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Abstract

This paper investigates the forecasting performance of the diffusion index approach for the Australian economy, and considers the forecasting performance of the diffusion index approach relative to composite forecasts. Weighted and unweighted factor forecasts are benchmarked against composite forecasts, and forecasts derived from individual forecasting models. The results suggest that diffusion index forecasts tend to improve on the benchmark AR forecasts. We also observe that weighted factors tend to produce better forecasts than their unweighted counterparts. We find, however, that the size of the forecasting improvement is less marked than previous research, with the diffusion index forecasts typically producing mean square errors of a similar magnitude to the VAR and BVAR approaches.

Keywords: Diffusion indexes; Forecasting; Australia.

JEL classification: C22; C53; E17

1 Introduction

Given the abundance of economic information available to forecasters, it is not surprising that extensive research has been undertaken on methods aimed at representing the information inherent in large datasets using a small number of variables. Stock and Watson (2002a,b) find that the forecasts generated using a small number of common factors outperform forecasts obtained from AR or VAR models for US macroeconomic variables. Similarly, Forni et al. (2005) find that factor-based forecasts performed better than AR forecasts for European inflation and production. Outside of the major North American and European economies, however, there is little evidence regarding the properties of forecasts generated using diffusion indexes or common factors.

This paper augments the existing literature in two ways. First, it investigates the forecasting performance of the diffusion index approach for the Australian economy. And second, it considers the relative forecasting performance of the diffusion index approach relative to composite forecasts.

To evaluate the forecasting performance of the diffusion index approach we consider two methods for obtaining forecasts using common factors. The methods are applied to principal components estimated using both unweighted and weighted estimation methods. The factor-based forecasts are benchmarked against forecasts derived from AR, VAR, Bayesian VAR and standard multivariate models. The forecasting performance of the factor models is also compared to the performance of composite forecasts generated using the individual forecasting models.

This paper is structured as follows. Section 2 defines the models employed to generate forecasts. Section 3 describes the data used to estimate the forecasting models. The fourth section presents and discusses the forecasting results. The paper concludes with Section 5.

2 Forecasting models

We forecast the quarterly percentage changes in real and nominal GDP, the annual unemployment rate observed at each quarter, and the quarterly headline inflation rate. For each of these four variables, up to $4-$step ahead out of sample forecasts are generated using two diffusion index approaches with both unweighted and weighted factor estimates, an AR model, a multivariate forecasting approach without a common factor component, a VAR and a BVAR. The AR and multivariate approaches are chosen as popular single equation forecasting methods, while the VAR and BVAR methods are chosen due to their popularity as macroeconomic forecasting tools. Composite forecasts from the large set of available forecasts are also constructed. The out of sample forecasts are generated for the 40 quarters ending December 2006.

2.1 Unweighted PCA forecasts

The factors are extracted as the principal components of the available data set as at time t (Stock and Watson, 2002a,b). Pursuant to this method, the variance-covariance matrix of the $T \times N$ data matrix X is decomposed as:

$$V(X) = \Lambda V(F)\Lambda' + V(E) \tag{1}$$

where $\Lambda V(F)\Lambda'$ is the reduced-rank common component of the variance-covariance matrix $V(X)$ and $V(E)$ is the idiosyncratic component. The principal components are obtained as $F = \Lambda' X$ (see, Bai and Ng, 2002, and Stock and Watson, 2002a, regarding the convergence properties of F). Before undertaking the decomposition in equation (1) for any given time period, the vectors in X are standardised as zero mean, unit variance processes.

Two approaches are used to derive the forecasts $\widehat{y}_{t+h|t}$. Pursuant to the first approach, the principal components of the data set X are extracted and regressed on y using the factor equation

$$y_{t+h} = \alpha_h + \beta_h'(L)F_t + \gamma_h(L)y_t + e_{t+h} \tag{2}$$

where $e_{t+h} \sim iidN\left(0, \sigma_h^2\right)$, $F_t = [f_{1t}, ..., f_{Kt}]'$, $\beta_h(L) = \beta_{h,0} + \beta_{h,1}L + ... + \beta_{h,n_1}L^{n_1}$, $\gamma_h(L) = \gamma_{h,0} + \gamma_{h,1}L + ... + \gamma_{h,n_2}L^{n_2}$ and $h = 1, 2, 3$ or 4. For the second approach, the principal components are obtained from an augmented matrix $X^\star$. The $(T - n_1) \times (N \times \ n_1)$ matrix $X^\star$ is constructed by augmented each vector in the data matrix X with up to n_1 lags of itself. The forecast $\widehat{y}_{t+h|t}$ is then obtained using equation (2) subject to $\beta_h(L) = \beta_{h,0}$. The parameters α_h, β_h and γ_h are updated with each time step t.

