Automated Forecasts of Asia-Pacific Economic Activity*

Peter C. B. Phillips
Cowles Foundation for Research in Economics
Yale University

Introduction and Overview

The purpose of this section of the Journal is to report regular forecasts of macroeconomic activity in several Asia-Pacific nations. Starting with this issue we will provide quarterly *ex ante* forecasts for the USA, Japan and Australia. In future issues, as our access to national economic data permits, we intend to expand our coverage to include other countries in the region.

Our forecasts are based on procedures that perform what may be described as data-based model determination. In consequence, they are almost completely automated. In fact, once model classes and maximal parameter settings are prescribed, our procedures are fully automatic. They are intended to be useful in cases where there are limited resources for the construction of complicated econometric models, when there are large numbers of series that need to be forecasted, or when automated forecasts are needed as benchmarks in the evaluation of structural models. The methods are illustrated here in the context of macroeconomic forecasts, but they have many other potential forecasting applications, and they may also be used to conduct automated policy analysis exercises.

One difficult issue of model determination that our procedures deal with automatically is the treatment of nonstationarity in the data. Potential choices that arise in some classes of time series models between deterministic and stochastic trends are built into our modelling algorithms. Thus, if the presence of a unit root is detected in the data, then the model is adjusted accordingly and the forecasts reflect this model choice. Similarly, if co-movement in the data or cointegration among series is detected, then the corresponding feature is built into the forecasting model.

Both single equation and multiple equation time series models are used in the construction of our forecasts. Some models are parameterised in their original format. This applies to autoregressions (AR's), vector autoregressions (VAR's), reduced rank regressions (RRR's), and error correction models (ECM's). All of these models may also include parameterised deterministic trends (Tr's). Within these classes of models, our approach is to employ a coherent model selection methodology to select the "best" model for the data and use this model for forecasting. The model selection procedure we use in our forecasting algorithm is an asymptotic form of predictive odds and is based on the posterior information criterion (PIC) of Phillips and Ploberger(1994). The criterion is derived and discussed in Phillips(1994a). It is used here to determine lag length, trend degree, the presence of autoregressive unit roots, and the cointegrating rank in a RRR. The resulting models are called "PIC'ed" models within their given individual class. They are parsimonious in parameters and have data-determined unit root and cointegration features. Some previous applications of PIC'ed models in forecasting are given in Phillips(1992,1994b,1995).

We also present forecasts from Bayesian vector autoregressions (BVAR's) and use our predictive odds criterion in this context as well. BVAR models have been used in forecasting exercises for over a decade and have achieved some success in producing forecasts that are competitive with structural econometric models, especially over the short to medium term (particularly one to three years ahead). Litterman(1986), McNees(1986), Fair and Shiller(1989) and Webb(1991) report some recent experience in the use of these methods in forecasting for the

* The computations and graphics reported in this paper were performed by the author on a Pentium-66 (replacement chip) PC using programs written in GAUSS. Special thanks are due to Ray Fair for permission to reproduce here the *ex ante* forecasts of the US economy from his structural econometric model - see Fair(1994). Thanks also go to Ray Fair and Colin Hargreaves for supplying the data.

USA; and Trevor and Thorp(1988) and Wong and Jolly(1994) provide successful implementations of the approach with Australian and New Zealand macroeconomic data. BVAR's reduce the tendency of unrestricted VAR's to be over-parameterised by placing prior distributions over the parameters of the unrestricted VAR. Litterman(1980,1986) introduced a class of priors for VAR models that induce a random walk mean for the coefficients and have a parsimonious set of hyperparameters -called tightness parameters- that govern their variances. These priors are now popularly known as Minnesota priors and we call the resulting time series model a BVARM.

BVARM's are not fully automatic forecasting devices. These models require the prespecification of several parameters, including the lag length of the VAR, the degree of any deterministic trend that is to be included and the settings of the hyperparameters that govern the Minnesota prior variances. One option that we adopt to deal with this difficulty is to use the settings suggested by Litterman(1986) for the tightness hyperparameters. The resulting model is called a BVAR(lit). Another option, suggested in Phillips(1994a), is to use model determination methods to find the "best" choice of these hyperparameters. This approach is an empirical Bayes procedure. We determine the values of the hyperparameters using the predictive version of the PIC criterion mentioned above. This approach to BVAR model choice is described in detail in Phillips(1994a). The resulting model has data-determined hyperparameters and we call it a BVAR(opt).

BVARM's may be restricted to single equation autoregressions, in which case the hyperparameters govern only the own-lag coefficients. We employ the same procedures in setting the hyperparameters in this case as we do for the vector case. The resulting models are called BAR(lit) and BAR(opt).

Model Classes and Judgemental Elements.

There are three judgemental elements involved in the use of our methods: (i) the choice of the model classes to be used in generating the forecasts; (ii) the setting of the maximal orders of the lag length and trend degrees to be considered in the model selection process; and (iii) the selection of variables to be included in the modelling exercise.

