.4; bottom) 1994.1–1994.4.

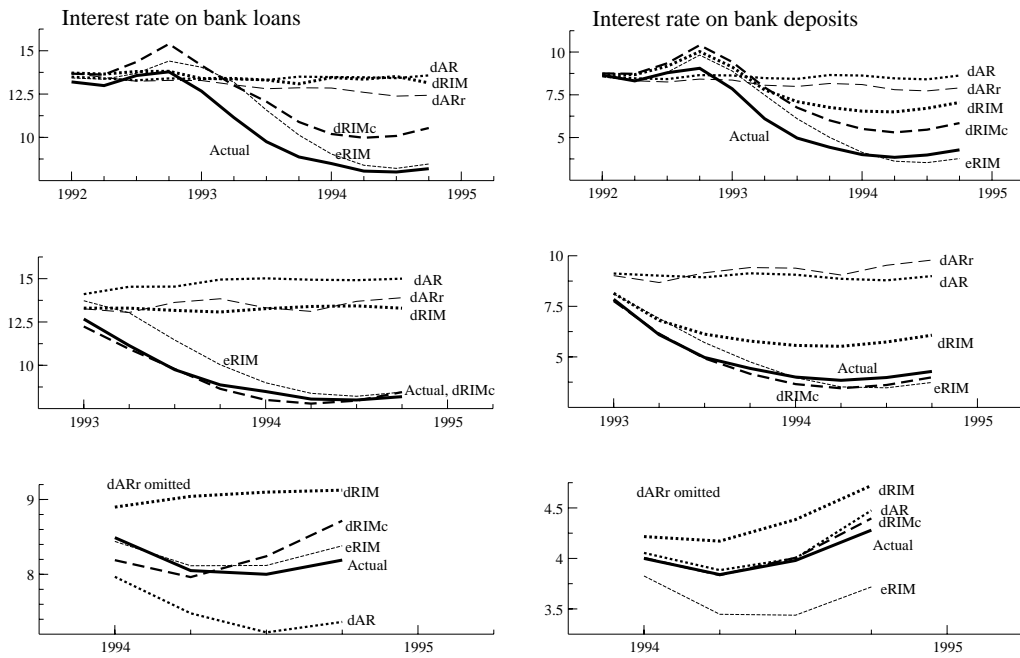


Figure B.17: Average interest rates on bank loans ( $RLB_t$ ) and deposits ( $RMB_t$ ) top) 1992.1–1994.4; middle) 1993.1–1994.4; bottom) 1994.1–1994.4.

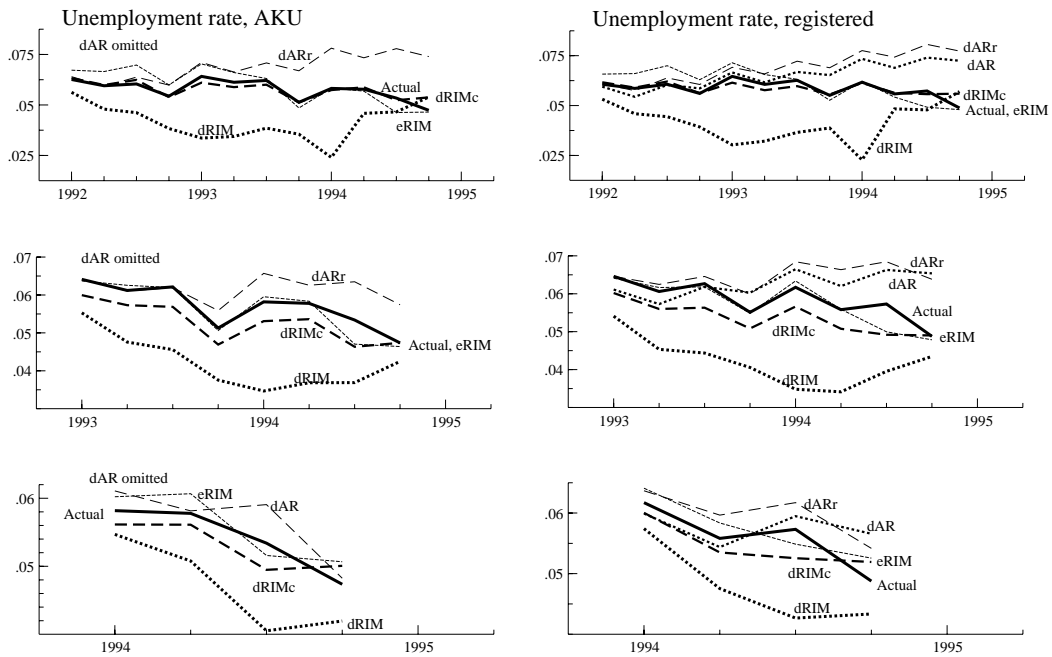


Figure B.18: Unemployment rates, AKU ( $UAKU_t$ ) and registered ( $UR_t$ ) top) 1992.1–1994.4; middle) 1993.1–1994.4; bottom) 1994.1–1994.4.

