FORECASTING NEW ZEALAND'S REAL GDP

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Recent time series methods are applied to the problem of forecasting New Zealand's real GDP. Model selection is conducted within autoregressive (AR) and vector autoregressive (VAR) classes, allowing for evolution in the form of the models over time. The selections are performed using the Schwarz (1978) BIC and the Phillips-Ploberger (1996) PIC criteria. The forecasts generated by the data-determined AR models and an international VAR model are found to be competitive with forecasts from fixed format models and forecasts produced by the NZIER. Two illustrations of the methodology in conditional forecasting settings are performed with the VAR models. The first provides conditional predictions of New Zealand's real GDP when there is a future recession in the United States. The second gives conditional predictions of New Zealand's real GDP under a variety of profiles that allow for tightening in monetary conditions by the Reserve Bank.

1. Introduction

Forecasting future economic activity is an issue of importance to both policy makers and economic agents since most economic decisions depend upon expectations of future conditions. Consequently, a considerable amount of research has been devoted to developing the tools and techniques of macroeconomic forecasting. This paper applies a small subset of these methods to just one variable that is of interest in applications – real gross domestic product (GDP) – to illustrate our automated approach. In principle, however, the techniques used here can be applied to almost any time dependent variable.

Macroeconomic forecasting methods can be regarded as lying along a continuum between "structural" and "pure time series" approaches. One advantage

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of using an approach that lies towards the time series end of the spectrum is that such models are relatively simple to construct. Further, as the present paper shows, forecasting with these models is easily and inexpensively implemented and can be automated on a computer. This paper seeks to demonstrate these advantages. It shows that parsimonious time series models can produce forecasts of New Zealand's real GDP that are useful and that can compete with forecasts generated by far more complex procedures. It further shows how the same methods can be used to analyse interesting scenarios for policy analysis, such as the potential effects on New Zealand of recession abroad and changes in domestic monetary conditions.

When using time series models, the first issue that arises is the selection of the appropriate class of model. This is an important problem, but is not the focus of the present paper. Once the general class of functions has been chosen, the second problem is to decide the most appropriate form that the model should take within this class. Empirical applications of some recent techniques for addressing this problem are the main feature of this paper. In particular, our empirical applications use the Bayesian Information Criterion (BIC) of Schwarz (1978), and the Posterior Information Criterion (PIC) developed in Phillips and Ploberger (1994, 1996) and Phillips (1996). These model selection techniques have both Bayesian and classical (prequential) justifications, which are discussed in Phillips (1996). They are implemented here in the context of a class of univariate autoregressive models that allow for a unit root and a class of multivariate vector autoregressive models that allow for cointegration. The model selection procedures have been automated in terms of *GAUSS* programs, following the lines of Phillips's (1995a) application to historical economic time series for the United States.[1]

A feature of the approach used here, following that of Phillips (1994, 1995a), is that it offers the flexibility of allowing the optimal model in the given classes to be re-evaluated at each date as new data becomes available. Thus, not only are the estimated coefficients of the models allowed to change, but the form of models themselves may adapt with the arrival of new information. Separately, the issue of nonstationarity is particularly important for economic time series and many techniques have been developed for confirming its presence and identifying its form. A further advantage of the approach taken in the present paper is that the possibility of nonstationarity in the data as well as some of the forms it may take

[1] These methods have been used by the second author for the past several years in producing forecasts of several Asia-Pacific nations – see Phillips (1995c) for a discussion of these applications. An interactive version of similar methods applied to New Zealand data has been developed and a prototype is now available on a web site at the University of Auckland developed by Phillips (http://predicta.eco.auckland.ac.nz). This web site allows remote users to obtain forecasts of macroeconomic activity in the New Zealand economy, and is being extended is to perform policy simulations similar to those presented in the present paper. All calculations and graphics on this web site are done in real time on a dedicated server at the University of Auckland.

are introduced straightforwardly as an extension of the model selection procedure. In particular, the order of integration of the variable of interest in the univariate models, the cointegrating rank in the VAR models, and the deterministic trend degree are simply additional order parameters to be selected as part of a coherent system of model choice.

The organisation of the remainder of the paper is as follows. Section two gives a brief overview of the operational features of model determination using BIC and PIC. Section three applies these techniques to generate *ex-ante* forecasts of New Zealand's real GDP series. The first application is in the context of a class of univariate 'AR(p) + Trend(q)' models (see (4) below) that includes only New Zealand's real GDP. The second application is a multivariate 'VAR(p) + Trend(q)' model (see (5) below) incorporating the real GDP series for New Zealand, Australia, Japan, and the United States. The forecasting performance of the selected models is compared with fixed (i.e. non-evolving) time series models of the same classes and with forecasts of the NZIER. Section four briefly demonstrates the usefulness of such VAR models in predicting the effects of some hypothetical scenarios of interest. First, the international VAR model of section three is used to analyse the effects of a recession in the United States. Second, a VAR model of New Zealand's real GDP and short-term interest rates is used to predict the effects of different domestic monetary conditions. Section five offers some concluding remarks.

2. Model Selection with BIC and PIC

Having chosen an appropriate class of model for a particular data series, the next step is to decide which model within the chosen class best captures the characteristics of the data. This may involve selecting the number of lags in the dynamic specification, the deterministic trend degree, whether a unit root should be incorporated in the model formulation, and so on. Model selection of this type is of fundamental importance in time series modelling, and it is critically important in empirical applications. It has therefore received a great deal of attention in the literature. One approach to the problem is to adopt Bayesian criteria, based essentially on the selection of the most probable model *a posteriori*.

In time series as well as other applications, Bayesian analysis is conducted conditional on the realised history of the series. Broadly speaking, the Bayesian approach to the model selection problem is to attach a probability measure to the parameter space and to the models themselves, and then compute the posterior probability of each of the candidate models given the realised data series. The model with the highest posterior probability amongst all the candidates is then selected.

To illustrate and fix ideas, consider the single equation stochastic linear regression model

$$y_t = \beta' x_t + \varepsilon_t, \quad (t = 1, 2, \ldots), \tag{1}$$

where the dependent variable y_t and error ε_t are real valued stochastic processes on a probability space (Ω, F, P) and x_t is a vector of predetermined regressors. An example of such a model is an 'AR(p) + Trend(q)' model, as will be considered in the univariate empirical analysis later in this paper. Assuming that such a model includes the actual data generating process, the true values of the order parameters (p, q) are not known, and hence various criteria have been developed for choosing the optimal values of these parameters. More generally, models may be regarded as nothing more than approximations of the true data generating process and the issue is then which combination of p and q is best, given the data at hand.

In fitting a historical time series trajectory, improvements in fit, as measured by the residual sum of squares of the regression, are always possible by increasing the dimension of the parameter space. Viewed from this perspective, model selection criteria such as BIC and PIC are essentially penalised versions of the residual sum of squares from an estimated regression. The penalty increases with the number of estimated parameters, and, in the case of PIC, the type of regressors that are included. While more complex models may fit the sample data better, their additional complexity may not be justified by the cost of having to estimate more unknown parameters with the given data. Model selection criteria seek to balance such factors in determining which of a group of models is the most satisfactory for given data. Ploberger and Phillips (1999) have recently shown that in such a process there is an empirical limit on how close we can get to the true model and that limit gets larger as the model size increases. In such situations, we may not only expect smaller models to be chosen, but on average we may expect them to do better as tools of prediction.