The model classes employed in our analysis are all linear time series models. In principle, our methods are applicable to much more general model classes, as the theory in Phillips and Ploberger(1995) and Phillips(1994a) indicates. However, the software that is necessary to fully implement these procedures is substantial and has been developed by the author so far only for linear systems. In the forecasting exercises reported here we therefore confine our attention to the following models:

AR(p) + Tr(t): single equation autoregression with p lags and a deterministic trend of degree t (t>= -1, with -1 corresponding to the no intercept case). The lag order and trend degree are determined automatically by model selection using predictive PIC.

BAR(lit & opt): single equation BAR with pre-set trend degree t = 0 (*i.e.* an intercept is included), uniform prior on the intercept, and Minnesota prior on the AR coefficients with both Litterman(lit) and data-determined (opt) settings for the tightness hyperparameter.

BVAR(lit & opt): BVAR models with pre-set trend degree t = 0, uniform prior on the intercept, and a symmetric Minnesota prior on the matrices of AR coefficients using both Litterman(lit) and data-determined (opt) settings for the tightness hyperparameters.

RRR: a VAR + Tr(t) model with lag-one coefficient matrix of possible reduced rank(r) to allow for cointegration among the variables. Lag length(p), trend degree(t) and cointegrating rank(r) are all data-determined by predictive PIC.

ECM: a VAR(p) + TR(t) model formulated in differences with a specific coefficient matrix on the lag-one levels variable that allows for some variables to be cointegrated or co-moving in certain equations and some equations to have unit autoregressive roots. In our empirical application we allow for three explicit forms of co-movement among the variables: (i) co-movement among the price level, GDP, the short term interest rate and money stock in the equation for the money stock; (ii) co-movement between consumption and GDP in the consumption equation; and (iii) co-movement between investment and GDP in the investment equation. These effects are included in a data-dependent way using predictive PIC. The lag length p is the common lag length for all variables in the equation. We also allow for the own lag length in each equation to be longer than p and, like p, this own-lag length is set using predictive PIC. Finally, the trend component of the ECM model is determined by predictive PIC on an equation by equation basis, so that in the ECM forecasting model some equations may have intercepts while others do not.

Our settings for the maximum lag length and trend degrees in model classes 1, 4 and 5 above are as follows: lag length, pmax = 6; trend degree, tmax = 1. In the BAR and BVAR models we set these parameters to p = 6, t = 0. Past experience with BVAR models in forecasting has shown that the inclusion of a linear trend generally causes a deterioration in forecasting performance - some recent evidence is reported in Phillips (1992,1995). This is partly because of the presence of other variables with trending behaviour in the equation and partly because the presence of unit roots or near unit roots in an equation subtly changes the role of an intercept to that of a linear drift (and a linear trend, if it were included, to that of a quadratic trend). Our setting of t = 0 in models 2 and 4 reflects this experience.

Variables and Data

The variables included in our forecasting exercises are given below. Our intent is to be able to forecast some key real and monetary variables without making the multiple equation systems too large given the available data. All variables are transformed to natural logarithms except for the interest rate. The final sample observation available at the time these forecasts were generated were as follows: for the US data, 1994:4; for the Japanese data, 1994:3; and for the Australian data, 1994:3. The initializations of the data sets (1954:1 for the USA, 1965:1 for Japan, and 1975:1 for Australia) were selected on the basis of the quarterly data that was available for all of the series to ensure a balanced data set for each country.

USA

Real gross domestic product (1987$bil., SA)
Real personal consumption expenditure
(1987$bil., SA)
Real fixed investment (1987$bil., SA)
Price deflator of GDP
3-month Treasury Bill rate (percentage points)
M1-Money stock, end of quarter ($bil., SA)
Unemployment rate, all workers 16 and over
(percentage points, SA)

Sample Period: 1954:1 - 1994:4
Source: National Income and Product Accounts
Forecast Period: 1995:1 - 1997:4 (12 quarters)

Japan

Real gross domestic product (1985Ybil., SA)
Real personal consumption expenditure
(1985Ybil., SA)
Real fixed investment (1985Ybil., SA)
Price deflator of GDP
M1-Money stock, end of quarter (Y100mil., SA)
Unemployment rate (percentage points, SA)

Sample Period: 1965:1 - 1994:3
Source: Nikkei Database
Forecast period: 1994:4 - 1997:4 (13 quarters)

Australia

Real gross domestic product (1989/90$mil., SA)
Real personal consumption expenditure
(1989/90$mil., SA)
Real fixed investment (1989/90$mil., SA)
Price deflator of GDP
M1-Money stock, end of quarter (currency + demand deposits, $mil., SA)
90-day Money market rate (percentage points)

Sample Period: 1975:1 - 1994:4
Source: Australian Bureau of Statistics
Forecast period: 1995:1 - 1997:4 (12 quarters)