# C Comparing RMSFEs from five models

Table C.1: 12 quarter dynamic forecasts, 1992.1—1994.4. RMSFEs of annual growth rates and levels (prices, quantities, values)

Variable	p/q/v	eRIM92	dRIMc92	dRIM92	dAR92	dARr92
<i>RMSFE of annual growth rates:</i>						
$A_t$	q	0.0340	0.0201	0.0321	0.0472	0.0473
$B_t$	q	0.0376	0.0369	0.0490	0.0475	0.0452
$CP_t$	q	0.0249	0.0241	0.0653	0.0215	0.0185
$CPI_t$	p	0.0058	0.0146	0.0192	0.0098	0.0048
$FYHP_t$	v	0.0124	0.0164	0.0356	0.0223	0.0221
$HC_t$	q	0.0978	0.1565	0.1449	0.1493	0.1537
$HIP_t$	q	0.0945	0.1453	0.1356	0.1667	0.1499
$HS_t$	q	0.1590	0.2214	0.2435	0.2340	0.2414
$HUSBOL_t$	v	0.0154	0.0316	1.4039	0.0815	0.0764
$HUSHL_t$	v	0.0100	0.0337	1.3646	0.0295	0.0173
$J_t$	q	0.0450	0.0346	0.0577	0.0824	0.0817
$JBOL_t$	q	0.1861	0.1906	0.1837	0.1899	0.1973
$JIBA_t$	q	0.1783	0.1578	0.1048	0.0675	0.0845
$JTV_t$	q	0.1415	0.0953	0.3324	0.0844	0.0624
$M2M_t$	v	0.0139	0.0183	0.0248	0.0147	0.0224
$NW_t$	q	0.0047	0.0054	0.0571	0.0098	0.0091
$NWIBA_t$	q	0.0178	0.0219	0.2227	0.0303	0.0320
$NWTV_t$	q	0.0043	0.0041	0.0109	0.0116	0.0095
$PA_t$	p	0.0088	0.0088	0.0100	0.0444	0.0502
$PB_t$	p	0.0109	0.0107	0.0170	0.0161	0.0189
$PH_t$	p	0.0169	0.0329	1.4022	0.0833	0.0769
$PHN_t$	p	0.0183	0.0291	0.0470	0.0331	0.0318
$PJBOL_t$	p	0.0128	0.0117	0.0785	0.0173	0.0211
$PY_t$	p	0.0066	0.0151	0.0130	0.0228	0.0184
$WCF_t$	p	0.0057	0.0192	0.0236	0.0144	0.0100
$WCIBA_t$	p	0.0079	0.0155	0.0219	0.0134	0.0087
$WCO_t$	p	0.0132	0.0243	0.0252	0.0134	0.0116
$WCTVJ_t$	p	0.0063	0.0182	0.0313	0.0140	0.0105
$Y_t$	q	0.0112	0.0144	0.0308	0.0188	0.0175
$YIBA_t$	q	0.0177	0.0153	0.1855	0.0264	0.0214
$YTV_t$	q	0.0093	0.0172	0.0185	0.0132	0.0167
$ZYF_t$	q	0.0073	0.0091	0.0257	0.0202	0.0142
$ZYIBA_t$	q	0.0215	0.0155	0.0484	0.0230	0.0198
$ZYTV_t$	q	0.0095	0.0176	0.0237	0.0273	0.0236
<i>RMSFE of levels:</i>						
$LX_t$	v	0.2510	0.2806	0.2981	0.2851	-
$D_4CPI_t$	p	0.0059	0.0152	0.0203	0.0101	0.0049
$D_4M2M_t$	p	0.0147	0.0193	0.0247	0.0154	0.0237
$D_4WCF_t$	p	0.0059	0.0205	0.0257	0.0149	0.0102
$D_4WCIBA_t$	p	0.0081	0.0162	0.0236	0.0139	0.0089
$R.BS_t$	p	0.0208	0.0136	0.0162	0.0144	0.0136
$RLB_t$	p	0.6477	0.6148	2.2803	2.3322	1.9386
$RMB_t$	p	0.6159	0.5481	0.9718	2.0672	1.8623
$UTOT_t$	q	0.0050	0.0022	0.0158	0.0086	0.0094

