VAR FORECASTING MODELS OF THE AUSTRALIAN ECONOMY:

A PRELIMINARY ANALYSIS

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ABSTRACT

Vector autoregressions (VARs) have been proposed as good forecasting models of macroeconomic variables. This paper presents three naive VAR models of the Australian economy estimated on quarterly data for fifteen variables to 1985(4). Their performance in "forecasting" the calendar and financial year outcomes for 1986-87 (on an ex-ante basis) is compared with that of three sets of private sector forecasts, the 1986-87 Budget forecasts and the actual outcomes from the same period. In general, the VAR forecasts perform at least as well or better than comparable private sector forecasts. Each VAR model is estimated using a different method for allowing for trends in the data. The detrending procedure is an important determinant of the quality of forecasts, with the best forecasts produced by the two models which employ detrending processes appropriate for data which follow a random walk.

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1. Introduction

A difficulty regularly faced by economists, particularly in policy making and advisory roles, is the production of reliable forecasts of important macroeconomic variables. Forecasting may involve the development of complex and expensive macroeconomic models, and often relies heavily on the judgment of the forecaster in prescribing future paths of exogenous variables or in adjusting model-generated forecasts in line with his subjective expectations.

This paper investigates whether extremely cheap and relatively simple vector autoregressive models (VARs) produce sensible forecasts of major Australian macroeconomic variables. In particular, we examine the accuracy of <u>ex-ante</u> forecasts produced by some representative VARs, relative to the accuracy of other publically available forecasts. The forecasting accuracy of similar VAR models (eg. Litterman, 1986b) has been examined in the United States over the last decade, with encouraging results - they tend to do no worse than much more complex and expensive macroeconometric models of the economy and private forecasting services.

In any model building exercise, certain decisions about the structure of the model need to be made. For a VAR forecasting model these decisions concern the list of variables to be included in the model, the lag length of the model and the detrending procedure to be used for detrending data[1]. The choice of detrending procedure is likely to be particularly important for forecasting horizons of more than a few periods. VAR (and other econometric) models are based on an assumption of stationarity in the data-generating mechanism. If a series displays non-stationarity, that is, if it has no fixed long-term stochastic distribution, then we cannot expect to determine stable econometric relationships from the data, especially of the sort needed for useful forecasting. A study by Nelson and Plosser (1982) produced evidence that the non-stationarity of some historical time series for the U.S. was of a type which could not be corrected by simple procedures. More recent work on

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1. When a VAR model is being used to interpret intertemporal relationships between variables, one also has to make decisions about contemporaneous causality. See, for instance, Trevor and Donald (1986).

co-integration (Engle and Granger, 1987 and Hendry, 1986), stochastic trends (Harvey, Henry, Peters and Wren-Lewis, 1986 and Watson, 1986) and common trends (Fernandez-Macho, Harvey and Stock, 1986 and Stock and Watson, 1986) has emphasised the potential importance of using appropriate detrending methods.[2]

To partially accommodate these results, three different VAR models (each with a different detrending scheme) are considered. One model uses a first-difference detrending process, another uses a first-order deterministic process and the third is estimated under Bayesian-like priors which lean heavily towards random walk models.[3] We also, unsuccessfully, consider a fairly general stochastic trend procedure. No allowance is made for common trends at this stage of our research as they often involve complex estimation strategies.

In each case, we apply the techniques in a relatively mechanical fashion to generate estimates and forecasts from data as they existed at the time of the release of the December 1985 Quarterly Estimates of the National Accounts. Although we believe that there are large potential gains in accuracy to be realised, we have not used our technical expertise or the tracking performance of the models to undertake any fine-tuning. In essence, our three VAR models (and their forecasts) could have been obtained in early 1986 by any relatively unsophisticated user of commercially available personal computer or mainframe software.

Forecasts over a six-quarter horizon (i.e. till June 1987) are generated from each of the three VAR models. These ex-ante forecasts are evaluated by comparing them with publicly available forecasts and actual outcomes (as at the release of the June 1987 Quarterly Estimates of the National Accounts).

Section 2 surveys some of the literature on VAR forecasting models. Section 3 details the VAR models estimated here, the data and estimation techniques employed. Section 4 sets out our results and Section 5 our conclusions and views on how the models may be improved.

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2. Integration refers to the presence of unit roots in the data (i.e. the data are difference stationary). Stochastic trends is a broader concept which includes most trends other than purely deterministic ones (such as time trends). Common trends and co-integration refer to the fact that some variables (e.g. income and consumption) are likely to "trend" together. That is, the same factor gives rise to non-stationary in both series.

3. A random walk model is: $X_t = X_{t-1} + \varepsilon_t$.

2. Evidence on VAR Forecasting

A VAR is a general unrestricted vector autoregressive time series model, often with deterministic components. Consider a (nx1) vector of variables, Y_t, generated by a mth order vector autoregressive process

$$Y_t = D_t + \sum_{j=1}^{m} \beta_j Y_{t-j} + \varepsilon_t$$

where D_t is a (nx1) vector representing the net deterministic component of Y_t, β_j are (nxn) matrices of coefficients and ε_t is a (nx1) vector of multivariate white noise residuals at each point in time t.

The distinctive feature of VAR models is that no exclusion restrictions are applied to the β_j matrices. In other words, each equation in the model includes the same number of lags on each and every variable. Each equation thus has (mxn) coefficients on lagged variables and possibly some coefficients on trend variables.

The advantages gained from the high generality of VAR models are often offset by problems of over-parameterisation. Signals from important variables can be obscured by noise from distant lags or from unrelated variables. Over-parameterised models tend to give very good within-sample fit, but poor out-of-sample forecasts. Large VAR models also tend to encounter degrees of freedom problems on typical macro-economic data sets.

Litterman and others in the United States have developed techniques for combating these problems. Litterman (1986a) argues that many economic variables behave like random walks; hence, the systematic variation in the data is relatively small compared with the random variation. This argument provides a basis for applying "prior" restrictions in the estimation of VAR models, resulting in coefficients "close" to those which would pertain to random walk models. For most models, Litterman assumes that all parameters have distributions with zero means, except the coefficient on the first lag of the own variable in each equation which is given a prior mean of one. The standard deviations of the prior distributions are forced to decrease as the lag length increases, "tightening" the distribution around the prior mean of zero at later lags. VAR models estimated under these priors usually show

coefficients on first own lags close to one and most other coefficients close to zero, depending on the (imposed) tightness of the prior.

Litterman argues that this so-called "Bayesian filtering technique" effectively isolates the systematic components of variation in the series, reducing the effects of over-parameterisation, and generating more accurate forecasts than traditional structural or time series models.

McNees (1986) compares traditional macroeconometric models (which produce forecasts conditional on assumed paths for exogenous variables) and VAR models on theoretical criteria, and evaluates the forecasting record of Litterman's BVAR (Bayesian VAR) model against the records of a number of prominent forecasting models in the United States. He compares forecasts of six macroeconomic variables over the period 1980:2-1985:1, and finds that no single set of forecasts dominates for all variables. However, he concludes that BVAR-generated forecasts "can present a strong challenge to conventional practice and serve as a powerful standard of comparison for other forecasts".