Results

USA

Table 1 gives 8 different sets of forecasts for the USA variables over the time horizon 1995:1- 1997:4. The Table is organised into panels each of which gives the forecasts for an individual variable. (Real Consumption is not included in the reported results to save space as the outcomes are similar to those for GDP). All of the model classes described above are used in the exercise and 7 sets of automated forecasts are produced in all. Note that there are two sets of BAR and two sets of BVAR forecasts, corresponding to the hyperparameter options (lit) and (opt). The final column in each panel of Table 1 reports *ex ante* forecasts for the variables obtained from the structural econometric model of Fair(1994) and were kindly supplied by Fair from his latest forecast memorandum (1995) for the USA economy. These latter forecasts were obtained using the Fair model of the US economy and they rely on Fair's personal forecasts of the exogenous variables that enter his model. The Fair

Model forecasts give us the opportunity to compare over time the *ex ante* forecasting performance of our automated procedures with that of a well established structural econometric model. All models were estimated with the same sample data.

Figures 1(a)-(d) graph the last three years of the sample data (1992-1994), extended by the forecasts over 1995:1-1997:4. The figures plot real GDP growth, real investment growth, inflation, and the 3-month Treasury Bill rate and show the forecasts obtained from the ECM, RRR, BVAR(opt), BAR(opt), and Fair models.

The main results are as follows:

(i) All models forecast a slowing down in GDP growth. In the first half of 1995 the forecasted slow-down is sharpest for the Fair model, which predicts that growth declines from 4.5% in the last observed quarter 1994 to 1.2% in the first quarter 1995, and least for the single equation BAR(opt), which forecasts growth of 3.9% in the first quarter 1995. All the other models forecast a dip in GDP growth in the first two quarters of 1995. The RRR and BVAR(opt) forecasts are quite close over the full forecast horizon. The ECM and Fair model forecasts are generally similar and both predict a pick-up in GDP growth during the second half of 1995, which is sustained through the end of the forecast period. The ECM model predicts growth in real GDP of 3.0-3.4% through 1996-1997, the Fair model predicts 2.6-2.8% growth, and the RRR model predicts 1.0-1.25% growth over this period. Thus, there are some substantial differences between the models in medium term forecasts.

(ii) The RRR model and Fair model both forecast dips in short term interest rates during 1995. The ECM model forecasts small but steady increases in short rates over the full period and the BVAR(opt) model forecasts very small declines.

(iii) There are big differences in the inflation forecasts. The RRR model forecasts inflation rising to 4.1% by early 1996, whereas the ECM model predicts that inflation will stay below 3% until 1996:4, rising to 3.3% by 1997:4. The Fair model has by far the lowest forecasts of inflation and predicts that inflation will stay below 3% for the entire forecast period.

(iv) All models predict a decline in the growth of real investment during 1995. The multiple equation model forecasts are all similar. They indicate sharper declines in investment than the single equation procedures.

Japan

Table 2 is organised in the same way for the Japan forecasts. To conserve space we only report results for real GDP growth in the table. The Japan models did not include a short term interest rate but were otherwise of the same form as those used for the USA. The time horizon for these forecasts is 1994:4-1997:4, as data for the final quarter of 1994 were not available at the time the forecasts were generated. As with the US forecasts, all of the model classes described earlier were used in the automated forecasting exercise, giving 7 sets of forecasts in all. Figures 2(a)-(d) graph the final years of the sample data together with 13 quarters of forecasts for real GDP growth, real investment growth, inflation and M1-money stock growth.

(i) There is a wide dispersion of forecasts for real GDP growth. For the first three quarters of 1995 the forecasted growth ranges from 1.7% (for the univariate AR+TR model) to 5.4% (for the ECM model). This dispersion increases with the forecast horizon: by 1997:4 the range is from 0.6% growth predicted by the BVAR(opt) model to 5.7% growth predicted by the ECM model. As these figures indicate, the BVAR forecasted growth in real GDP is generally much lower than that of the ECM model. Note that the BVAR model also forecasts higher inflation than the other models. There is a similar wide dispersion in forecasts of inflation, with an especially big difference between the univariate and the multivariate methods, as is apparent in Figure 2(c).

(ii) For all variables , the RRR and ECM model forecasts correspond quite closely for the first few quarters out, but tend to diverge at longer forecast horizons. For the M1-Money stock variable, forecasted growth paths are similar for all models.

(iii) The univariate BAR model forecasts seem to be the most conservative, indicating the least change (relative to the last data point at 1994:3) in real GDP growth, investment growth and inflation.

Australia

Table 3 and Figures 3 (a)-(d) give the forecasts for Australia over 1995:1-1997:4. Again, we only tabulate the forecasts for the growth rate in real GDP to conserve space. The Australia models were the same as the US models with the exception that the unemployment rate was not included. We obtained 7 sets of predictions and Figues 3(a)-(d) graph the forecasts for real GDP growth, real investment growth, inflation and M1-money stock growth, all calculated on an annual basis.