In the case of BIC, the penalty depends only on the number of parameters in the model. In particular, when applied to (1), BIC is computed from an estimated model according to the formula[2]

$$\ln(BIC_k) = \ln\left(\tilde{\sigma}^2\right) + \frac{k\ln(n)}{n}, \tag{2}$$

where $\tilde{\sigma}^2 = e'e/n$ (or $\tilde{\sigma}^2 = e'e/[n-k]$), with e being the OLS regression residuals, k the number of regressors, and n the sample size. Using this criterion, we can choose the most appropriate value of k, as suggested by the data, by minimising the value of BIC.

The penalty employed by PIC is more general than that of BIC because it depends not only on the number but also the *type* of regressors included in the model. The theory underlying the form of the PIC criterion is developed in Phillips

[2] This formula relies on the Gaussianity of the errors. Formulae for other cases are available and rely on the form of the likelihood (Phillips, 1996).

and Ploberger (1994) and Phillips (1996), and is summarized in Phillips (1994, 1995a).

Taking a Bayesian approach, Phillips and Ploberger (1994, theorem 2) first show that there is a *Bayes model* with time-varying parameters, corresponding to the parametric model (1). In effect, the data conditioning implicit in Bayesian analysis is to translate the model (1) into a Bayes model in which the parameters are time varying and data dependent. Rather than committing to a "true" value of a parameter, as in the classical approach, the operation of the likelihood principle commits the analyst to a new model where the parameters evolve according to the latest best estimate from the data available up to that point on the trajectory. These models proceed conditional on the given data up to a certain point in the trajectory and use this fraction of the sample to produce an optimal estimate of the location of the data to come (Phillips, 1995b). The Bayes models obtained in this way are natural predictive models, given the historical trajectory to the present.

Phillips and Ploberger (1994) derive PIC by considering the probability measure associated with the Bayes model corresponding to (1). This probability measure is a forward-looking measure that can be described by the conditional density of y_t given F_{t-1}, where the latter signifies information to time $t - 1$. This measure can be obtained for each prospective model and thereby be used to compare models and test hypotheses. The mechanism for doing so is the likelihood ratio of the respective measures of the two competing models (Phillips, 1995a). In the context of the univariate model (1), PIC has the following general form

$$\ln(PIC_k) = \ln\left(\tilde{\sigma}_k^{\,2}\right) + \frac{\ln\left|X_k' X_k / \tilde{\sigma}_K^{\,2}\right|}{n}, \tag{3}$$

where $\tilde{\sigma}_k^{\,2}$ is the maximum likelihood estimate of the residual variance of a model with k parameters, $\tilde{\sigma}_K^{\,2}$ is the maximum likelihood estimate of the residual variance of a model with the maximum number of parameters allowed (within the given class of models), and X_k is the matrix of regressors from the model with k parameters. As with BIC, the optimal order parameters are those that minimise the value of PIC.

As well as being used for the selection of order parameters, Phillips and Ploberger (1994) and Phillips (1996) show that PIC can be used to test point null hypotheses such as that of a unit root. The procedure to do this is straightforward. We simply calculate PIC for a given model with and without a unit root explicitly incorporated. Choosing the model with the minimum value of PIC is equivalent to testing the null hypothesis of a unit root against a two-sided classical alternative. Phillips and Ploberger (1994, theorem 4) show that this test is completely consistent in the sense that both type I and type II errors tend to zero as the sample size tends to infinity.

Furthermore, PIC can be applied to model selection in the context of multivariate regression and VAR models. The theory behind the operation of PIC in this context is given in Phillips (1996). Of particular relevance to the applications given in this paper, model selection by PIC may be performed in the context of a VAR system with p lags and deterministic trend of degree q, or VAR(p, q) system. In particular, PIC can be used to jointly or sequentially select the VAR order and trend degree by minimising the relevant PIC value. Moreover, PIC has been extended to the case of partially nonstationary VAR models with reduced rank structure (VAR-RRR) by Phillips (1996) and Chao and Phillips (1999). They show that PIC can be used to jointly select the lag length and cointegrating rank in such a model and that this process leads to consistent estimates of both order parameters. In that context, PIC has the following form, which is maximised over k,

$$\ln(PIC_k) = \ell_n\left(\hat{\theta}_k\right) - \tfrac{1}{2}\ln\left|B_{nk}\right|,$$

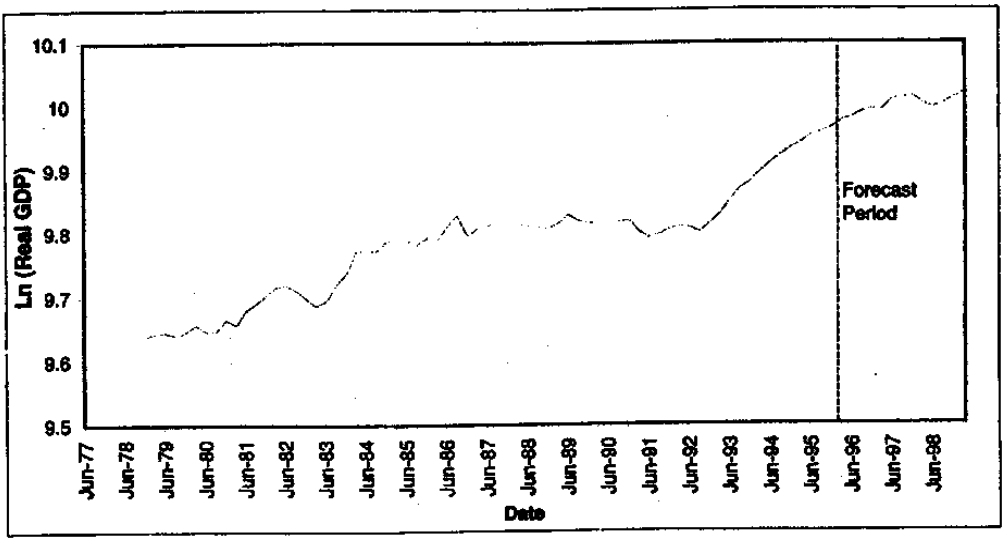
where $\ell_n\left(\hat{\theta}_k\right)$ is the log likelihood evaluated at the maximum likelihood estimator $\hat{\theta}_k$ for the model with parameter vector θ_k and sample conditional Fisher information B_{nk}. Explicit formulae for the reduced rank regression case are given in Phillips (1996).

3. *Ex-Ante* Forecast Comparisons

The model selection techniques outlined above are used here to select models for forecasting New Zealand's real GDP. The data series comprise quarterly seasonally adjusted gross domestic product at 1991/92 prices from the *PC-INFOS* database of Statistics New Zealand (SNBQ.S2SZT). The series runs from June 1977 to March 1999, giving 88 quarterly observations. Observations for June and September 1999 are currently available, but the shorter series is chosen to maintain comparability with the forecasts that are obtained using international data to be reported later in this section. The forecast period chosen for analysis is March 1996 to March 1999 (inclusive), being 13 quarters.

There is a tendency for economic time series to exhibit variations that increase in mean and dispersion in proportion to the absolute level of the series (Nelson and Plosser, 1982), and so it is common practice to transform the data by taking logarithms prior to analysis. The data is shown in log form in Figure 1. While New Zealand's real GDP series has followed a general upward trend over the sample period, there are periods of clear deviation from this trend. Indeed, the graph indicates the possibility of a structural break in the data in the early 1990s, which may be a consequence of the many economic reforms that were undertaken in New Zealand at that time and over the prior decade. The subsequent period of growth has shown signs of tailing off in 1998 and 1999. Good forecasting models need to have the flexibility to take these changes into account.