Table C.2: 8 quarter dynamic forecasts, 1993.1—1994.4. RMSFEs of annual growth rates and levels (*p*,*q*,*v*)

Variable	p/q/v	eRIM93	dRIMc93	dRIM93	dAR93	dARr93
<i>RMSFE of annual growth rates:</i>						
$A_t$	q	0.0068	0.0084	0.0041	0.0158	0.0484
$B_t$	q	0.0322	0.0367	0.0322	0.0436	0.0587
$CP_t$	q	0.0195	0.0194	0.0269	0.0208	0.0188
$CPI_t$	p	0.0009	0.0080	0.0139	0.0053	0.0024
$FYHP_t$	q	0.0235	0.0257	0.0214	0.0442	0.0304
$HC_t$	q	0.1315	0.1145	0.0894	0.0949	0.0985
$HIP_t$	q	0.0514	0.0603	0.0577	0.0777	0.0733
$HS_t$	q	0.0728	0.0869	0.1123	0.1821	0.1897
$HUSBOL_t$	v	0.0103	0.0133	0.0992	0.0426	0.0601
$HUSHL_t$	v	0.0076	0.0129	0.0732	0.0084	0.0036
$J_t$	q	0.0171	0.0195	0.0206	0.0568	0.0840
$JBOL_t$	q	0.1437	0.1055	0.0830	0.0998	0.0992
$JIBA_t$	q	0.0721	0.0605	0.0662	0.0569	0.0737
$JTV_t$	q	0.0546	0.0512	0.0716	0.0726	0.0570
$M2M_t$	v	0.0024	0.0060	0.0033	0.0138	0.0153
$NW_t$	q	0.0018	0.0012	0.0074	0.0059	0.0042
$NWIBA_t$	q	0.0092	0.0124	0.0311	0.0243	0.0201
$NWTV_t$	q	0.0074	0.0043	0.0021	0.0024	0.0000
$PA_t$	p	0.0045	0.0046	0.0059	0.0339	0.0312
$PB_t$	p	0.0040	0.0047	0.0053	0.0087	0.0100
$PH_t$	p	0.0107	0.0130	0.0988	0.0516	0.0608
$PHN_t$	p	0.0076	0.0050	0.0042	0.0095	0.0031
$PJBOL_t$	p	0.0054	0.0037	0.0013	0.0066	0.0067
$PY_t$	p	0.0031	0.0086	0.0102	0.0227	0.0155
$WCF_t$	p	0.0064	0.0140	0.0163	0.0100	0.0018
$WCIBA_t$	p	0.0077	0.0110	0.0123	0.0115	0.0033
$WCO_t$	p	0.0070	0.0171	0.0161	0.0129	0.0038
$WCTVJ_t$	p	0.0072	0.0144	0.0200	0.0060	0.0017
$Y_t$	q	0.0120	0.0105	0.0181	0.0142	0.0168
$YIBA_t$	q	0.0260	0.0112	0.0343	0.0191	0.0112
$YTV_t$	q	0.0092	0.0109	0.0120	0.0145	0.0131
$ZYF_t$	q	0.0070	0.0051	0.0078	0.0210	0.0178
$ZYIBA_t$	q	0.0207	0.0052	0.0113	0.0175	0.0133
$ZYTV_t$	q	0.0073	0.0133	0.0130	0.0240	0.0232
<i>RMSFE of levels:</i>						
$LX_t$	v	0.2297	0.2368	0.1992	0.3101	0.3893
$D_4CPI_t$	p	0.0010	0.0083	0.0144	0.0055	0.0025
$D_4M2M_t$	p	0.0025	0.0062	0.0034	0.0144	0.0160
$D_4WCF_t$	p	0.0065	0.0145	0.0169	0.0106	0.0019
$D_4WCIBA_t$	p	0.0078	0.0113	0.0128	0.0121	0.0033
$R.BS_t$	p	0.0079	0.0049	0.0110	0.0096	0.0137
$RLB_t$	p	0.3521	0.1653	1.4008	1.7222	1.6990
$RMB_t$	p	0.2377	0.1158	0.4083	1.2879	1.4735
$UTOT_t$	q	0.0007	0.0008	0.0026	0.0042	0.0028