(i) The biggest differences in the real GDP growth forecasts occur in 1995 and early 1996. The RRR and BVAR models both predict a significant slow-down in growth, and the BVAR model forecasts a minor contraction through 1995:3 - 1996:1. Forecasts from the ECM model are for growth to be around a 2% annual rate throughout the period 1996-1997. By the end of 1997, forecasts of real GDP growth from all of the models appear to be converging and are in the range 1.6-2.9%.

(ii) The inflation forecasts are in serious disagreement. The ECM model predicts that inflation stays around 2-3%, which is a slight rise over its present level. The other models predict that inflation declines over 1995-1997; and the BVAR and BAR models predict that inflation becomes negative by 1996.

(iii) The ECM model forecasts a slow decline in the growth of real investment from its present rate around 10%. The other multivariate models predict a sharper decline, followed by a recovery in 1996. But by the end of 1997 the model forecasts for real investment growth are all much closer.

(iv) All the models predict a decline in M1 growth in the first quarter of 1995, followed by a rise in M1 growth later in 1995 through to the end of the period. There is a big difference in the range of growth rates predicted for M1 by the end of 1997, from around 7% by the ECM model to around 16% by the RRR model.

Conclusions

The above results show that pure time series models can produce a wide diversity of short to medium term forecasts, even when the individual models belong to the same general time series family. Small differences in models sometimes lead to substantial disagreements in forecasts. In consequence, an important empirical issue is discrimination between models in different classes but within the same overall family, like a reduced rank regression (which has no prior structure) and an error correction model (where there is some prior structure). We also need to distinguish between models in different families like classical time series models of the type just mentioned and models like Bayesian vector autoregressions, which have quite different parameterizations. The predictive PIC criterion that has been used here to choose the best model within the same class can also be used to compare models in different classes and families. Subsequent work in this Section of the Journal will explore such comparisons and report empirical forecasts from the most favoured model across classes and families.

Table 1: USA Forecasts

(a) Real GDP: growth rate (% annual rate)

	ECM	RRR	BVAR(opt)	BVAR(lit)	BAR(opt)	BAR(lit)	AR+TR	Fair
95.1	3.77	3.23	2.61	2.03	3.95	3.85	3.32	1.21
95.2	2.59	1.43	0.64	1.29	3.85	3.73	3.12	1.53
95.3	2.73	1.37	0.72	0.95	3.74	3.64	3.06	2.26
95.4	3.03	1.12	0.60	0.88	3.70	3.61	3.04	2.52
96.1	3.19	1.10	0.75	0.90	3.66	3.58	3.03	2.75
96.2	3.30	1.07	0.91	0.95	3.63	3.56	3.03	2.84
96.3	3.37	1.10	1.13	1.02	3.61	3.54	3.03	2.85
96.4	3.38	1.13	1.23	1.09	3.58	3.52	3.03	2.85
97.1	3.34	1.16	1.28	1.14	3.56	3.50	3.03	2.80
97.2	3.29	1.20	1.30	1.18	3.53	3.48	3.03	2.72
97.3	3.24	1.23	1.28	1.21	3.51	3.46	3.03	2.66
97.4	3.18	1.25	1.24	1.24	3.49	3.44	3.03	2.64

(b) Real Investment: growth rate (% annual rate)

	ECM	RRR	BVAR(opt)	BVAR(lit)	BAR(opt)	BAR(lit)	AR+TR	Fair
95.1	4.53	5.45	5.35	5.57	9.76	8.86	9.34	4.28
95.2	4.58	3.43	2.80	2.61	7.67	6.86	7.36	2.18
95.3	1.39	1.25	0.19	0.58	6.13	5.55	5.91	2.06
95.4	-0.91	0.79	-1.99	-0.72	5.10	4.75	5.17	1.51
96.1	-0.64	0.50	-2.60	-1.19	4.50	4.35	4.75	0.99
96.2	-0.74	0.46	-2.39	-1.26	4.14	4.13	4.52	1.59
96.3	-0.46	0.47	-1.77	-1.10	3.93	4.02	4.39	2.14
96.4	0.22	0.54	-0.92	-0.82	3.82	3.97	4.32	2.33
97.1	0.74	0.62	-0.13	-0.49	3.77	3.95	4.28	2.39
97.2	1.22	0.72	0.49	-0.18	3.76	3.96	4.26	2.31
97.3	1.69	0.80	0.91	0.10	3.78	3.97	4.25	2.18
97.4	2.06	0.88	1.14	0.35	3.80	3.99	4.24	2.05

(c) Inflation - GDP deflator (% annual rate)