Instead of selecting the number of common factors to include in the forecasting model, and in contrast to previous work (Stock and Watson, 2002a,b; Boivin and Ng, 2006), the factors F are deduced by reference to the proportion of total variance explained by the principal components. For both the unweighted PCA approaches, forecasts are constructed by reference to the principal components explaining the first 10, 20, 30, 40 and 50 percentiles of the variance in X (or, in the case of the second approach, $X^\star$). This enables an assessment of the relative change in forecast performance as the proportion of volatility explained by the common regressors F increases.

At each time step, forecasts are constructed using up to $n_1 = 6$ lags of F_t (or, in the case of the second approach, up to $n_1 = 6$ lags of the vectors in X to construct $X^\star$) and up to $n_2 = 12$ lags of y_t. Forecasts are also constructed for the pure factor approach where $\gamma_h(L)$ is set to zero. Consequently, $5\,(n_1 + 1)\,(n_2 + 2) = 490$ forecasts are constructed for each approach at each time step. The Bayesian (or Schwarz) information criterion (BIC) is used to select the model characteristics (the proportion of volatility explained by F, the lags of F, and the lags of y) for the forecast $\widehat{y}_{t+h|t}$ attributed to each approach at time t.[1]

2.2 Weighted PCA forecasts

The estimation of F using weighted principal components is given by the solution to the problem

$$\min_{F,\Lambda} \sum_{\forall t} (X_t - \Lambda F_t)' \, V(E)^{-1} \, (X_t - \Lambda F_t) \tag{3}$$

where the idiosyncratic variance-covariance matrix $V(E)$ constitutes the weighting component. In contrast, and without loss of generality, $V(E)$ is set to an identity matrix of order N under the unweighted approach. The difference between the unweighted and weighted estimates of F may be interpreted in terms of the dis-

[1] Evidence suggesting that the BIC may be used to determine the number of common factors is available in Stock and Watson, 2002a.

tinction between OLS and GLS parameter estimation. Since $V(E)$ is not directly observed, equation (3) cannot be minimised directly. An iterative solution to the problem is proposed in Jones (2001) and implemented here (see also, Forni et al., 2005; Boivin and Ng, 2006).[2] Forecasts are obtained using the approach adopted for the unweighted principal component estimates. We do, however, impose the restriction that forecasts are only constructed by reference to the principal components explaining the first 10 or 20 percentiles of the variance in X (or, given the second approach, $X^{\star}$). This restriction is imposed to eliminate the convergence difficulties encountered when estimating larger numbers of factors.

2.3 AR forecasts

The AR forecast of $\widehat{y}_{t+h|t}$ is constructed using the parameters obtained by regressing y_t on a constant and lags of y_{t-h+1}. The estimation process is equivalent to equation (2) subject to the restriction $\beta_h(L) = 0$. Consequently, the forecast deviations between the factor and AR approaches are determined solely by reference to $\beta_h'(L)F_t$. Up to 12 lags are considered and the lag length is chosen by reference to the BIC.

2.4 OLS forecasts with optional AR component and no factor component

The parameters for the forecast $\widehat{y}_{t+h|t}$ are determined by regressing y_t onto Z_{t-h}. The elements in Z_t, being a subset of the X used to generate the common factors, are the five variables exhibiting the highest h-step ahead correlation with y_t using information up to time t. Z_t may include y_t in its standardised form, and also contains a constant and up to 12 lags of the five correlated variables. As with the other forecasting approaches, the appropriate lag length is chosen using the BIC.