McNees draws attention to the problems of unrestricted VAR's - they are constrained in size by degrees of freedom and can produce poor post-sample predictions when overparameterised. These particular problems may be alleviated in VARs estimated under Litterman's priors, but the BVAR models themselves are bound by the strong assumption that all variables behave like random walks.

Modellers estimating traditional structural-style models also make strong assumptions. As Litterman points out, traditional models implicitly apply zero restrictions to all variables excluded from the model, whereas variables which are included in the model are treated as if the modeller has no prior idea of the value of their coefficients. Litterman (1986a) defends his position by arguing that these are far stronger "priors" than those of the BVAR technique. There is, of course, nothing in the BVAR technique which requires one to stick with Litterman's priors - a fairly important point that we shall have occasion to return to later on.

When forecasting with traditional models, the forecaster must supply estimates of future values of exogenous variables to generate estimates of endogenous variables. The accuracy of any forecasts depend on the foresight of the

modeller in choosing these future values of exogenous variables and in adjusting the mechanically generated forecast (the most inappropriately named "constant-term adjustments").

By contrast, VAR models require only past information for forecasting. Of course, if the forecaster wishes to allow for information on, say, some expected change in monetary or fiscal policy, he will also have to adjust the VAR forecast-generating process appropriately.

The apparent success of VAR models of the U.S. economy (especially ones estimated under Litterman's random walk priors) in providing cheap and accurate forecasts (relative to those provided by other means), suggests that they might be usefully employed in Australia. A first step in this direction is provided in the next sections.

3. Three Vector Autoregression Models

(a) Some Preliminaries

The basic structure of a VAR model, as noted earlier, is based on the assumption that the vector of variables Y_t is generated by a mth order vector autoregressive process

$$Y_t = D_t + \sum_{j=1}^{m} \beta_j Y_{t-j} + \varepsilon_t \tag{1}$$

The first decision facing a VAR model builder is the list of variables to be included in the model (i.e., in the vector Y_t). We constructed our list partly by taking an informal survey of some economists within the public sector involved in the provision or consumption of forecasts, and partly by imposing our own priors. At the macroeconomic level, one clearly needs forecasts of output, consumption, investment, prices and the labour market (wages, employment and unemployment). Recent events suggest that forecasts of the external sector (imports, exports and current account) are desired, and a number of our colleagues wanted a forecast of the change in stocks. We added several financial variables (money supply, a short-term interest rate, an exchange rate and stock market prices) which we thought might contain information relevant to future movements in the activity variables. Hence, Y_t contains fifteen economic variables:

- real non-farm GDP (log);
- real final private consumption (log);
- real gross fixed private capital expenditure (log);
- consumer price index (log);
- average weekly earnings (log);
- employment (log);
- unemployment level (log);
- real increase in private non-farm stocks (ratio to real non-farm GDP);
- real exports of goods and services (log);
- real imports of goods and services (log);
- nominal balance on current account (ratio to real non-farm GDP);
- money supply (M3)(log);
- exchange rate (log);
- short-term interest rate;
- stock prices (log).

(Full definitions and sources are set out in the Data Appendix.)

Data availability for the activity variables restricts us to a quarterly basis, starting in March 1960. We use data available at the release of the December 1985 Quarterly Estimates of the National Accounts, yielding just over one hundred observations on each variable.

The second choice facing the VAR modeller is the length of the autoregressive lags. Our preferred strategy is to choose the shortest lag length such that there is no within, or across-equation serial correlation, and the matrix of coefficients on the longest lag is significantly different from the zero matrix[4]. This we do for the two standard VARs. For the Bayesian VAR we set the lag length quite a bit longer than for the first two models, letting the priors tighten around zero rather than truncating the lag distribution.

The remaining decision concerns the detrending method. There has been an abundance of recent work on appropriate detrending of macroeconomic data. A particularly persuasive piece is Stock and Watson's (1987) examination of some puzzlingly different conclusions about the usefulness of money for forecasting

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4. This criteria is compared with other available criteria in Trevor and Donald (1986).

real output using VARs estimated on U.S. data. Stock and Watson claim to resolve these puzzles by carefully allowing for orders of integration and co-integration of (i.e, common trends in) the data, as well as allowing for polynomial time trends.

On econometric grounds, our preferred approach would be to use similar techniques to Stock and Watson (1987); first testing the data for deterministic, stochastic and common trends, and then allowing for the detected trends when estimating the VAR. While such a procedure is attractive, it relies heavily on technical expertise, removing it from our current objective of examining cheap, simple forecasting models.

Our alternative strategy is to consider the two most commonly used, simple detrending methods in a mutually exclusive manner. One VAR is estimated allowing for deterministic trends and another is estimated in first differences. The third VAR is Litterman's BVAR which indirectly deals with trends through its random walk prior.

(b) **Deterministic Trend - VAR(T)**

The first VAR we consider, models the trend component of the vector Y_t as a first-order polynomial in time. That is, the ith component of the vector D_t in equation (1) is modelled as

$$d_t^i = \alpha + \gamma t \tag{2}$$

It is fairly simple to show that, in this deterministic case, prior detrending of the data is equivalent to substituting equation (2) into equation (1) and estimating a net trend in each equation of the VAR.

Our testing procedures indicated that a lag length of three quarters and a first order polynomial in time were required to fit the data. Neither a fourth lag nor a second-order time trend significantly added to the explanatory power of the model.[5]

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5. Computational details on all the models are available from the authors on request.

(c) First Differences - VAR(D)

Trend terms are included in models such as a VAR to induce stationarity in the data series. (Including a time trend is equivalent to prior detrending of the variables.) The modeller then works on the assumption that, once detrended, the series are stationary.

Clearly, the inclusion of a deterministic trend will overcome problems of non-stationarity where the time series are best characterized as stationary fluctuations around a deterministic trend. However, Nelson and Plosser (1982) give evidence suggesting that (U.S.) macroeconomic time series are better characterized as "non-stationary processes that have no tendency to return to a deterministic path". The process of detrending by a deterministic trend is derived from the idea that the secular component of a time series fluctuates only a little and moves slowly over time. If this hypothesis is wrong (as Nelson and Plosser claim, although there is considerable debate in the literature over this issue) then detrending by a deterministic trend is inappropriate.

The most commonly used alternative to a deterministic time trend is to induce stationarity by first differencing the data prior to estimating the VAR. The second model, VAR(D), is estimated on first differenced data. Our tests indicated a lag length of three for this VAR.

In forecasting mode, this model generates forecasts for first differences which are then summed to produce forecasts in levels terms.

(d) An Encompassing Alternative

Harvey, Henry, Peters and Wren-Lewis (1986) propose a stochastic trend formulation which has both a level (d_t^i) and slope (γ_t) component evolving over time

$$d_t^i = d_{t-1}^i + Y_t + \mu_t \quad \text{where } \mu_t \text{ is distributed N } (0, \sigma_\mu^2) \tag{3a}$$

$$Y_t = Y_{t-1} + v_t \quad \text{and } v_t \text{ is distributed N } (0, s_v^2) \tag{3b}$$

and where the disturbances μ_t and v_t are independent of each other in
all time periods.