	ECM	RRR	BVAR(opt)	BVAR(lit)	BAR(opt)	BAR(lit)	AR+TR	Fair
95.1	2.41	2.68	2.45	2.77	2.51	2.72	2.29	2.10
95.2	2.43	3.33	2.61	3.07	2.73	3.04	2.05	1.91
95.3	2.38	3.73	2.73	3.31	2.94	3.35	1.89	1.90
95.4	2.61	3.98	2.99	3.61	3.30	3.75	1.94	1.99
96.1	2.74	4.13	3.13	3.78	3.55	4.04	1.93	2.06
96.2	2.81	4.20	3.23	3.90	3.78	4.29	1.88	2.13
96.3	2.92	4.22	3.33	3.99	4.01	4.51	1.86	2.24
96.4	3.02	4.22	3.39	4.04	4.21	4.70	1.84	2.35
97.1	3.10	4.19	3.44	4.06	4.39	4.86	1.81	2.46
97.2	3.18	4.16	3.47	4.06	4.56	5.00	1.79	2.55
97.3	3.25	4.11	3.49	4.04	4.71	5.12	1.76	2.64
97.4	3.32	4.07	3.50	4.02	4.85	5.21	1.74	2.72

(d) 3-Month Treasury Bill Rate

	ECM	RRR	BVAR(opt)	BVAR(lit)	BAR(opt)	BAR(lit)	AR+TR	Fair
95.1	5.70	5.16	5.48	5.57	5.70	5.55	5.21	5.02
95.2	5.74	5.03	5.41	5.68	5.86	5.66	5.03	4.66
95.3	5.82	4.91	5.43	5.82	6.07	5.81	5.19	4.65
95.4	5.94	4.81	5.41	5.93	6.29	5.95	5.28	4.78
96.1	5.96	4.73	5.31	6.00	6.43	6.07	5.21	4.85
96.2	5.98	4.65	5.23	6.06	6.56	6.18	5.20	4.87
96.3	6.03	4.58	5.18	6.10	6.69	6.28	5.24	4.92
96.4	6.07	4.52	5.13	6.13	6.81	6.38	5.24	4.99
97.1	6.12	4.46	5.10	6.16	6.92	6.48	5.22	5.06
97.2	6.17	4.40	5.08	6.17	7.02	6.57	5.23	5.12
97.3	6.22	4.35	5.07	6.18	7.12	6.66	5.23	5.17
97.4	6.28	4.30	5.06	6.19	7.20	6.74	5.23	5.22

(e) M1 - Money Stock growth (% annual rate)

	ECM	RRR	BVAR(opt)	BVAR(lit)	BAR(opt)	BAR(lit)	AR+TR	Fair
95.1	4.03	6.80	5.50	5.87	7.99	8.09	7.67	5.91
95.2	3.04	5.48	3.93	4.55	7.01	6.97	6.69	4.94
95.3	4.90	6.50	5.24	4.98	7.40	7.44	6.71	5.18
95.4	4.54	6.12	4.91	4.71	7.23	7.23	6.72	4.87
96.1	4.88	6.13	5.30	4.71	7.28	7.29	6.74	4.77
96.2	5.08	5.99	5.30	4.64	7.26	7.27	6.75	4.69
96.3	5.18	5.91	5.19	4.60	7.27	7.28	6.77	4.60
96.4	5.11	5.82	4.98	4.55	7.27	7.28	6.79	4.48
97.1	5.10	5.74	4.82	4.52	7.27	7.28	6.80	4.38
97.2	5.08	5.67	4.63	4.50	7.28	7.28	6.82	4.30
97.3	5.03	5.61	4.48	4.48	7.28	7.29	6.83	4.22
97.4	4.98	5.54	4.36	4.47	7.28	7.29	6.85	4.12

(f) Unemployment (% rate)

	ECM	RRR	BVAR(opt)	BVAR(lit)	BAR(opt)	BAR(lit)	AR+TR	Fair
95.1	5.43	5.32	5.40	5.41	5.42	5.47	5.93	5.40
95.2	5.45	5.23	5.40	5.40	5.48	5.53	6.30	5.32
95.3	5.56	5.22	5.52	5.48	5.66	5.69	6.60	5.27
95.4	5.65	5.24	5.68	5.60	5.89	5.88	6.71	5.25
96.1	5.72	5.28	5.84	5.73	6.13	6.07	6.68	5.23
96.2	5.76	5.33	5.98	5.85	6.35	6.25	6.59	5.21
96.3	5.78	5.38	6.08	5.96	6.52	6.41	6.49	5.20
96.4	5.79	5.42	6.15	6.05	6.67	6.55	6.41	5.19
97.1	5.79	5.45	6.20	6.13	6.78	6.67	6.35	5.19
97.2	5.81	5.48	6.23	6.19	6.88	6.78	6.32	5.20
97.3	5.83	5.51	6.24	6.25	6.96	6.87	6.30	5.22
97.4	5.85	5.53	6.26	6.29	7.04	6.95	6.29	5.25

Table 2: JAPAN Forecasts

Real GDP: growth rate (% annual rate)