Figure 1: Natural Logarithm of New Zealand's Quarterly Seasonally-Adjusted Real GDP Series.



3.1 Univariate Modelling

We consider first a simple class of univariate time series models of the 'AR(p) + Trend(q)' form

$$y_t = \sum_{j=1}^{p} a_j y_{t-j} + \sum_{k=-1}^{q} b_k t^k + u_t, \tag{4}$$

where y_t is the natural logarithm of real GDP at date t and u_t is assumed to be iid(0, σ^2). We set $b_{-1} = 0$, so that $q = -1$ corresponds to the case of a pure autoregression with no fitted intercept. The domains set for the order parameters are $p \in \{1, 2, 3, 4\}$ and $q \in \{-1, 0, 1, 2\}$, thereby allowing for internal dynamics over four quarters and the possibility of a linear or quadratic trend. The presence of a unit root is also accommodated through the provision that the long run autoregressive coefficient, represented by the sum $\sum_{j=1}^{p} a_j$, may or may not be restricted to unity. This model specification is the same as that used in empirical applications of PIC to Australian and United States data by Phillips (1994, 1995a). Some fixed format models of the same class are also considered for comparative purposes.

Within the context of the general model (4), BIC is given by (2) with $k = p + q + 1$ and PIC is given by (3) with $k = p + q + 1$ and $K = 7$. Each of the 16 alternative models that fall in this framework will be tested with and without the unit root restriction imposed. Therefore, 32 different models in all are evaluated by BIC and PIC in the selection process. An algorithm for model selection and data-based unit root testing based on PIC was given by Phillips and Ploberger (1994) in the context of autoregressive moving-average models. Since autoregressive models with trends are considered here, we use a simplified version of that algorithm, which proceeds as follows:

Step 1: Using the relevant subsample of the data, obtain the maximum likelihood estimate of the residual variance, $\tilde{\sigma}_K^{\,2}$, from the maximum model, with $(p, q) = (4, 2)$. This estimate is used in the calculation of PIC.

Step 2: Estimate an array of regressions of the form (4) with $p \in \{1, 2, 3, 4\}$ and $q \in \{-1, 0, 1, 2\}$ and use BIC and PIC to select the autoregressive order and trend degree simultaneously. Models within this class that minimise the values of BIC and PIC are selected.

Step 3: Re-estimate the selected models under the unit root restriction, $\sum_{j=1}^{p} a_j = 1$.

If the value of BIC or PIC for this model is smaller than that calculated in step 2, then the criterion supports the presence of a unit root in the data and the corresponding unit root model is chosen.

When this algorithm is implemented on a period by period basis, the chosen models evolve with time-varying and data-dependent order parameters. Since all steps are repeated each period, including testing the unit root restriction, the possibility of the unit root formulation switching on and off as new data are introduced allows for structural change in the specification for forecasting. On the other hand, fixed format models keep the same formulation each period and only the estimated coefficients change as new data are introduced.

The model selection algorithm described above was implemented in programs written by the authors in *GAUSS* version 3.2.37 for Windows 95/NT. Although the process allowed for potential evolution in model form over the forecast period, the models actually chosen by the two criteria, BIC and PIC, remained constant. The model selected by BIC was an AR(3) with no trend or intercept and a unit root while the model selected by PIC was an AR(3) with an intercept and no unit root.

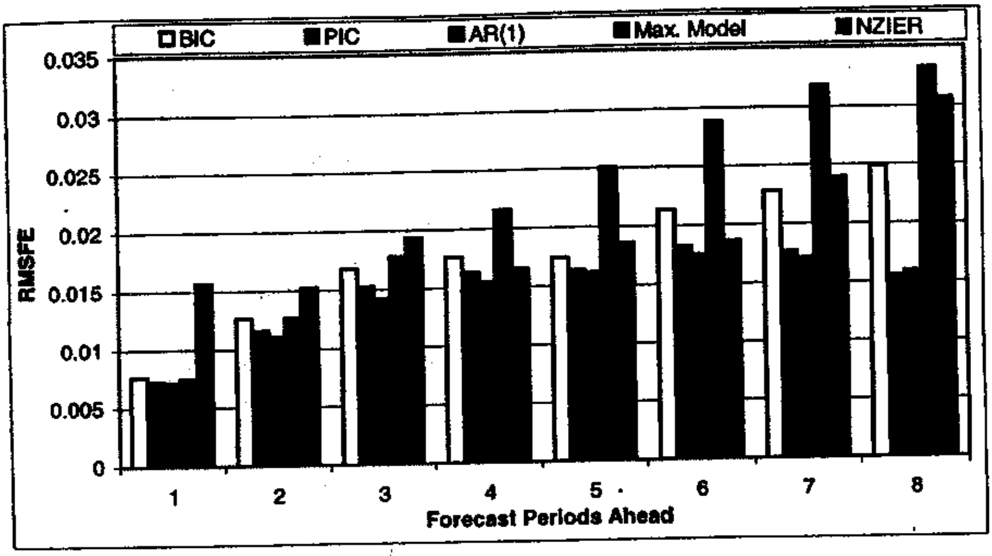
These evolving models were used to generate *ex-ante* forecasts for various forecast horizons[3] and these forecasts were compared with those of the following fixed format models of the same class: (i) an AR(1) model with no deterministic

[3] For example, a four quarter ahead forecast is generated by first forecasting one quarter ahead and then using this forecast together with the sub-sample of the data to generate a two quarter ahead forecast, and so on up to four quarters ahead.

trend and no unit root (representing the simplest non trivial dynamic model in the class), and (ii) the maximum model allowed, i.e. an AR(4) model with a quadratic trend and no unit root. In addition, the New Zealand Institute of Economic Research (NZIER) publishes regular quarterly forecasts of the same series as used here, in its publication *Quarterly Predictions*. The forecasts produced by the time series models can therefore be compared with each other and those of the NZIER. We used a root mean square forecast error (RMSFE) basis in these comparisons.

Figure 2 shows the RMSFE values[4] for the univariate time series models and the NZIER forecasts[5] over horizons up to eight quarters ahead. The Figure shows that, on an RMSFE basis, the best of the univariate models considered here is the fixed AR(1) model, closely followed by the evolving model selected by PIC. The PIC model outperforms the BIC model at all forecast horizons. Furthermore, the RMSFEs of the time series models, except for the maximum model, are comparable in magnitude to those of the NZIER forecasts at all horizons. The performance of all the models relative to the maximum univariate model suggests that more parsimonious models are clearly dominant in forecasting.

Figure 2: RMSFEs for *Ex-Ante* Forecasts from the Evolving and Fixed Univariate Models, and the NZIER.



[4] These values are calculated using the natural logarithms of the forecasts and actual values.

[5] The NZIER forecast for a particular date has been taken from the subsequent issue of *Quarterly Predictions*. For example, the one-period ahead forecast of March 1998 GDP is taken from the June 1998 issue of *Quarterly Predictions*, when GDP data up to and including December 1997 was available.