[2] Unlike Jones (2001), we do not assume that convergence has been achieved at the fifth iteration. Instead, we iterate until the sum of squared deviations of the current factor estimates (relative to the estimates for the previous iteration) is less than 1e-05. Convergence typically occurs with about ten iterations.

2.5 VAR and BVAR forecasts

The VAR models are constructed using the the four dependent variables: real GDP, nominal GDP, unemployment and inflation. The ith equation, $i = 1, 2, 3$ and 4, in the VAR structure is given by

$$y_{i,t+h} = \alpha_{i,h} + \beta'_{i,h}(L) Y_t + e_{i,t+h} \tag{4}$$

where $Y_t = [y_{1,t}, y_{2,t}, y_{3,t}, y_{4,t}]'$. A normal error distribution is assumed and maximum likelihood estimates of the parameters are obtained at each time step t.

For the Bayesian variants, we follow LeSage (1990) in adopting a Minnesota (or Litterman) prior for α_i and $\beta_i(L)$ (see, also, Litterman, 1986). Pursuant to the Minnesota prior, we assume an a priori random walk forecasting framework. We apply 'tight' hyperparameters for the prior, thereby reducing the weight attached to higher lags of Y_t.[3] We also applied a 'loose prior' but omit discussion of its performance since the resulting forecasts were similar to the standard VAR forecasts.[4] The parameters are estimated using Theil's mixed estimation approach (Bessler and Kling, 1986).

Forecasts were obtained from VAR(p) and BVAR(p), $p = 1$ to 12, models and the BIC was used to select the final VAR and BVAR forecasts. Forecasts were also obtained by setting $p = 4$. In contrast to the direct forecasting method adopted for the above mentioned models, the VAR (and BVAR) forecasts were computed in the standard VAR manner by rolling the 1-quarter ahead forecasts forward to obtain $2-$, $3-$ and $4-$quarter ahead forecasts.

2.6 Composite forecasts

Composite forecasts are constructed for $h = 1, 2, 3$ and 4 using the forecasts from the individual forecasting models. Two forms of composite forecasting are considered for the $r = 1422$ forecasts obtained at each time period. First, we estimate

[3] For equation i, we adopt an overall tightness parameter of 0.1, a harmonic lag decay of 1, a weight of 0.1 for lags of variable i, and symmetric weights of 0.1 for lags of other variables.

[4] The loose Minnesota prior for equation i uses an overall tightness parameter of 1, a harmonic lag decay of 1, a weight of 2 for lags of variable i, and symmetric weights of 0.5 for lags of other variables.

the (five percent) trimmed mean and median of the set of available forecasts for a given time period. Second, we exploit the BIC statistics, and the assumption that ceteris paribus lower BIC statistics are preferred, in arriving at a final estimate. Pursuant to the second approach, forecasts are ordered according to their BIC statistic (in ascending form). The composite forecasts are then derived as the weighted sums

$$\widehat{y}_{t+h,comp} = \sum_{m=1}^{r} w_m \widehat{y}_{t+h,m}, \tag{5}$$

where $\widehat{y}_{t+h,m}$ is the forecast of y_{t+h} for the model associated with the mth lowest BIC value. The weights w_m are based on the penalty rate $\frac{1}{m}$ and constructed as $w_m = \frac{1/m}{H(r)}$, where $H(r)$ is the $r-$th harmonic number. Consequently, models with ceteris paribus smaller SSE values as at time t play a greater role in the h-step ahead composite forecast $\widehat{y}_{t+h,comp}$. Weights are also constructed using the more severe penalty rate $\frac{1}{m^2}$ to further minimize the impact of forecasts for models with higher BIC values. In this case, the weights are constructed as $w_m = \frac{1/m^2}{H_2(r)}$,where $H_2(r)$ is the $r-$th harmonic number of order 2.

3 Data

A panel of $N = 118$ variables spanning $T = 144$ quarters over the time period March 1971 to December 2006 is used to construct the factors. All but one of the variables are selected from the variable set used by the Australian Treasury department to model the Australian economy, while the remaining variable is quarterly inflation. Some variables used by the Australian Treasury have been omitted due to their inappropriateness for forecasting purposes (such as dummy or trend variables) or their perfect correlation with existing variables in the set.