By substituting this process into the VAR model (equation (1)) and second
differencing the resulting equations, the net error term in each equation
reduces to a stationary disturbance term which follows a second order moving
average process. In the special case $\sigma_v^2 = \sigma_\mu^2 = 0$, the trend in
that equation collapses to a deterministic trend. Alternatively, if (from
equation (1)) $\sigma_\varepsilon^2 = \sigma_v^2 = 0$ then the model is equivalent to a
VAR in first differences. The formulation proposed by Harvey et.al. is thus
a fairly general trend specification from which the two common alternatives
can be derived as special cases.

Direct estimation of a stochastic trend of this type is a complex procedure
often involving Kalman filtering of the unobservable trend components.
Alternatively, one may allow for, but not identify, the stochastic trends by
second differencing all variables in the VAR and estimating a second-order
moving average error process.[6]

While this encompassing model of trends is an attractive one, it proved
intractible in our case. The presence of a moving average error term
necessitates a non-linear estimation strategy. With three or four lags on
each of fifteen variables (as well as the two moving average parameters) in
each equation, convergence problems were rampant. Accordingly, we consider
this specification unusable in a large VAR.

(e) __Bayesian Priors - BVAR__

As discussed above, Bayesian priors can be applied to alleviate the
inefficiency of over-parameterised VAR models as well as to allow for

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6. If the moving average process is parameterised as $e_t + ae_{t-1} + be_{t-2}$, then the original parameters underlying the model comprising equations (1) and (3) are given by

$$\sigma_\varepsilon^2 = b\sigma_e^2$$

$$\sigma_\mu^2 = (a+ab-4b)\sigma_e^2$$

$$\sigma_v^2 = [-a(a+2+2b)+(b+1)(b-1)]\sigma_e^2$$

non-stationarity in the data. Restricting the parameters of the VAR may improve out-of-sample forecasts.

Litterman's (1986a) random walk priors allow us to build a model which includes all the β_j parameters, but where influence is restricted mainly to the first own-lag and any other variables or lags which have consistently strong explanatory power.

Our BVAR model is estimated using the facilities of the RATS regression package[7]. RATS allows the modeller to parameterise the priors in a fairly general way. The program assumes that the prior distributions for all coefficients are independent normal; hence they are fully specified by two parameters (mean and standard deviation) for each coefficient[8]. It further assumes that the means of the priors for all coefficients except the first lag on the own variable in each equation are zero. Thus, it requires the user to provide the mean of the prior for the first own lag in each equation and the matrix comprised of each of the standard deviations $s(i,j,k)$ for the coefficient on lag k of variable j in equation i.

Consistent with our desire to develop simple models, we used the default (or recommended) settings for these parameters as provided by the RATS manual. Namely, that the mean of the first own lag is unity and that the standard deviations are given by

$$s(i,j,k) = \tau g(k) f(i,j) s_j / s_i \qquad\qquad (4)$$

$$f(i,i) \equiv g(1) \equiv 1$$

where:

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7. RATS is available for mainframes, the Apple Macintosh and IBM and compatible personal computers. We used version 2.05 for the PC. The other models could also have been easily estimated with this software, but we used the macro facilities of version 5.16 of the SAS software.

8. Flat priors are provided for deterministic variables such as a constant term or time trend. We include constant terms in our BVAR to allow for drift in the trends of variables.

- τ is the overall tightness (standard deviation) of the prior on the coefficient for the first own lag (default value of 0.2);

- g(k) is the tightness on the prior for lag k relative to the first lag (g(k) = $\frac{1}{k}$, a harmonic decay of the standard deviation with increasing lag length);

- f(i,j) is the tightness of the prior on the coefficient on variable j in equation i relative to that on variable i in the same equation (we used 0.75, implying that other variables have 75 per cent of the weight of the own variable); and

- s_i is the standard error from a univariate autoregression model for variable i (to correct for differences in scales of the variables).

With respect to the choice of lag length, we chose to use double the length of the first two models (i.e. a length of six quarters), allowing the above specification of the prior distributions to taper the lag length off rather than truncating it a priori. Estimation was carried out with Theil's (1971) mixed estimator, as provided for in the RATS program.[9]

4.   Forecast Evaluation

The most obvious method of evaluating these forecasting models is to compare their ex-ante predictions with the actual outcomes. Benchmarks for this comparison can be provided by forecasts from other sources, preferably forecasts made on the basis of the same information as the models under scrutiny. Presumably, if a particular model performs better than alternative forecasts in ex-ante situations, then there is an a priori case that it may continue to do so in the future.

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9.   The other two models were estimated with ordinary least squares.

For this reason, we compare ex-ante forecasts from the three VAR models with nearly equivalent (publicly available) forecasts made by private and public sector organisations, as well as with the actual outcomes as per the June 1987 Quarterly Estimates of the National Accounts. The VARs are used to produce forecasts on the basis of data available at the time of the release of the December 1985 Quarterly Estimates of the National Accounts. The private sector forecasts are those obtained from surveys of private sector economists conducted by Business Review Weekly (Ries, 1986) and The Age (McCrann, 1986) and those provided by the Institute of Applied Economic and Social Research (Dixon and McDonald, 1986); public sector forecasts are taken from the Budget papers.

(a) Private Sector Forecasts

The Age, published a survey for calendar 1986 in January 1986.[10] Economists from thirty-six organisations were asked for forecasts of twenty domestic and international economic variables. Eight of these variables are contained in our VARs. Table 1 shows the actual outcomes for calendar 1986 (as per the June 1987 Quarterly Estimates), the average from The Age survey and unadjusted ex-ante forecasts from the VAR models. The figures in brackets give the proportions of individual forecasters who performed no better than the VAR models. An asterisk indicates that the survey average performed no-better than the VAR model.

Given the mechanical way we have constructed these VARs, and the large number (15) of variables in the models, their ex-ante forecasting performance rates reasonably well against the economists surveyed by The Age. VAR(T), which incorporates time trends, is relatively unimpressive. The remaining two VARs, which incorporate unit-root-like detrending, perform no-worse than a sizeable proportion of the survey respondents on most variables. The survey average is no better than VAR(D) for three of the eight variables, and no better than

10. The economists surveyed by the The Age would not have had the benefits of
     the information in the December 1985 Quarterly Estimates. However, they
     did have current information on most of the variables. Any bias is
     likely to be offset by our use of the survey average.

Table 1

Comparison of Forecasts with Age Survey

(Calendar 1986)

Variable	Actual	Survey	VAR(T)	VAR(D)	BVAR
GDPNF	1.7	3.1	5.7(0)	3.1*(16/35)	7.5(0)
Prvte Invest.	-4.4	2.5	34.2(0)	3.8(15/35)	2.5*(22/35)
Unemployment	629.7	616.7	671.2(13/35)	661.9(19/35)	673.8(11/35)
Current Acct.	14.5	10.1	20.0(5/36)	19.6(7/36)	18.9*(25/36)
AWE	7.1	7.8	9.7(1/35)	11.8(0)	6.5*(24/35)
CPI	9.8	7.6	10.7*(34/36)	8.4*(30/36)	5.8(0)
TWI	54.3	61.5	54.9*(35/36)	59.4*(30/36)	54.1*(36/36)
Bill Rate	15.1	14.3	29.8(0)	26.8(0)	19.7(0)

Note The variables are defined as follows:

GDPNF - Gross non-farm domestic product (seasonally adjusted, constant price), calendar year 1986 on 1985, percentage change.