	ECM	RRR	BVAR(opt)	BVAR(lit)	BAR(opt)	BAR(lit)	AR+TR
94.4	5.01	4.90	3.67	2.51	3.27	3.59	-1.82
95.1	4.64	4.85	3.53	2.38	3.26	3.67	1.76
95.2	5.29	4.74	3.07	2.19	3.25	3.77	1.74
95.3	5.42	4.55	2.50	1.95	3.24	3.75	1.71
95.4	5.48	3.96	1.98	1.76	3.23	3.74	1.69
96.1	5.59	3.64	1.43	1.57	3.22	3.72	1.66
96.2	5.64	3.55	1.18	1.42	3.21	3.70	1.64
96.3	5.66	3.31	0.90	1.28	3.20	3.68	1.61
96.4	5.69	3.14	0.74	1.17	3.19	3.66	1.59
97.1	5.69	3.07	0.68	1.06	3.18	3.64	1.57
97.2	5.70	2.93	0.63	0.98	3.18	3.62	1.54
97.3	5.70	2.83	0.62	0.90	3.17	3.60	1.52
97.4	5.69	2.76	0.65	0.83	3.16	3.59	1.50

Table 3: AUSTRALIA Forecasts

Real GDP: growth rate (% annual rate)

	ECM	RRR	BVAR(opt)	BVAR(lit)	BAR(opt)	BAR(lit)	AR+TR
95.1	3.92	1.01	0.73	1.99	2.37	1.75	1.68
95.2	3.21	1.00	0.23	2.00	3.08	2.89	3.04
95.3	1.41	0.39	-0.65	1.88	2.86	2.80	2.96
95.4	1.62	0.97	-0.46	1.89	2.68	2.74	2.94
96.1	2.15	2.05	-0.11	1.91	2.57	2.73	2.94
96.2	1.97	2.82	0.19	1.91	2.57	2.75	2.94
96.3	2.01	3.37	0.57	1.92	2.60	2.78	2.93
96.4	2.18	3.87	0.94	1.92	2.64	2.80	2.93
97.1	2.31	4.13	1.24	1.91	2.70	2.82	2.93
97.2	2.36	4.14	1.46	1.91	2.76	2.84	2.93
97.3	2.37	4.07	1.60	1.90	2.81	2.86	2.93
97.4	2.39	3.92	1.65	1.88	2.85	2.87	2.93

References

Fair, Ray C., 1995. "*Fairmodel Forecast*" mimeographed, January 30 1995.

—, 1994. "*Testing Macroeconometric Models*", Cambridge: Harvard University Press.

Fair, Ray C. & R. J. Shiller, 1990. "Comparing Information in Forecasts from Econometric Models", *American Economic Review*, 80:375-389.

Litterman, R. B., 1980. "A Bayesian Procedure for forecasting with Vector Autoregression", Working Paper, Department of Economics, Massachusetts Institute of Technology.

—, 1986. "Forecasting with Bayesian Vector Autoregressions - five years of experience", *Journal of Business and Economic Statistics*, 4:25-38.

McNees, S. K. (1986), "Forecasting Accuracy of Alternative Techniques: A Comparison of U.S. Macroeconomic Forecasts", *Journal of Business and Economic Statistics*, 4:5-15.

Phillips Peter C. B., 1992. "Bayes Methods for Trending Multiple Time Series with an Empirical Application to the U.S. Economy", Cowles Foundation Discussion Paper, No. 1025.

—, 1994a. "Model Determination and Macroeconomic Activity", Cowles Foundation Discussion Paper, No. 1083.

—, 1994b. "Bayes Models and Forecasts of Australian Macroeconomic Time Series", pp.53-86 in Colin P. Hargreaves (ed.) "*Nonstationary Time Series and Cointegration*", Oxford: Oxford University Press.

—, 1995. "Bayesian Model Selection and Prediction with Empirical Applications"; *Journal of Econometrics* (in press).