The final set of N variables represents all sectors of the Australian economy: private business, households, the public sector, imports and exports, and the financial market. 11 of the variables represent global economic activity such as world production, inflation, oil and commodity prices, and interest rates. All data are transformed to ensure stationarity (the data and the transformations are specified in the appendix).

4 Results and discussion

The $h = 1-$, $2-$, $3-$ and $4-$quarter ahead forecasts were computed for the 40 quarters ending December, 2006. For each forecasting model, the model parameters for the forecast $\widehat{y}_{t+h}$ were estimated using data up to time t. To ensure 40 forecast quarters for each value of h, the $h-$step ahead forecasts were initiated using data up to time $T - 40 - h$. The factor-based forecasts were also obtained using factors estimated from X (or X^*) treated for outliers, with little change in forecasting performance. Accordingly, the results and discussion below pertain to the untreated X (or X^*).

4.1 The characteristics of the diffusion index forecasting models

The BIC criterion was used to select the three dominant characteristics of the diffusion index forecasting models: the proportion of volatility explained by F; the lags of F in equation (2) (or, in the case of the second factor approach, the number of lags used to generate X^*); and the lags of y in equation (2). The BIC selections are presented in Tables 1-4. The unweighted PCA(1) and weighted PCA(1) models referred to in Tables 1-4 pertain to the first factor approach, while unweighted PCA(2) and weighted PCA(2) pertain to the second factor approach. The rows under the heading 'Percentage of total variance accounted for by factors' denote the number of times the BIC selected the common factors explaining the first n per cent (where n=10, 20, 30, 40 or 50) of the variance in the explanatory dataset as the regressors in the forecasting equation (this selection is made at each of the 40 forecasts such that the sum of the rows is always 40). The factor lags and dependent lags are the mode number of lags of the common factors and the dependent variables included in the forecasting equation (or, in the case of approach (2), the factor lags are the number of lags of the explanatory dataset included in the matrix X^* used to obtain the principal components).

For the unweighted PCA models, the BIC tends to avoid selecting the set of common factors that explain a high proportion of the variance in the dataset X. Instead the common factors explaining the first 10 or 20 percent of the variance in

X are preferred. There are, however, some exceptions. The BIC tends to select the factors explaining the first 40 per cent of the variance in X for the unemployment forecasts, as well as for nominal GDP (for the first quarter ahead forecasts) and inflation (for the year ahead forecasts). For the weighted PCA models, the BIC generally selects the common factors explaining the first 10 percent of the variance in X (with the exception of the unemployment forecasts).

Table 1. Properties of the diffusion index forecasts of real GDP

Model		Percentage of total variance accounted for by factors					Lags	
	h	10	20	30	40	50	Dependent	Factors
	1	0	25	15	0	0	0	0
Unweighted	2	40	0	0	0	0	12	0
PCA(1)	3	40	0	0	0	0	12	0
	4	22	18	0	0	0	12	0
	1	40	0	0	0	0	-1	0
Unweighted	2	37	0	3	0	0	-1	0
PCA(2)	3	29	0	11	0	0	-1	0
	4	40	0	0	0	0	-1	0
	1	15	25	-	-	-	-1	0
Weighted	2	40	0	-	-	-	-1	0
PCA(1)	3	40	0	-	-	-	-1	1
	4	36	4	-	-	-	-1	0
	1	22	18	-	-	-	-1	1
Weighted	2	40	0	-	-	-	-1	6
PCA(2)	3	40	0	-	-	-	0	0
	4	40	0	-	-	-	0	0

Notes: This table shows the BIC-based selections for the diffusion index parameters. For the two columns under the heading 'Lags', a value of -1 signifies that the dependent variable is not included in the factor equation, a value of 0 signifies that only y_t (or, in the case of the column entitled 'Factors', F_t) is included in the factor equation whereas values 1 to 12 signify the number of lags of y_t (or, in the case of the column entitled 'Factors', F_t) in the factor equation.