A caveat to these comparisons with the NZIER forecasts is that the GDP series is subject to revisions after the initial data is released. Such revisions can affect recent sample period observations as well as the latest observation. The time series models used here employ the latest available data set for generating all of the forecasts, while the NZIER forecasts would have been generated using the GDP series (and, presumably, other data series as well) that was available at the time the *ex ante* forecast was made. To the extent that the data revisions may make forecasts more accurate, the time series models employed here may have an advantage over those of the NZIER.

3.2 Multivariate Modelling

New Zealand is often described as being a 'small open economy'. The OECD measure of openness as the ratio of imports plus exports to GDP has averaged approximately 0.6 for New Zealand over the period from 1975 to 1995, compared with 0.35 for Australia and 0.2 for the United States. One feature of this highly open structure is that the New Zealand economy is likely to be sensitive to external shocks. The empirical analysis in this section attempts to capture and quantify such effects by extending the univariate analysis of the previous section to an international VAR context.

VAR models have an advantage over large structural models in that they are straightforward to estimate and use to generate forecasts. However, macroeconomic VAR models quickly become over-parameterised as the number of variables increases, a problem that is typically overcome by imposing structural restrictions on the model or by implementing a Bayesian hyperparameter methodology. Given the relatively short data series available for New Zealand's real GDP, we attempt to attenuate this problem by using a small international VAR model that includes only the real GDP series of New Zealand and its three major trading partners. This approach has two other advantages. First, it complements some existing empirical work on using VARs with New Zealand data, such as Wong and Jolly (1993, 1994) and Phillips (1995c), which confine the system to domestic variables. Second, it allows us to focus attention on the potential effects of external shocks on economic activity in New Zealand, thereby directly complementing the univariate analyses.

The framework adopted is a VAR model with trend, or VAR(p, q) model of the form

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \sum_{j=-1}^{q} c_j t^j + \varepsilon_t , \qquad (5)$$

where y_t is a $(K \times 1)$ vector of endogenous variables and ε_t is a random error which is assumed to be iid $(0, \Sigma)$. The possibility of no deterministic trend is allowed for, by setting $c_{-1} = 0$. We set $p \in \{1, 2, 3, 4\}$ and $q \in \{-1, 0, 1, 2\}$ as the domains for the two order parameters. In addition, cointegration is permitted by way of the usual reduced rank regression (RRR) restrictions. Phillips (1996) and Chao and Phillips (1999) show that we can use PIC to select the cointegrating rank (r) together with the lag order (p) and trend degree (q) in the context of reduced rank regression VARs of this type. The model then has three order parameters, thereby allowing for cointegrating relationships between the GDPs of the countries under consideration here.[6] In what follows, therefore, model selection is conducted using the RRR version of model (5) and the corresponding form of PIC was used in the empirical work.[7]

New Zealand's three main trading partners are Australia, Japan, and the United States. Combined, these three countries constitute approximately 50% of New Zealand's external trade by value. Accordingly, the variables in the VAR are the quarterly seasonally adjusted real GDPs of these four countries. The New Zealand data is the same as in the previous section. The data for the other countries was obtained from the December 1999 edition of the OECD *Statistical Compendium* CD-ROM, from the quarterly national accounts section. In this edition of the CD-ROM, data up to and including March 1999 is available.

Model selection was performed by using PIC to select the lag order, trend degree, and cointegrating rank at each step in the forecast period, thus allowing for evolving Bayes models with time-varying and data-dependent parameters, including the order parameters. The estimated coefficients were also re-estimated at each step in the forecasting period. Again this was accomplished in terms of an automated *GAUSS* program. The evolving model selected by PIC is represented in Figure 3. For most of the forecast period, the selected model is a VAR(1) with a constant. At two points, the selected model briefly changes to a VAR(2) with no intercept. A cointegrating rank of unity is maintained throughout. In this case, the cointegrating vector can be estimated from the reduced rank regression and the effects of each of the endogenous variables can be identified. If the coefficient on the first lag of New Zealand's real GDP is normalised to unity, the cointegrating vector using the full sample is estimated to be (1, -3.25, 0.08, 3.13). The last three coefficients in this vector relate to the United States, Japan and Australia

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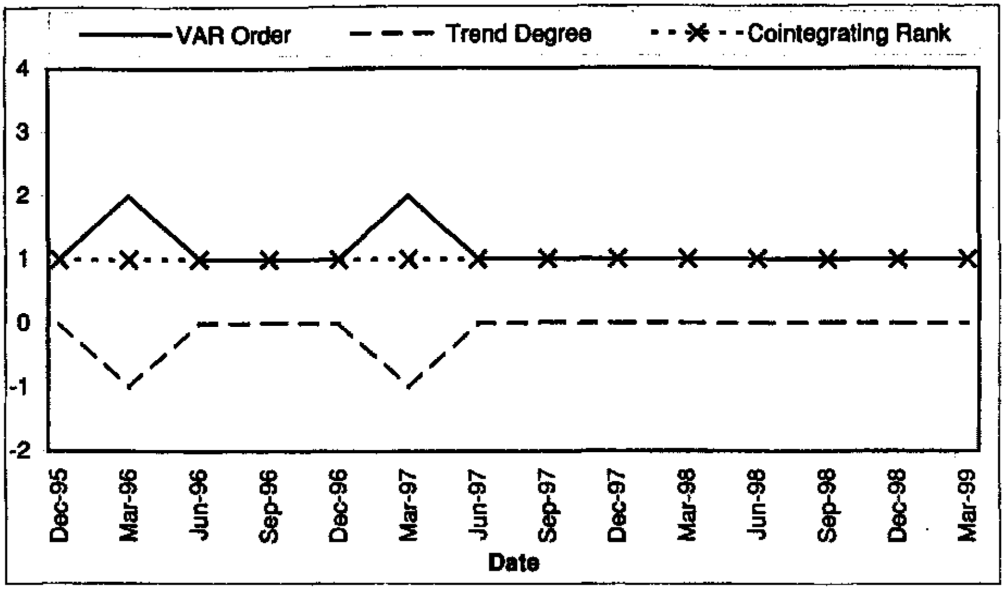
[6] Classical Augmented Dickey Fuller and Phillips-Ouliaris tests do not give evidence to suggest cointegrating relationships, except between the series for Australia and the United States. However, Davidson and MacKinnon (1993) point out that such tests lack power when used with seasonally-adjusted data. Therefore, failing to reject the null hypothesis of no cointegration is only weak evidence that two or more of the series are not cointegrated.

[7] For the theory and details of the practical implementation of PIC in RRR-VAR models, see Phillips (1996).

respectively and these coefficients have standard errors (0.66, 0.23, 0.55). Thus, the United States and Australian real GDP enter significantly into the cointegrating regression, while Japanese real GDP does not. The signs of the fitted coefficients in this cointegrating vector indicate that United States real GDP is balanced in the long run against a specific positive linear combination of the real GDPs of New Zealand, Australia and Japan. The latter might be regarded as constituting a certain index of Asia-Pacific real GDP that is relevant to a long run relation with the United States.