Table C.3: 4 quarter dynamic forecasts, 1994.1—1994.4. RMSFEs of annual growth rates and levels (*p*,*q*,*v*)

Variable	p/q/v	eRIM94	dRIMc94	dRIM94	dAR94	dARr94
<i>RMSFE of annual growth rates:</i>						
$A_t$	q	0.0142	0.0133	0.0138	0.0095	0.0268
$B_t$	q	0.0314	0.0584	0.0366	0.0561	0.0211
$CP_t$	q	0.0169	0.0165	0.0257	0.0118	0.0124
$CPI_t$	p	0.0011	0.0063	0.0115	0.0014	0.0031
$FYHP_t$	q	0.0084	0.0094	0.0137	0.0527	0.0114
$HC_t$	q	0.1606	0.1390	0.1609	0.1757	0.0974
$HIP_t$	q	0.0793	0.0563	0.0574	0.0734	0.0552
$HS_t$	q	0.1345	0.0422	0.0924	0.1082	0.0713
$HUSBOL_t$	v	0.0182	0.0092	0.1050	0.0067	0.0248
$HUSHL_t$	v	0.0094	0.0228	0.1132	0.0066	0.0112
$J_t$	q	0.0203	0.0299	0.0308	0.0749	0.0379
$JBOL_t$	q	0.1182	0.0691	0.0999	0.0833	0.0455
$JIBA_t$	q	0.0565	0.0538	0.0574	0.1036	0.0335
$JTV_t$	q	0.0432	0.0918	0.1028	0.1181	0.0442
$M2M_t$	v	0.0117	0.0091	0.0143	0.0113	0.0177
$NW_t$	q	0.0032	0.0015	0.0089	0.0025	0.0008
$NWIBA_t$	q	0.0032	0.0056	0.0303	0.0153	0.0039
$NWTV_t$	q	0.0088	0.0062	0.0037	0.0023	0.0000
$PA_t$	p	0.0087	0.0081	0.0059	0.0239	0.0283
$PB_t$	p	0.0044	0.0046	0.0042	0.0114	0.0095
$PH_t$	p	0.0194	0.0089	0.1041	0.0024	0.0263
$PHN_t$	p	0.0116	0.0135	0.0130	0.0117	0.0133
$PJBOL_t$	p	0.0099	0.0102	0.0083	0.0093	0.0075
$PY_t$	p	0.0038	0.0075	0.0095	0.0195	0.0143
$WCF_t$	p	0.0070	0.0159	0.0194	0.0130	0.0024
$WCIBA_t$	p	0.0058	0.0080	0.0122	0.0126	0.0033
$WCO_t$	p	0.0100	0.0227	0.0223	0.0169	0.0043
$WCTVJ_t$	p	0.0090	0.0167	0.0228	0.0096	0.0029
$Y_t$	q	0.0029	0.0063	0.0136	0.0111	0.0144
$YIBA_t$	q	0.0269	0.0208	0.0165	0.0333	0.0169
$YTV_t$	q	0.0099	0.0140	0.0116	0.0133	0.0082
$ZYF_t$	q	0.0035	0.0063	0.0107	0.0102	0.0095
$ZYIBA_t$	q	0.0238	0.0165	0.0274	0.0230	0.0117
$ZYTV_t$	q	0.0072	0.0149	0.0143	0.0118	0.0137
<i>RMSFE of levels:</i>						
$LX_t$	v	0.1905	0.2950	0.1787	0.3337	0.3731
$D_4CPI_t$	p	0.0011	0.0066	0.0122	0.0015	0.0032
$D_4M2M_t$	p	0.0123	0.0096	0.0150	0.0119	0.0186
$D_4WCF_t$	p	0.0073	0.0168	0.0206	0.0136	0.0025
$D_4WCIBA_t$	p	0.0060	0.0083	0.0129	0.0134	0.0034
$R.BS_t$	p	0.0121	0.0100	0.0098	0.0130	0.0225
$RLB_t$	p	0.0969	0.3150	0.3003	0.1292	1.3250
$RMB_t$	p	0.1555	0.0477	0.0859	0.0682	1.3957
$UTOT_t$	q	0.0012	0.0016	0.0032	0.0040	0.0021