The BIC preference for choosing sets of common factors explaining only a relatively small proportion of the variance in X is confirmed in forecasts obtained by fixing the proportion of volatility explained by the common factors in equation

(2) to 10, 20, 30, ..., 90 percent of the variance in X. The fixed proportion forecasts tend to produce higher root mean square error (RMSE) values upon introducing the additional factors needed to explain beyond 30 or 40 percent of the variance in X.[5] This suggests that the improved forecasts obtained by using a smaller, rather than larger, number of factors (see, for example, Stock and Watson, 2002a,b; Artis, Banerjee and Marcellino, 2006) may be associated with the omission of noisier factors needed to explain further variance in the dataset, rather than the possibility that the forecasts generated by a small number of factors are satisfactory because they explain a sufficient amount of the volatility in a dataset.[6]

Table 2. Properties of the diffusion index forecasts of nominal GDP

Model		Percentage of total variance accounted for by factors					Lags	
	h	10	20	30	40	50	Dependent	Factors
Unweighted PCA(1)	1	0	0	0	40	0	12	0
	2	24	0	0	13	3	12	0
	3	40	0	0	0	0	12	0
	4	26	14	0	0	0	12	0
Unweighted PCA(2)	1	0	40	0	0	0	-1	0
	2	0	40	0	0	0	-1	0
	3	40	0	0	0	0	-1	0
	4	40	0	0	0	0	-1	0
Weighted PCA(1)	1	25	15	-	-	-	-1	0
	2	40	0	-	-	-	-1	0
	3	40	0	-	-	-	-1	1
	4	0	40	-	-	-	-1	0
Weighted PCA(2)	1	0	40	-	-	-	-1	2
	2	0	40	-	-	-	-1	1
	3	40	0	-	-	-	-1	1
	4	40	0	-	-	-	-1	6

Notes: refer to the notes for Table 1.

[5] These results are available upon request to the corresponding author.

[6] The factors needed to explain higher levels of the variance in a dataset may also be noiser (therefore leading to negligible forecasting gains) due to the difficulty in obtaining accurate estimates of their values. See, Jones (2001).

Significant deviation is observed in the BIC selection of the number lags of the common factors F and the dependent variable y used in the diffusion index forecasting equations. The BIC tends to select 12 lags of y for the real GDP forecasts based on the first unweighted factor approach (at h = 2, 3 and 4). In contrast y is omitted in the remaining factor forecasting models, implying that the information in y is adequately accounted for by F. The dependent variable y is present in all the unemployment forecasts but absent from the majority of the inflation forecasts.

Table 3. Properties of the diffusion index forecasts of unemployment

Model	h	Percentage of total variance accounted for by factors					Lags	
		10	20	30	40	50	Dependent	Factors
	1	0	0	0	38	0	0	0
Unweighted	2	0	0	0	37	3	0	0
PCA(1)	3	0	0	0	36	4	0	0
	4	0	0	0	40	0	9	0
	1	0	40	0	0	0	0	1
Unweighted	2	0	0	32	8	0	0	0
PCA(2)	3	0	9	23	8	0	0	0
	4	0	18	22	0	0	0	0
	1	0	40	-	-	-	0	0
Weighted	2	0	40	-	-	-	0	0
PCA(1)	3	0	40	-	-	-	1	0
	4	18	22	-	-	-	1	0
	1	0	40	-	-	-	1	1
Weighted	2	0	40	-	-	-	1	1
PCA(2)	3	0	40	-	-	-	1	1
	4	0	40	-	-	-	1	1

Notes: refer to the notes for Table 1.

The BIC appears to be most uniform in its choice of the number of lags of F for the first factor approach, where lags of F are used in the forecasting equation. The BIC tends to select forecasts that rely only on the most recent value F_t, suggesting that higher lags of F_t add little to equation (2). Empirical evidence obtained by fixing the lags of F leads to a similar conclusion, with little RMSE improvement observed through the addition of more lags. In terms of the second approach, the BIC generally selects an $X^{\star}$ containing a higher number of lags of the variables in X for the weighted PCA approach (except in the case of inflation, where lags of the variables in X are used to generate the factors utilised by both the unweighted and weighted PCA forecasts). The inclusion of lags of X in $X^{\star}$ suggests that the principal components estimated using lagged values of the dataset, especially where weighted PCA is adopted, are useful for modelling y.