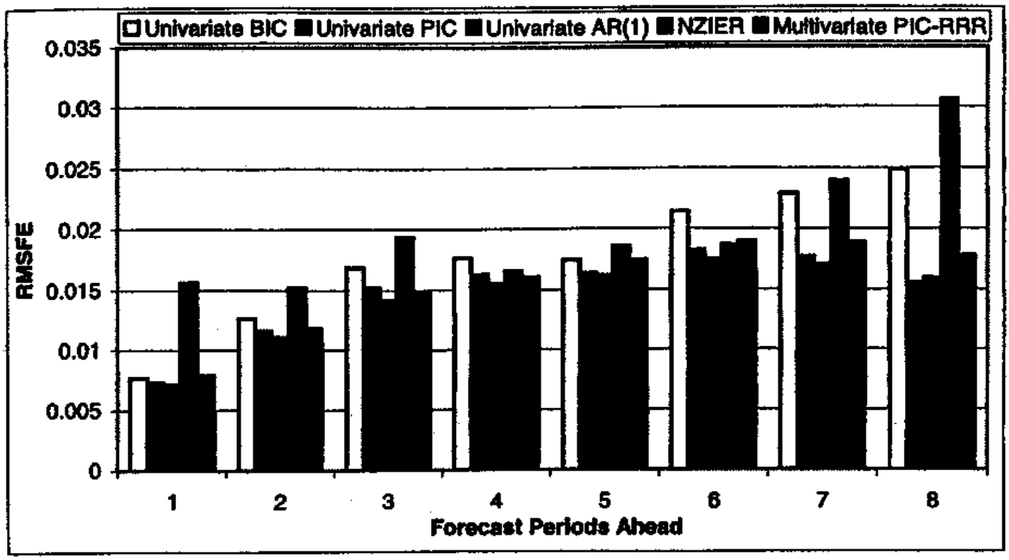
Figure 3: Multivariate Evolving Model Selected by PIC-RRR.



The evolving RRR model is used to generate *ex-ante* forecasts and these are compared with the univariate model forecasts from the previous section, as well as the NZIER forecasts. Figure 4 shows the RMSFE values for forecasts up to eight quarters ahead. It is apparent that that the forecasting performance of the evolving multivariate model is approximately the same as the evolving univariate model selected by PIC. It is interesting to note that forecasts of the fixed univariate AR(1) model – the simplest dynamic model of all – have the lowest RMSFE at all forecast horizons except eight quarters ahead, where the univariate model chosen by PIC is best.

There are several reasons why simple models tend to do as well as large models. First, simple models reduce variance in forecasting, explaining why Bayesian versions of VAR models have been popular in forecasting work. Second, as mentioned earlier, Ploberger and Phillips (1999) show that in small models one can get closer to the optimal predictor than in larger models. Additionally, as a referee suggested, rational decision making by agents takes account of the costs of gathering and processing information, so that only when the perceived benefits outweigh the costs will a more sophisticated model be used. Such reasoning is partially captured by the concept of penalizing a likelihood function or other criterion of fit based on the costs of estimating the extra parameters of the more complex model, leading to criteria such as PIC.

Figure 4: RMSFEs for *Ex-Ante* Forecasts from the Evolving and Fixed Univariate Models, the Evolving Multivariate PIC-RRR Model, and the NZIER.



In addition, Table 1 shows the Theil U-statistics for the various models and forecast horizons.[8] A Theil U-statistic of less than one indicates that the forecasts in question outperform those of a pure random walk on an RMSFE basis. We can see that this is the case for the univariate and multivariate evolving Bayes models and the fixed univariate AR(1) model at all forecast horizons.

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[8] The Theil U-statistic used here for a series of h-period ahead forecasts commencing at period $T+1$ is $U = \dfrac{RMSFE_h}{\sqrt{\frac{1}{S}\sum_{i=1}^{S}(y_T - y_{T+i})^2}}$, where S is the number of forecasts.

Table 1: Theil U-Statistics for the Evolving Bayes Models, Fixed Univariate Models, and the NZIER.

Forecast Periods Ahead	Multivariate PIC-RRR	Univariate BIC	Univariate PIC	Univariate AR(1)	Maximum Univariate Model	NZIER
1	0.96	0.93	0.88	0.86	1.89	0.91
2	0.89	0.96	0.88	0.84	1.15	0.96
3	0.88	0.99	0.90	0.84	1.14	1.05
4	0.86	0.95	0.88	0.84	0.89	1.17
5	0.88	0.88	0.82	0.81	0.94	1.26
6	0.78	0.89	0.75	0.72	0.77	1.19
7	0.73	0.88	0.68	0.66	0.92	1.23
8	0.64	0.90	0.56	0.58	1.11	1.20

Next, we compare the forecasts generated by the time series models with those of the NZIER. Since the forecasts of all the time series models considered above (except for the maximum univariate model) are quite similar, the forecasts of the PIC-RRR model are taken as representative. Figures 5 (a) – (c) show respectively the one, four, and eight period ahead forecasts of the PIC-RRR model and the NZIER. We can see that for one quarter ahead forecasts, the time series models track the actual GDP series much more closely than the NZIER forecasts, as is reflected in the RMSFE values for this forecast horizon. As the horizon extends to four and eight quarters, the NZIER and time series forecasts appear to follow almost parallel paths, although the time series forecasts are generally much closer to the realised values. As indicated earlier, data revisions may play a role in these differences. However, the similarity in the paths suggests that, although the models underlying the forecasts may be quite different, their implications about the general shape of the forecast trajectory of GDP are not dissimilar.

Figure 5 (a): One Quarter Ahead Forecasts Generated by the Evolving PIC-RRR Model and the NZIER.

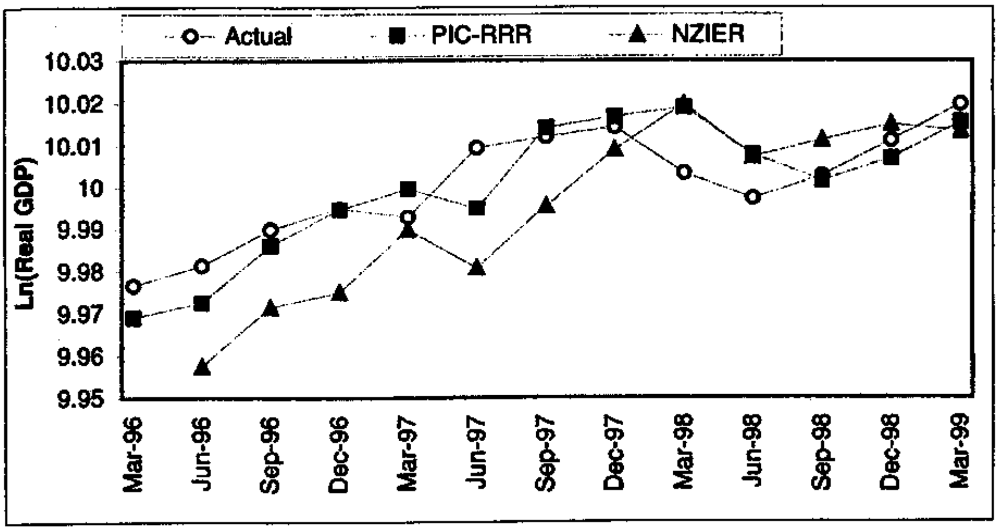


Figure 5 (b): Four Quarters Ahead Forecasts Generated by the Evolving PIC-RRR Model and the NZIER.