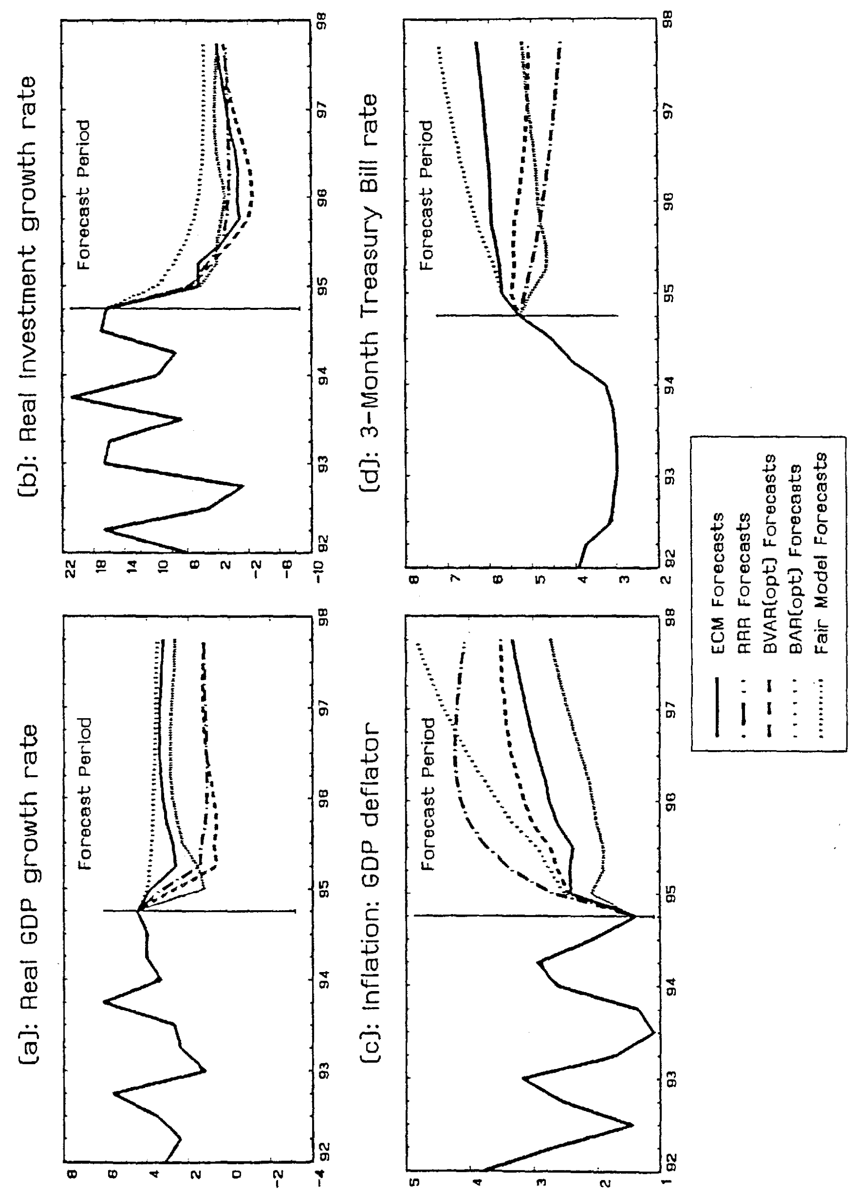
Phillips Peter C. B. & W. Ploberger, 1994. "Posterior Odds Testing for a Unit Root with Dat-Based Model Selection" *Econometric Theory*, 10:774-808.

—, 1995. "An Asymptotic Theory of Bayesian Inference for Time Series", *Econometrica* (forthcoming).

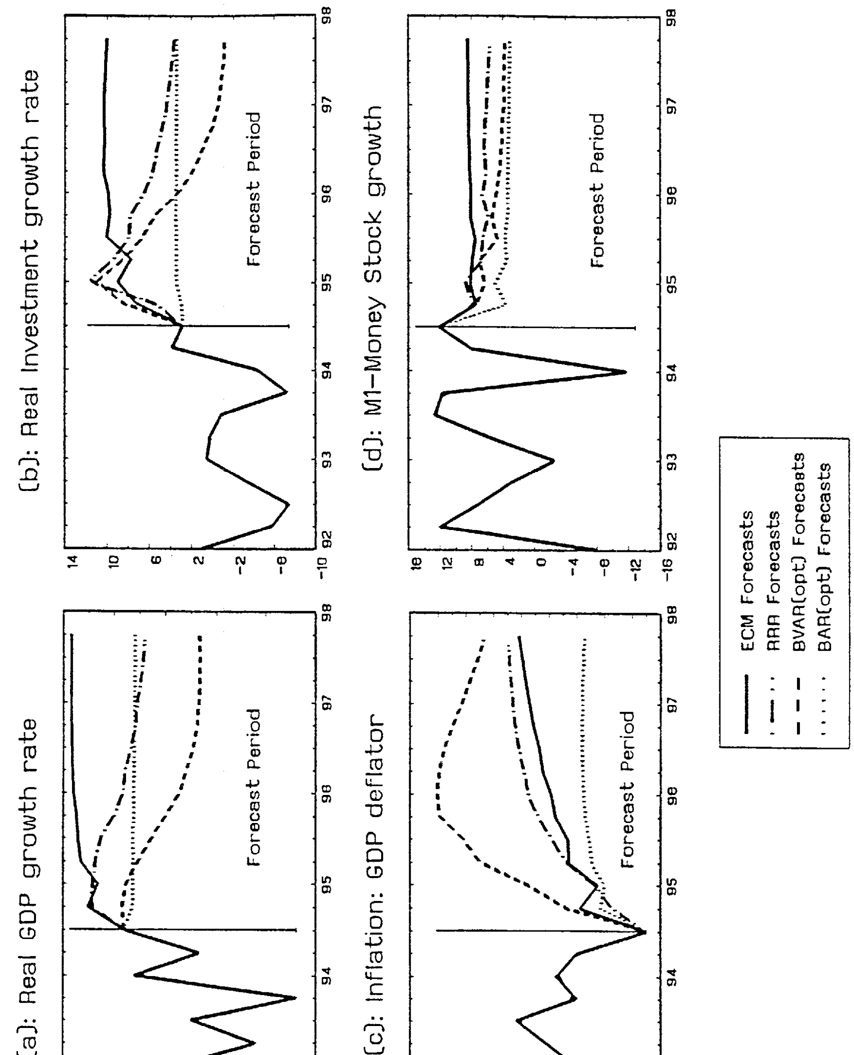
Trevor, R. G. & Thorp, S. J., 1988. "VAR Forecasting Models of the Australian Economy: A Preliminary Analysis", *Australian Economic Papers*, 27:108-120.