CPI - Consumer price index, December quarter 1986 on December quarter 1985, percentage change.

AWE - Average weekly earnings, December quarter 1986 on December quarter 1985, percentage change.

Unemployment - June 1986, survey forecasts converted to CES basis for comparison.

Bill Rate - 90 day bank accepted bill yield on annual basis, mid-month, December 1986 for survey. VAR models and actual outcome are average of daily yields for the week ended last Wednesday in December.

Private Investment - calendar year 1986 on 1985, percentage change.

TWI - Trade-weighted index of value of Australian dollar, mid-month, December 1986 for survey. VARs and actual, end-month.

Current Account Deficit - total over calendar year.

Figures in brackets give the proportions of individual forecasters who performed no-better than the VAR models. An asterisk denotes that the survey average performed no-better than the VAR model.

BVAR for four of the eight variables. What is particularly evident from the last two columns of Table 1 is that when the VARs miss the mark, they do so fairly significantly. This suggests that more attention to the trends or priors on certain individual variables may be particularly rewarding in terms of forecast accuracy.

Business Review Weekly (BRW) surveys eight economists each quarter. Forecasts in this survey cover changes in some sixteen economic variables for the next financial year. For example, forecasts published in April 1986 (drawing on information from the December 1985 Quarterly Estimates), forecast the financial year 1986-87.

As a result the forecasts generated with the VARs need to be compared with the BRW survey published in April 1986, when essentially the same information base was available to the economists as was used in generating the VAR forecasts. (The private sector economists did have the advantage of some additional monthly information.) Table 2 sets out the survey average of the BRW forecasts against the seven comparable forecasts from the VAR models. As for Table 1, an asterisk indicates that survey average performed no better than the VAR model, and the figures in brackets give the proportion of individual forecasts who performed no better.

Table 2
Comparison of Forecasts with BRW Survey
(Financial 1986-87)

Variable	Actual	Survey	VAR(T)	VAR(D)	BVAR
GDPNF	1.9	2.8	3.4 (0/8)	1.8*(8/8)	8.7 (0/8)
Prvte Cons	0.5	2.2	1.9*(8/8)	1.6*(7/8)	4.9 (0/8)
Prvte Invest	-2.7	3.2	31.9 (0/8)	-1.3*(8/8)	5.9 (1/8)
Imports	-4.7	3.4	4.7 (2/8)	8.2 (0/8)	8.7 (0/8)
Exports	8.0	11.0	6.5*(8/8)	8.0*(8/8)	8.4*(8/8)
AWE	5.7	7.8	7.5*(6/8)	10.5 (0/8)	3.7*(6/8)
CPI	9.3	6.7	17.1 (0/8)	8.6*(8/8)	3.6 (0/8)

Note: The first five variables are measured as 1986-87 on 1985-86 percentage changes; the last two are expressed as June quarter 1987 on June quarter 1986 percentage changes.

The comparison with BRW survey forecasts shows the VAR forecasts performing at least as well or better on most variables. Model VAR(D) forecasts better than survey average for five out of seven variables, VAR(T) forecasts better for three out of eight; BVAR shows the least accuracy of the VAR models.

A similar result emerges when the VAR forecasts are compared with those from the Institute of Applied Economic and Social Research (IAESR) in Melbourne, which publishes forecasts periodically in The Australian Economic Review. The forecasts published by Dixon and McDonald (1986), for financial year 1986-87, are compared with the VAR forecasts in Table 3.

Table 3
Comparison of Forecasts with IAESR
(Financial 1986-87)

Variable	Actual	IAESR	VAR(T)	VAR(D)	BVAR
GDPNF	1.9	3.2	3.4	1.8*	8.7
Prvte Cons.	0.5	1.7	1.9	1.6*	4.9
Prvte Invest.	-2.7	-1.1	31.9	-1.3*	5.9
Imports	-4.7	-3.0	4.7	8.2	8.7
Exports	8.0	4.0	6.5*	8.0*	8.4*
Employment	2.0	2.7	3.6	0.7	4.1

Note: The first five variables are measured as 1986-87 on 1985-86 percentage changes; the last is expressed as June quarter 1987 on June quarter 1986 percentage change.
An asterisk indicates that the VAR forecast is no less accurate than the IAESR forecast.

VAR(D) forecasts are better than the IAESR for four of the six variables reported here. The other two models appear much weaker, posting a better performance for one variable only.

Tables 1 - 3 provide evidence for the reasonable performance of VAR models against private sector forecasters. The most accurate forecasts are generated by the two VAR models which employ unit-root type detrending; larger errors appear when models are dominated by inappropriate detrending processes.

(b) Public Sector Forecasts

Each year some selective forecasts are presented with the Budget papers.
Table 4 sets out forecasts from the 1986-87 Budget for the nine comparable
variables.

Table 4
Comparison of Forecasts with Budget Papers
(Financial 1986-87)

Variable	Actual	Budget	VAR(T)	VAR(D)	BVAR
GDPNF[b]	1.9	2.5	3.4	1.8*	8.7
Prvte Cons[b]	0.5	1.25	1.9	1.6	4.9
Imports[b]	-2.7	-6.5	4.6	8.2	8.7
Exports[b]	8.0	2.5	6.5*	8.0*	8.4*
Current Account[c]	13.5	14.6	23.0	21.2	21.3
Employment[b]	2.0	1.75	3.6	0.7	4.1
AWE[b]	5.7	6.0	7.5	10.5	3.7
CPI[b]	9.3	8.0	17.1	8.6*	3.6
TWI[a]	53.6	52.0	53.5*	58.3	53.2*

Note:

(a) Assumed, not forecast, in Budget Papers. It is included here for
consistency checking. Actual and VAR TWIs are average of quarterly
figures.

(b) Year on year percentage change.

(c) Sum of quarterly deficits, $b.

VAR(D) and VAR(T) produce more accurate forecasts for two of the nine
variables listed in Table 4 so that although the Budget forecasts are closer
to "actual" on the whole, they do not completely dominate the naively
generated forecasts.

(c) Actual Outcomes

A final assessment of the forecasts is to graph the ex-ante predictions of the
VAR models quarter by quarter to see how well they track the actual outcomes
of each variable. Graphs of the variables, generally in twelve month ended

percentage changes with root mean square errors for the period March 1986 through June 1987, are shown in Figures 1 through 15. (Any difference between the model and actual values in December 1985 are due to revisions in the data since early 1986).

The BVAR model is the best predictor for ten out of the fifteen variables. These results confirm Litterman's hypothesis that VAR's with Bayesian priors perform better than unrestricted models, all other things being equal.