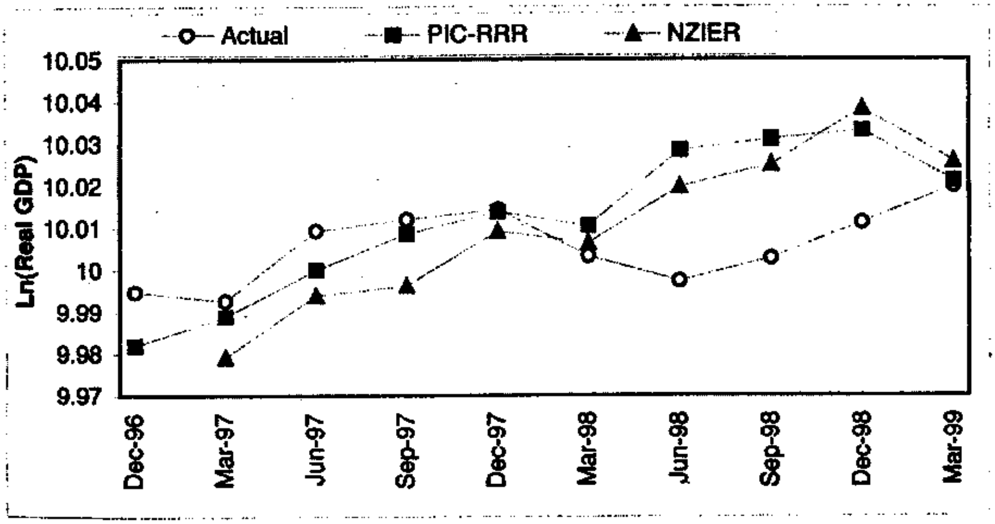
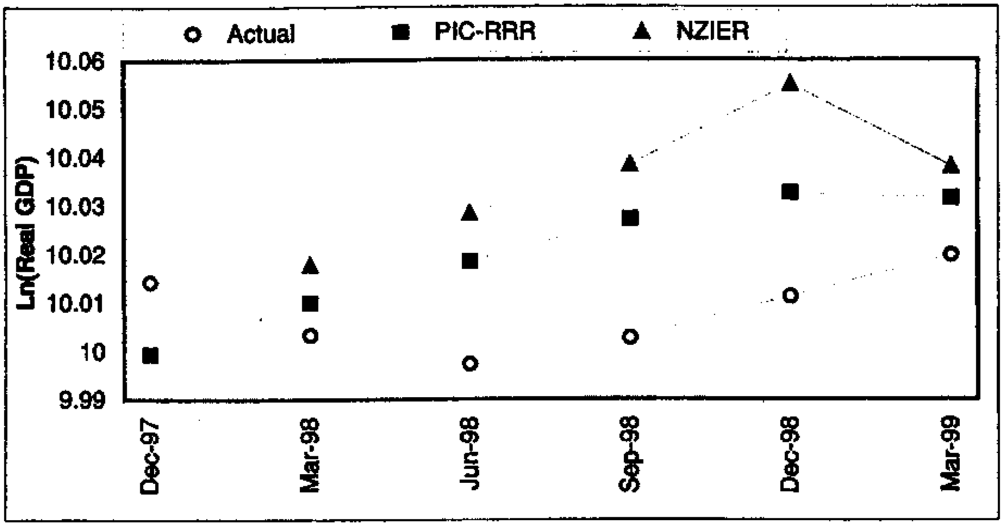


Figure 5 (c): Eight Quarters Ahead Forecasts Generated by the Evolving PIC-RRR Model and the NZIER.



More rigorous comparisons of forecast accuracy have been developed by Diebold and Mariano (1995) and extended by Harvey, *et al* (1997). Given two sequences of h-steps ahead forecast errors $\{e_{1t}, e_{2t}\}$; $t = 1, \ldots, n$, produced by two different models, these tests test the null hypothesis that $E[g(e_{1t}) - g(e_{2t})] = 0$, where $g(e)$ is some function of the forecast error. Using $g(e) = e^2$, the null hypothesis is that there is no difference in the mean squared forecast errors. We have tested this hypothesis for the time series forecasts against the NZIER and the test statistics for the "modified Diebold-Mariano test" proposed by Harvey, *et al* (1997), are shown in Table 2 for forecasts up to 4 quarters ahead. The test statistics for longer forecast horizons could not be calculated, due to the small number of forecasts available. We can see that the null hypothesis is rejected at the 5% level for one quarter ahead forecasts, but not for the other forecast horizons.

Table 2: Modified Diebold-Mariano Test Statistics for Forecast Comparisons with the NZIER.

Forecast Periods Ahead	5% Critical Value	Multivariate PIC-RRR	Univariate BIC	Univariate PIC	Univariate AR(1)
1	2.201	2.782	2.608	2.846	2.746
2	2.228	0.783	0.688	0.846	0.905
3	2.262	0.547	0.416	0.525	0.633
4	2.306	0.076	-0.332	0.195	0.353

4. Conditional Forecasting

This section illustrates the use of these automated forecasting methods in analysing the effects of external shocks and the impact of domestic monetary policy. The evolving VAR models selected by PIC are used to generate out of sample forecasts of New Zealand's real GDP, conditional upon certain assumed paths of other variables. These conditional forecasts allow investigation of the effects of a variety of hypothetical scenarios. We give two cases that are of some topical interest in these illustrations.

4.1 A Recession in the United States

The international VAR model can be used to produce forecasts of New Zealand real GDP under the assumption of a recession in one of its major trading partners, such as the United States. Such forecasts may have been deemed particularly relevant in the period following the Asian financial crisis, when New Zealand economic activity appeared vulnerable to a downturn in the U.S. economy which was perceived to be the main engine of world economic growth at the time.

Over the past decade, real GDP in the United States has grown at an average rate of approximately 0.65% per quarter. Starting from June 1999, we assume that this pattern continues for two further quarters, and is followed by a recession consisting of two consecutive quarters of contraction (-1% growth) and a quarter of 0% growth. We then assume that U.S. growth recovers to 0.65% for another four quarters. This scenario, together with the VAR model's predictions of the real GDP trajectories for New Zealand, Australia and Japan are shown in Figures 6 (a) – (c), respectively. In all three countries, the U.S. recession causes a slowdown in growth with a lag of one quarter, which reflects the lag order chosen for the model by PIC. The growth rate is slower to recover in all countries than the assumed path for the United States.

Based on GDP data alone, this international VAR model predicts that New Zealand's growth rate drops around 10%, from approximately 0.45% per quarter to 0.39% per quarter at its minimum. Similar results are obtained for Japan, where the growth rate drops from 0.75% to 0.65% per quarter. The results for Australia are more striking, with the Australian growth rate dropping from 0.9% per quarter to almost zero before recovering. The greater effect on Australian growth no doubt reflects the stronger role played by Australia in the cointegrating relation with the U.S.

Figure 6 (a): Forecast Quarterly Growth Rates for New Zealand Real GDP under the Assumption of a United States Recession.