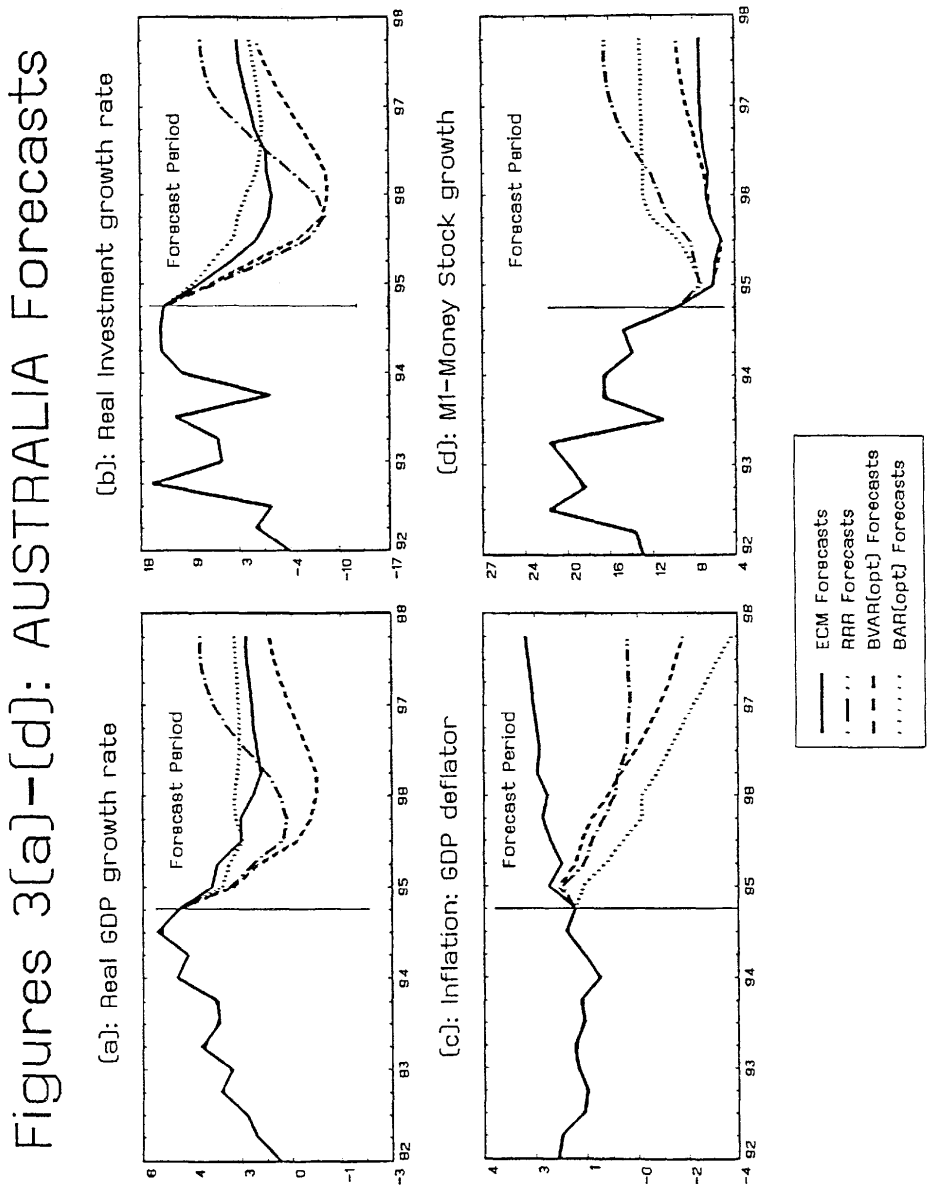
Wong J. K. & P. J. Jolly, 1994. "A Bayesian Vector Autoregression Model of Inflation", *New Zealand Economic Papers*, 28:117-131.

Figures 1(a)-(d): USA Forecasts



Figures 2(a)-(d): JAPAN Forecasts





Figures 3[a]-[d]: AUSTRALIA Forecasts
(a): Real GDP growth rate
(b): Real Investment growth rate
(c): Inflation: GDP deflator
(d): M1-Money Stock growth
Forecast Period
ECM Forecasts
RRR Forecasts
BVAR(opt) Forecasts
BAR(opt) Forecasts