However, all of the models have limitations as forecasting models. They appear to have been poor predictors of the turning points in some of the series, especially exports, imports and the current account balance. The end of 1985 marked a significant change in economic conditions. The general slowdown is evident in the downturn in GDPNF, consumption, investment and imports; a high proportion of the variables have turning points around the first quarter of 1986. The period for December 1985 to June 1987 provides a fairly stringent test of the VAR model's forecasting ability since most variables are not moving in line with earlier trends. The VAR(T) model in particular tends to move very strongly on trend and thus tends to perform badly over this period. The BVAR model is much less dominated by trend and consequently tracks the actual outcomes more closely.

5. Conclusions and Future Directions

We have considered the ex-ante forecasting performance of three relatively large (fifteen variable) vector autoregression models of the Australian economy. The first two models approach the issue of detrending in a fairly mechanical way - applying a linear time trend in one case and first differences in the other. The final model mechanically applied Litterman's (1986a) random walk priors on the coefficients of the VAR.

The main lesson to be drawn from the analysis of these models is the importance of capturing the "trends" in the variables in order to induce covariance stationarity into the data. This has some implications for the development of a better VAR forecasting model, which are canvassed below. The implications for other macroeconometric research are perhaps more important. Non-stationarity is an important property of most macroeconomic data, yet it is typically ignored.

FIGURE 1
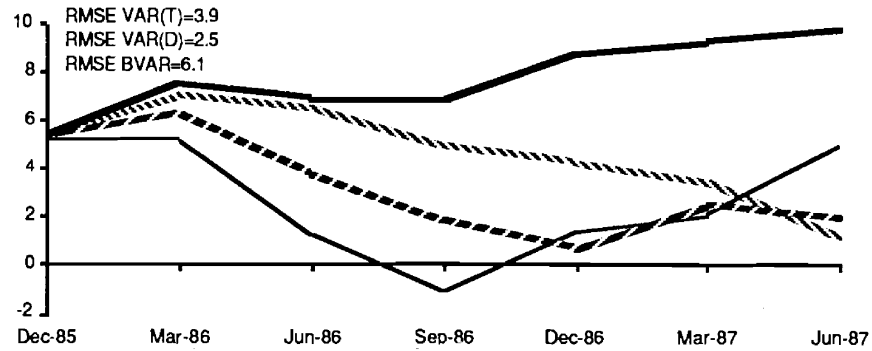### REAL GROSS DOMESTIC NON-FARM PRODUCT
12 months ended per cent change

%

RMSE VAR(T)=3.9
RMSE VAR(D)=2.5
RMSE BVAR=6.1

Dec-85 Mar-86 Jun-86 Sep-86 Dec-86 Mar-87 Jun-87

FIGURE 3
REAL GROSS FIXED PRIVATE CAPITAL EXPENDITURE
12 months ended per cent change

%

RMSE VAR(T)=35.5
RMSE VAR(D)=8.2
RMSE BVAR=7.8

Dec-85 Mar-86 Jun-86 Sep-86 Dec-86 Mar-87 Jun-87
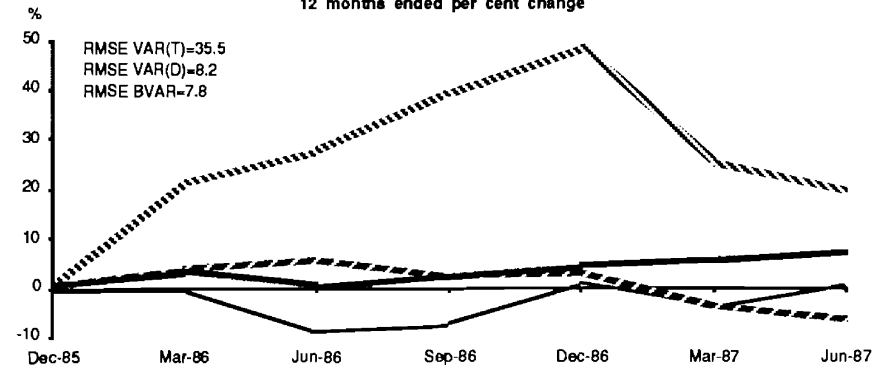
FIGURE 2
REAL FINAL PRIVATE CONSUMPTION EXPENDITURE
12 months ended per cent change

%

RMSE VAR(T)=1.2
RMSE VAR(D)=1.3
RMSE BVAR=3.9

Dec-85 Mar-86 Jun-86 Sep-86 Dec-86 Mar-87 Jun-87
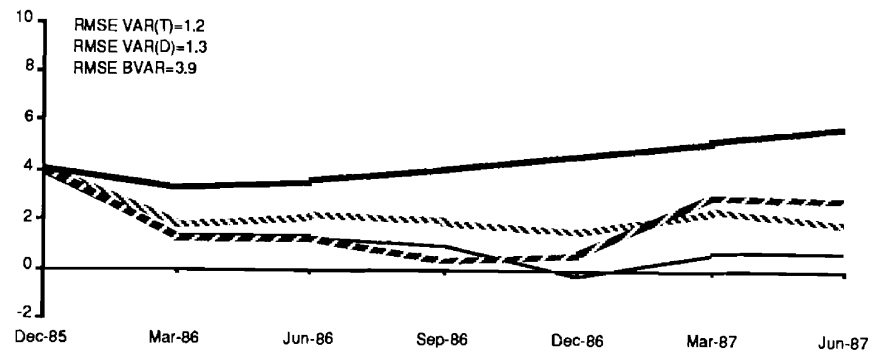
FIGURE 4
REAL INVESTMENT IN PRIVATE NON-FARM STOCKS

$M

RMSPE VAR(T)=12598.6
RMSPE VAR(D)=14908.4
RMSPE BVAR=7679.0

Dec-85 Mar-86 Jun-86 Sep-86 Dec-86 Mar-87 Jun-87
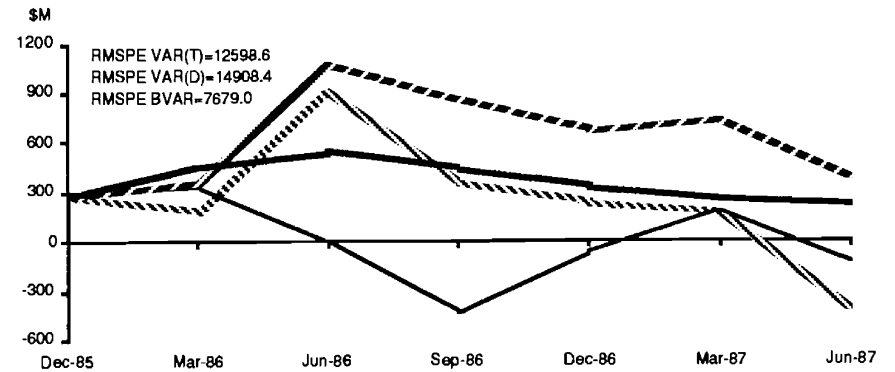
— ACTUAL ∿ VAR(T) ⌐ VAR(D) ■ BVAR