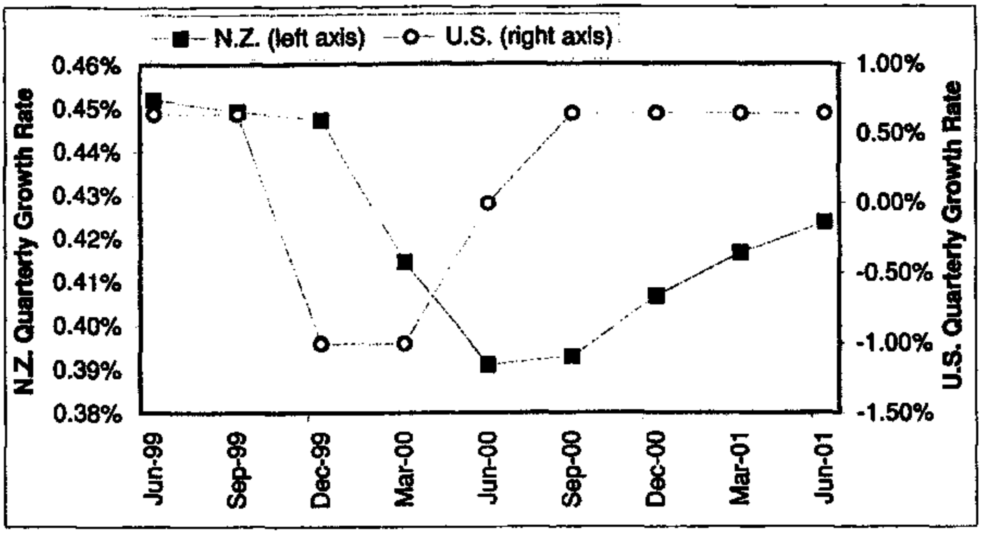


Figure 6 (b): Forecast Quarterly Growth Rates for Australian Real GDP under the Assumption of a United States Recession.

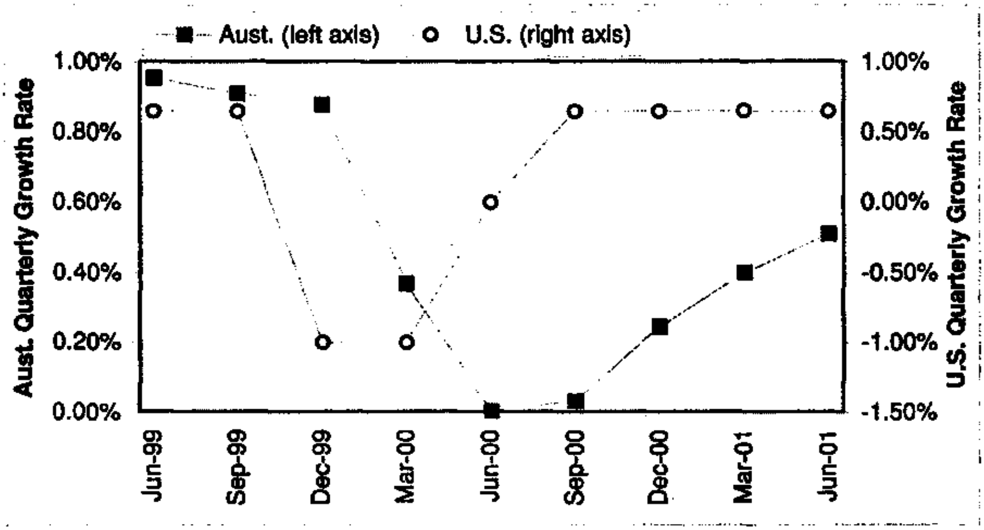
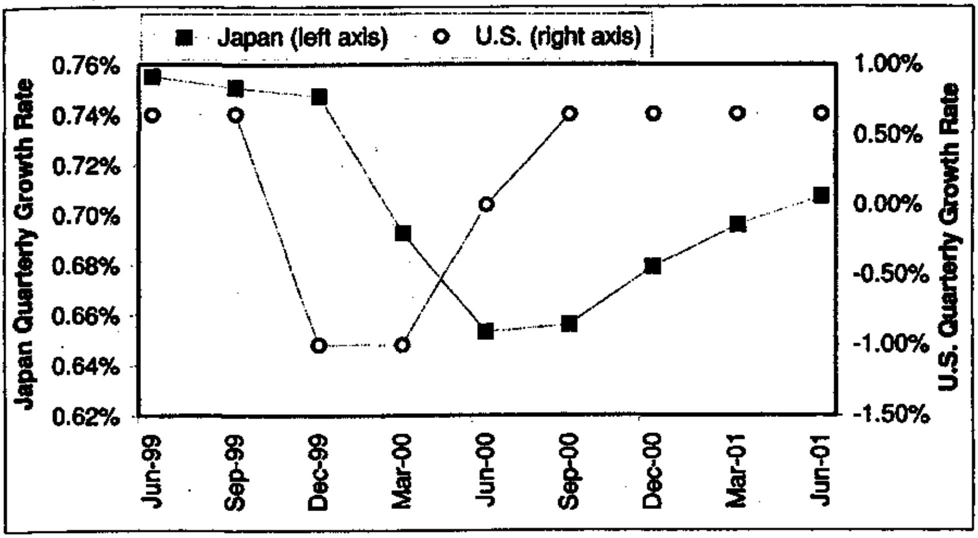


Figure 6 (c): Forecast Quarterly Growth Rates for Japanese Real GDP under the Assumption of a United States Recession.



4.2 Effects of Changes in Monetary Conditions

The second illustration involves a domestic VAR model where the endogenous variables are the natural logarithm of New Zealand's quarterly real GDP, the quarterly average of the overnight cash rate (OCR), and the quarterly average of the 90-day interest rate.[9] Since March 1999, the OCR is the instrument by which the Reserve Bank of New Zealand (RBNZ) implements monetary policy. Prior to March 1999, the OCR existed as a market interest rate that was not directly controlled by the RBNZ. The OCR and 90-day data were provided by the RBNZ and the series run from December 1984 to September 1999, giving 60 quarterly observations. The real GDP series is the same as before, with data for the June and September 1999 quarters now added. Using these data and the same class of models as those in (5), the model selected by PIC turned out to have a lag order of two, a constant in the regression, and a cointegrating rank of two. This model was then used to analyse the effects on New Zealand's real GDP growth of the following three scenarios of monetary conditions.

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[9] Larger VAR models with more interest rates, such as the 10-year bond rate, were also tried. These showed weaker links between real GDP and interest rates.

Scenario One (No tightening): The RBNZ actually raised the OCR by 50 basis points, from 4.5% to 5%, on the 19th of November, 1999, and by a further 25 basis points to 5.25% on the 19th of January, 2000. In this scenario, we suppose that the second interest rate rise had not occurred, with the OCR instead remaining constant at 5% for the rest of the forecast period.

Scenario Two (No further tightening): Suppose that the two actual OCR increases mentioned above are carried out, but that there are no further increases before December 2001.

Scenario Three (Further tightening): Suppose that, in addition to the two OCR increases of November 1999 and January 2000, the RBNZ further raises the cash rate at the beginning of the June 2000 quarter by 50 basis points, to 5.75%.

The estimated effects of these three scenarios on New Zealand's quarterly real GDP growth rate are shown in Figure 7. The forecast period is from December 1999 to December 2001, inclusive. We can see that as monetary conditions become tighter, the negative effect on real GDP growth is stronger. Comparing scenarios one and three, the difference in real GDP growth rates at the lowest points in the forecast period is approximately 0.16% per quarter. Recovery in GDP growth seems to be slower under scenario three than the other cases. The effects on 90-day interest rates are also predicted by the model and these are shown in Figure 8. The difference in 90-day rates between scenarios one and three is approximately 0.58% at the maximum, with the highest rates occurring in June 2001 for scenario one, and September 2001 for scenario three.

Figure 7: Forecast Quarterly Real GDP Growth Rates for New Zealand under Different Assumptions about Monetary Conditions.