FIGURE 5
CONSUMER PRICE INDEX
12 months ended per cent change

%

RMSE VAR(T)=1.0
RMSE VAR(D)=1.2
RMSE BVAR=3.6

Dec-85 Mar-86 Jun-86 Sep-86 Dec-86 Mar-87 Jun-87
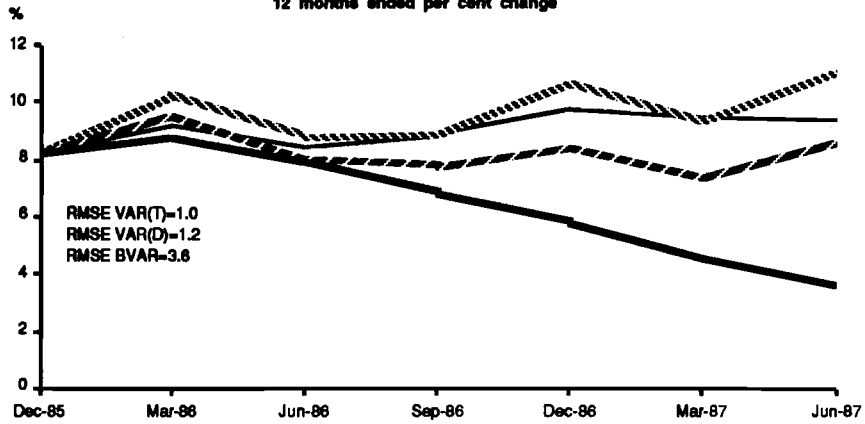
FIGURE 7
TOTAL EMPLOYMENT
12 months ended per cent change

%

RMSE VAR(T)=2.9
RMSE VAR(D)=1.4
RMSE BVAR=1.5

Dec-85 Mar-86 Jun-86 Sep-86 Dec-86 Mar-87 Jun-87
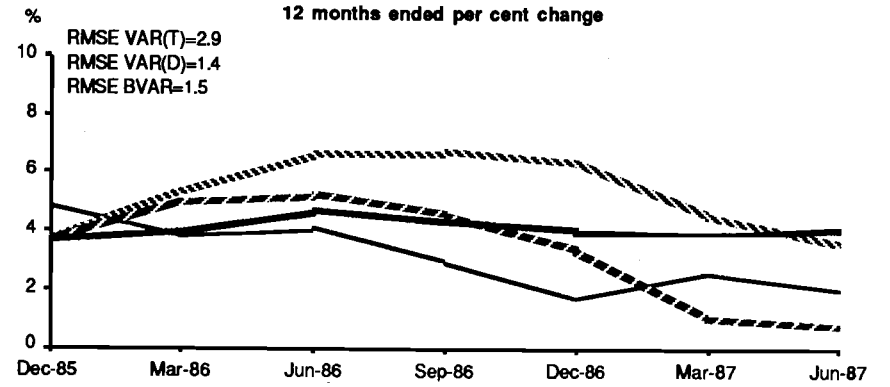
FIGURE 6
AVERAGE WEEKLY EARNINGS
12 months ended per cent change

%

RMSE VAR(T)=2.4
RMSE VAR(D)=4.9
RMSE BVAR=1.0

Dec-85 Mar-86 Jun-86 Sep-86 Dec-86 Mar-87 Jun-87
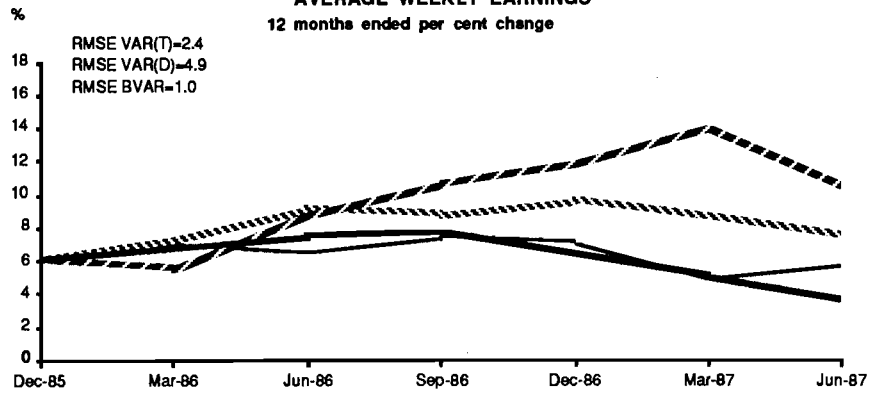
FIGURE 8
UNEMPLOYMENT
12 months ended per cent change

%

RMSE VAR(T)=30.3
RMSE VAR(D)=19.5
RMSE BVAR=11.8

Dec-85 Mar-86 Jun-86 Sep-86 Dec-86 Mar-87 Jun-87
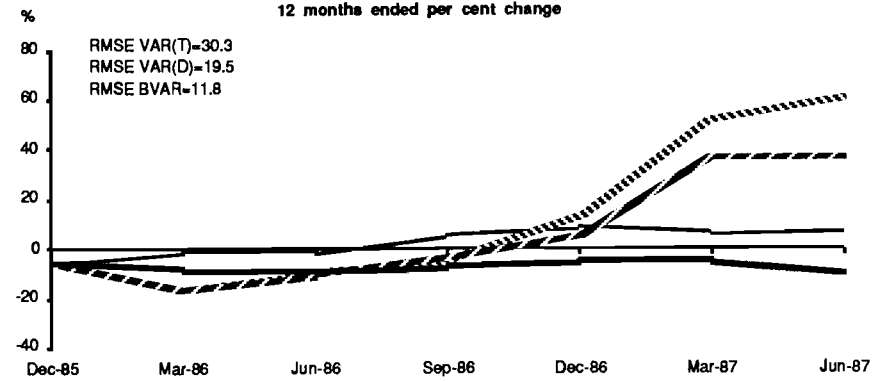
— ACTUAL   ⠈⠈ VAR(T)   ━ ⠄ VAR(D)   ━━ BVAR

FIGURE 9
TRADE WEIGHTED INDEX OF AUSTRALIAN DOLLAR
MAY 1970=100

RMSPE VAR(T)=7.4
RMSPE VAR(D)=10.7
RMSPE BVAR=6.5
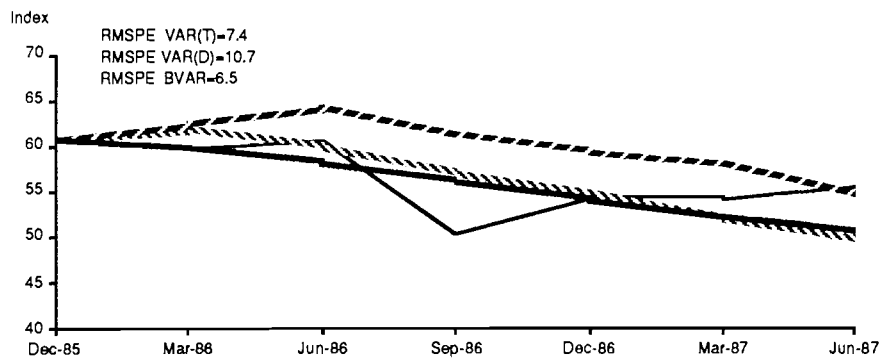
FIGURE 11
REAL EXPORTS OF GOODS AND SERVICES
12 months ended per cent change

RMSE VAR(T)=9.1
RMSE VAR(D)=8.9
RMSE BVAR=8.3
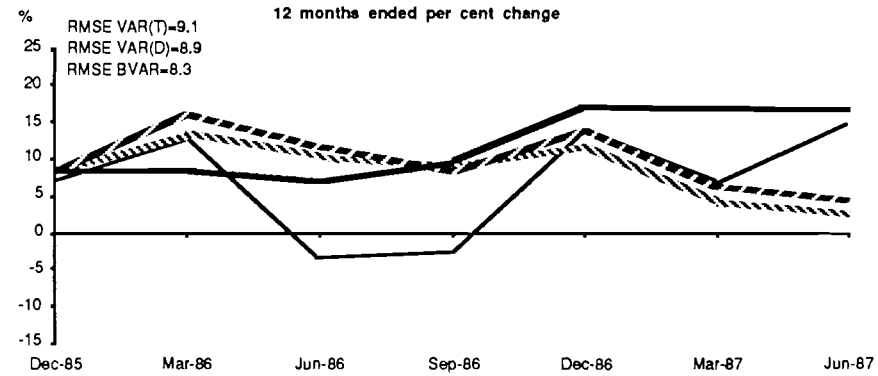
FIGURE 10
BALANCE ON CURRENT ACCOUNT
$M

RMSE VAR(T)=59.6
RMSEVAR(D)=49.2
RMSE BVAR=49.4
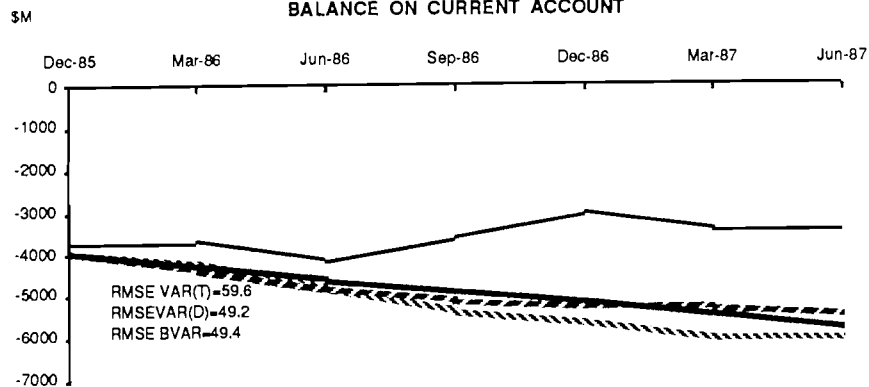
FIGURE 12
REAL IMPORTS OF GOODS AND SERVICES
12 months ended per cent change

RMSE VAR(T)=17.9
RMSE VAR(D)=18.0
RMSE BVAR=14.1
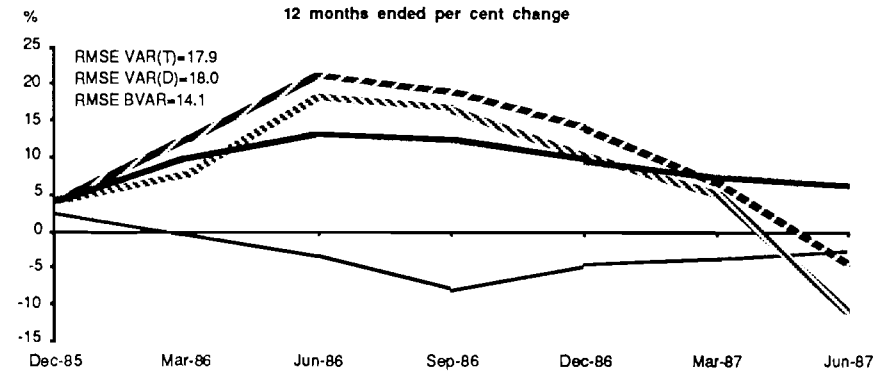
ACTUAL   VAR(T)   VAR(D)   BVAR

FIGURE 13
MONEY SUPPLY-M3
12 months ended per cent change

RMSE VAR(T)=7.3
RMSE VAR(D)=3.2
RMSE BVAR=1.3
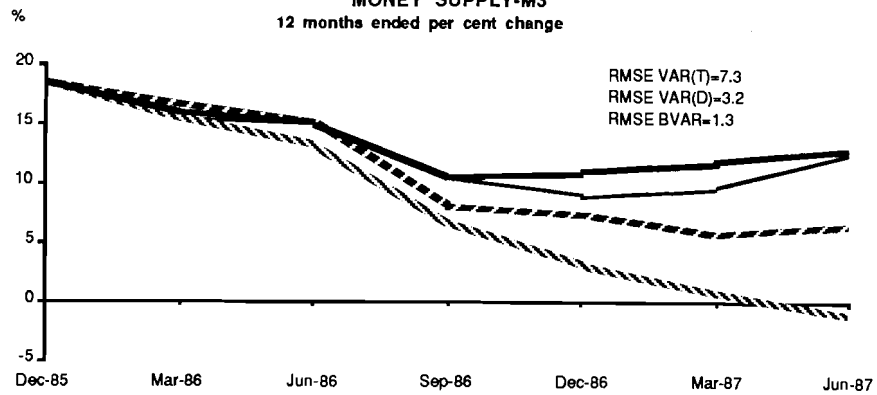
FIGURE 14
90 DAY BILL RATE

RMSE VAR(T)=13.2
RMSE VAR(D)=10.1
RMSE BVAR=4.3
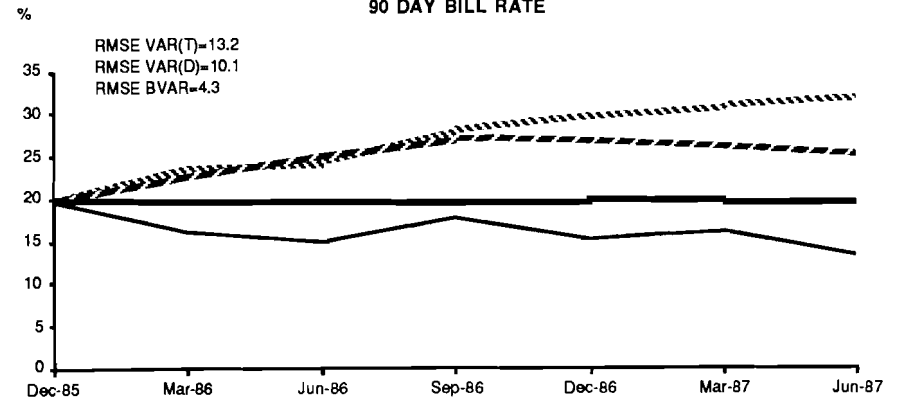
FIGURE 15
ALL ORDINARIES SHARE PRICE INDEX
31 DECEMBER 1979=500