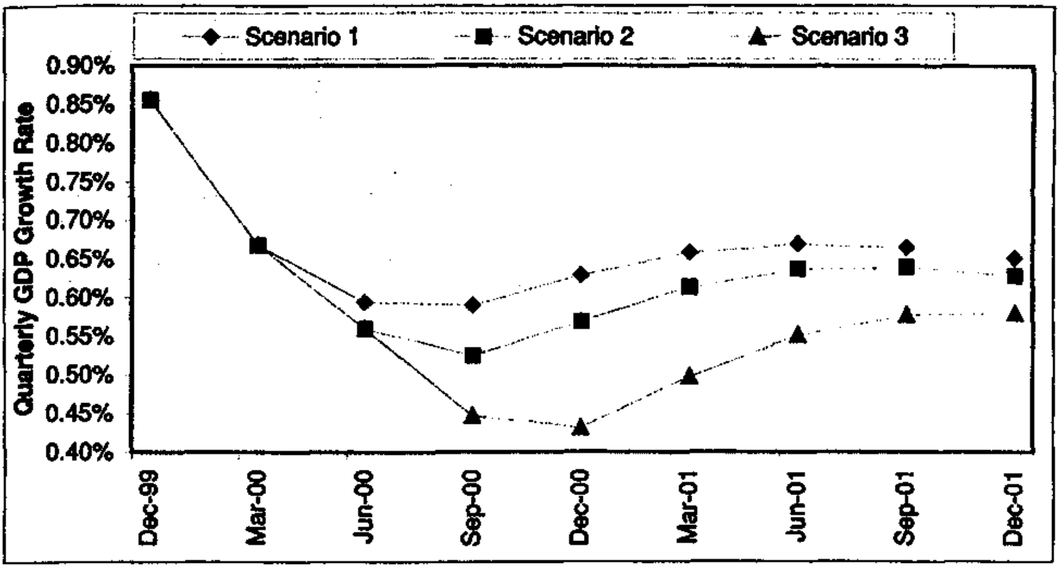
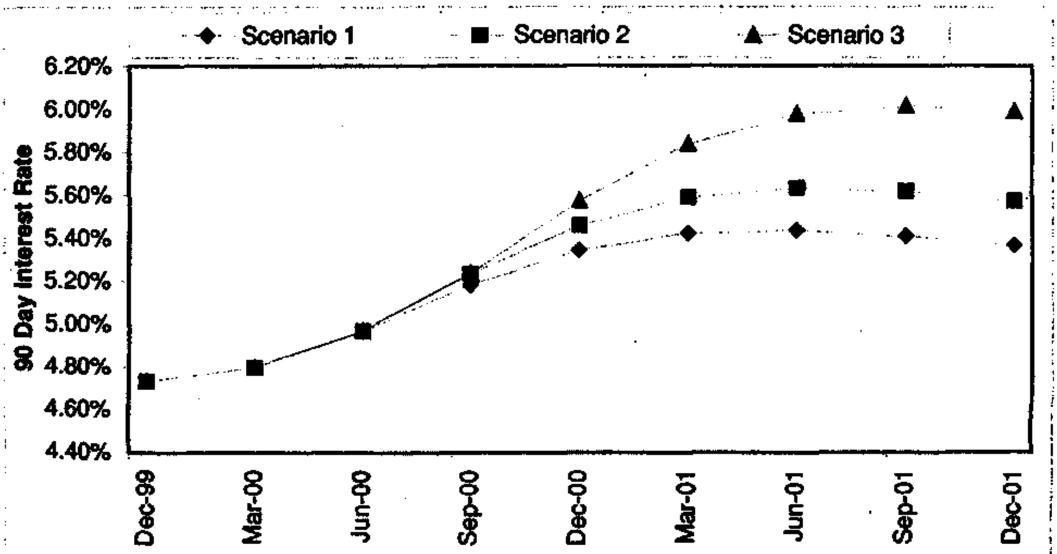


Figure 8: Forecast 90-day Interest Rates for New Zealand under Different Assumptions about Monetary Conditions.



5. Conclusion

This paper provides empirical applications of model selection techniques in time series forecasting within the context of 'AR(p) + Trend(q)' and VAR(p, q) models that allow for unit roots and cointegration. We have seen that parsimonious evolving time series models can generate forecasts of New Zealand's real GDP series that are competitive with fixed format models and with the forecasts of a professional forecasting institution. Furthermore, such models can be constructed and automated in computer software relatively easily. All that the researcher needs to do is to choose the appropriate class of model, and the optimal model within the class is automatically selected whenever new data becomes available. While the mechanistic nature of this approach certainly has limitations, the exercises shown here indicate that it can work well in practice and can provide competitive forecasts at very low cost.

We have also shown that such models are useful in certain types of policy analysis and in anticipating the effects of foreign country shocks. Indeed, automatic selection of the optimal model given the available data by the methods applied in this paper leaves an investigator free to experiment with input scenarios that cover a host of hypothesised situations that may be of interest. This approach seems particularly valuable when forecasting the effects of different economic policies and in studying the potential impact of international shocks on domestic economic activity. All of these features are planned for implementation in the University of Auckland website (see footnote 1) being developed by the second author.

References

Chao, J. C. and P. C. B. Phillips (1999). Model selection in partially nonstationary vector autoregressive processes with reduced rank structure. *Journal of Econometrics*, 91: 227 – 71.

Davidson, R. and J. G. MacKinnon (1993). *Estimation and Inference in Econometrics*. Oxford University Press: New York, Oxford.

Diebold, F. X. and R. S. Mariano (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics*, 13 (3): 253 – 263.

Harvey, D., S. Leybourne, and P. Newbold (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting*, 13: 281 – 291.

Nelson, C. R. and C. Plosser (1982). Trends and random walks in macroeconomic time series: Some evidence and implications. *Journal of Monetary Economics*, 10: 139 – 162.

Phillips, P. C. B. (1994). Bayes models and forecasts of Australian macroeconomic time series. In C. P. Hargreaves (Ed.), *Nonstationary Time Series Analysis and Cointegration*. Oxford University Press: New York, Oxford.

Phillips, P. C. B. (1995a). Bayesian model selection and prediction with empirical applications. *Journal of Econometrics*, 69: 289 – 331.

Phillips, P. C. B. (1995b). Bayesian prediction: A response. *Journal of Econometrics*, 69: 351 – 365.

Phillips, P. C. B. (1995c). Automated forecasts of Asia-Pacific economic activity. *Asia-Pacific Economic Review*, 1 (1): 92 – 102.

Phillips, P. C. B. (1996). Econometric model determination. *Econometrica*, 64, 4: 763 – 812.

Phillips, P. C. B. & W. Ploberger (1994). Posterior odds testing for a unit root with data-based model selection. *Econometric Theory*, 10: 774 – 808.

Phillips, P. C. B. and W. Ploberger (1996). An asymptotic theory of Bayesian inference for time series. *Econometrica*, 64, 2: 381-413.

Ploberger, W. and P. C. B. Phillips (1999). Empirical limits for time series econometric models. *Cowles Foundation Discussion Paper* #1220, Yale University.

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics*, 6: 461 – 464.

Wong, J. and P. Jolly (1993). Forecasting inflation and real GDP: Bayesian VAR models of the New Zealand economy. *Economics Department, RBNZ, Discussion Paper* G93/3.

Wong, J. and P. Jolly (1994). A Bayesian vector autoregression model of inflation. *New Zealand Economic Papers*, 28: 117 – 131.