RMSPE VAR(T)=43.5
RMSPE VAR(D)=37.9
RMSPE BVAR=5.6

— ACTUAL   ᴠ VAR(T)   ⸱▬ VAR(D)   ▬ BVAR
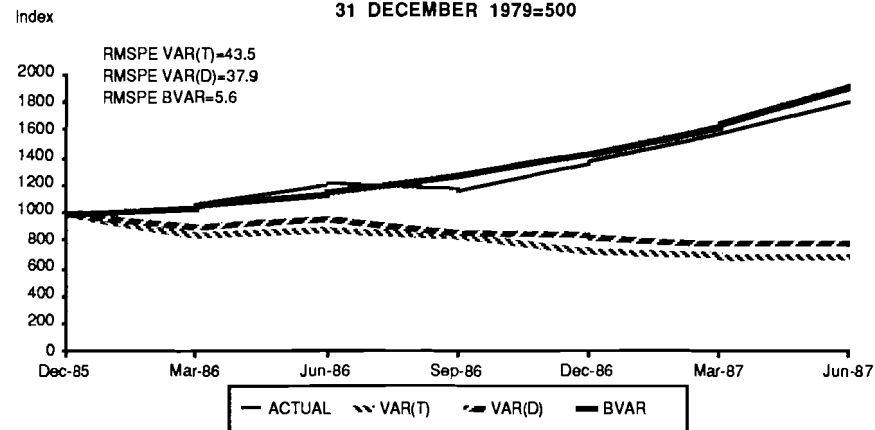
Classical examples of this problem are provided by the Murphy (Murphy, 1987) and NIF 88 (Simes, 1987) models of the Australian economy. Both lay claim to a certain amount of "econometric purity" by apparently extensive use of statistical diagnostics during model development. Yet many of these diagnostics, as well as the parameter estimates on lagged dependent variables, are inappropriate if the data are difference stationary.

We do not claim that the solutions to these problems are trivial (see, for instance, Stock and Watson, 1987). Nonetheless, they do suggest that accuracy in ex-ante forecasting should become an important part of a model builder's toolkit. It may be that forecasts from VAR models will set the standard by which these other models are judged.

Given our "cheap and simple" approach, the ex-ante forecasts, produced up to six quarters ahead by the VAR models, are generally competitive with forecasts prepared by private sector economists for many of the variables. However, an evaluation of the ex-ante forecasting performance of the three VAR models combined with some results from the economics literature, suggests two main ways in which the forecasting performance of VARs may be improved.

The first method would replace the VARs estimated with a time trend or first differences by a single VAR estimated on individually detrended variables. The potential importance of this is clear from the graphs; the forecasts from the model based on first differences are markedly superior for several variables. Techniques such as those used by Stock and Watson (1987) would be applied to each variable to determine the order and number of deterministic and/or stochastic time trends exhibited, and these would be allowed for in the estimation of the VAR. The resulting model would be more complex (in terms of its use of technical expertise) than those considered above, but still relatively cheap to develop and run.

However, this procedure is likely to have at least three limitations. First Meese and Rogoff (1983) and others have shown (in the case of exchange rates) that good estimation period fit does not necessarily produce good forecasts. Second, the floating of the dollar and other financial deregulation of the eighties suggests that one may not want to let the data from the regulated

regimes of the sixties and seventies speak too loudly in some of the equations. Given limited data availability from the deregulated period, one cannot simply throw out the sixties and seventies data. However, it may be possible to allow for structural change by imposing fairly strong priors in the equations for the financial variables. Finally, and probably most importantly, the sheer size of the VARs suggests that considerable payoffs in forecasting precision may be had from applying some kind of restrictions.

These arguments lead us to the second method of building a better VAR – namely, a more thoughtful application of priors in the Bayesian model. In the foregoing analysis, we mechanically applied Litterman's random walk prior to all variables. Yet both theory and empirical work suggest that stock prices, exchange rates (e.g. Meese and Rogoff, 1983) and interest rates (e.g. Trevor and Donald, 1986) are extremely likely to be well modelled by a tight random walk prior; consumption (e.g. Hall, 1978, Flavin, 1981 and Johnson, 1983) is likely to do well with a similar prior, perhaps without the mean of unity on the first own lag; but there is little reason to expect, for example, that the ratio of the change in stocks to real gross domestic product will follow a random walk.

Our models provide some evidence on this issue. An examination of the graphs presented above, and the impact of each variable in each equation of the three VARs,[11] suggests some areas where the priors need to be modified.

In particular, the random walk prior could be substantially tightened in the equations where the BVAR model performs best: stock prices, the exchange rate, interest rates and the money supply. Substantial loosening of this prior, especially in increasing the weights assigned to other variables, is required in the equations for output, consumption, trade and prices where the results of the other models suggest that other variables are important in these equations.

These results suggest that gains in forecast accuracy may be achieved by modifying the priors used in the estimation of the Bayesian VAR. The

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11. Tables documenting these effects may be obtained from the authors on request.

resulting model would still be relatively simple and cheap to develop and run. Of course, once it has been developed, we will need to await the passage of time to generate a new set of data to evaluate the new _ex-ante_ forecasts.

Data Appendix

GDPNF - Gross non-farm product, seasonally adjusted, 1979-80 prices
Australian Bureau of Statistics (ABS) Quarterly Estimates,
December 1985

C - Final private consumption expenditure, seasonally adjusted, 1979-80
prices; ABS Quarterly Estimates, December 1985

I - Gross fixed private capital expenditure, seasonally adjusted 1979-80
prices; ABS Quarterly Estimates, December 1985

X - Exports of goods and services, seasonally adjusted, 1979-80 prices;
ABS Quarterly Estimates, December 1985

M - Imports of goods and services, seasonally adjusted, 1979-80 prices;
ABS Quarterly Estimates, December 1985

BCSA - Balance on current account (end quarter), current price, seasonally
adjusted; ABS Quarterly Estimates, December 1985

CPI - Consumer price index, all items, base 1980-81=100; ABS 6401.0

WE - Average weekly earnings per person (prior to 81(4) males only),
seasonally adjusted; ABS 6301.0 or 6302.0

NE - Employment, '000s of persons (Mid-month of quarter), seasonally
adjusted; ABS Labour Force Survey 6202.0 or 6203.0; (prior 1969(3),
data from internal sources).

NU - Unemployment, '000s of persons, seasonally adjusted; Commonwealth
Employment Service basis.

AO - All Ordinaries index, 31 December 1979=500 (average of daily figures,
mid month of quarter); Reserve Bank of Australia Bulletin

TWI   –   Trade-weighted index of average value of Australian dollar vis-a-vis currencies of Australia's trading partners, May 1970=100; Reserve Bank of Australia Bulletin. (Rates prior to June 1970 constructed using weights based on visible trade for 1971-72 and IMF par values of exchange rates, as published in International Financial Statistics Vol.24. For method of calculation, see: "The Trade Weighted Index of value of the Australian Dollar" Reserve Bank of Australia Bulletin, April 1984 pp.696-697.)

IINF   –   Increase in private non-farm stocks, seasonally adjusted, 1979-80 prices; ABS Quarterly Estimates, December 1985.

RBILL –   Buying rate, 90 day bank accepted bills, (end month of quarter); for details see note (c), Table J1, RBA Bulletin

M3   –   M3 money supply, seasonally adjusted (mid-month of quarter); Table A.1, RBA Bulletin

All series run from March 1960 to December 1985. Actual values used for comparison with forecast are taken from June 1987 Quarterly Estimates of National Income and Expenditure and RBA Bulletin Database.

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