Table 4. Properties of the diffusion index forecasts of inflation

Model		Percentage of total variance accounted for by factors					Lags	
	h	10	20	30	40	50	Dependent	Factors
	1	40	0	0	0	0	-1	0
Unweighted	2	40	0	0	0	0	-1	0
PCA(1)	3	40	0	0	0	0	3	1
	4	0	0	0	31	9	2	0
	1	40	0	0	0	0	-1	4
Unweighted	2	0	40	0	0	0	-1	3
PCA(2)	3	0	38	0	2	0	0	2
	4	0	23	0	14	3	-1	0
	1	40	0	-	-	-	-1	0
Weighted	2	40	0	-	-	-	-1	0
PCA(1)	3	40	0	-	-	-	-1	1
	4	40	0	-	-	-	-1	1
	1	40	0	-	-	-	-1	0
Weighted	2	25	15	-	-	-	-1	3
PCA(2)	3	26	14	-	-	-	-1	2
	4	34	6	-	-	-	-1	1

Notes: refer to the notes for Table 1.

4.2 Comparison of the forecasting models

The RMSE statistics for all the forecasting models are presented in Tables 5-8. For the VAR and BVAR forecasts, the tables are restricted to the RMSE values obtained by setting $p = 4$. These forecasts are typically better than the forecasts obtained by allowing the BIC to determine p (the BIC often selected

$p = 1$; Stock and Watson (2002a) encountered a similar problem with respect to US macroeconomic data). The individual forecasts were screened for outliers before computation of the composite forecasts.[7]

Table 5. RMSE statistics for real GDP forecasts[a]

Model / Forecast steps	h=1	h=2	h=3	h=4	GM[b]
Unweighted PCA (approach 1)	1.0244	1.0023	0.9452	0.9746	0.9862
Unweighted PCA (approach 2)	0.9909	1.0373	0.9499	1.0140	0.9975
Weighted PCA (approach 1)	0.9627	1.0498	1.0094	0.9646	0.9960
Weighted PCA (approach 2)	1.0577	0.9834	0.9767	1.0057	1.0054
AR	1	1	1	1	1
VAR	1.0915	0.9722	0.9682	0.9777	1.0011
BVAR	0.9634	0.9280	0.9236	0.9794	0.9483
OLS	1.1370	1.0389	1.3101	1.2883	1.1883
Composite forecast ($1/m$)	0.9628	0.9673	0.9649	0.9974	0.9730
Composite forecast ($1/m^2$)	1.0077	0.9990	1.1127	1.0044	1.0299
Composite forecast (mean)	0.9801	1.0155	0.9800	1.0929	1.0161
Composite forecast (median)	0.9587	0.9761	0.9486	1.0009	0.9709

a. The RMSE statistics are presented relative to the RMSE for the AR benchmark. Values greater than unity indicate a higher RMSE than the AR benchmark (with an analogous meaning for values below unity).

b. GM is the geometric mean of the mean square errors for h=1,2,3 and 4.

The one-quarter ahead factor-based forecasts have lower RMS errors than the AR benchmark for three of the four variables that are forecast (the exception being real GDP where only two of the four factor models produce better forecasts than the AR model). The one-quarter ahead factor-based forecasts are similar to the VAR and BVAR forecasts for real GDP, unemployment and inflation, and improve on the VAR and BVAR forecasts for nominal GDP. A similar pattern emerges for the two-quarter ahead forecasts, with the factor models producing forecasts with

[7] Absolute forecasts exceeding the following cutting points were omitted: quarterly inflation, 15 per cent; quarterly growth in real GDP, 10 per cent; quarterly growth in nominal GDP, 20 per cent; unemployment rate, 30 per cent.

similar RMS errors to the VAR and BVAR models and tending to improve on the AR benchmark.

Table 6. RMSE statistics for nominal GDP forecasts[a]

Model / Forecast steps	h=1	h=2	h=3	h=4	GM[b]
Unweighted PCA (approach 1)	0.8384	0.8787	0.8556	0.8948	0.8666
Unweighted PCA (approach 2)	0.8347	0.8992	0.8382	0.7614	0.8319
Weighted PCA (approach 1)	0.8508	0.8358	0.8184	0.8436	0.8371
Weighted PCA (approach 2)	0.8135	0.8488	0.8352	0.7610	0.8139
AR	1	1	1	1	1
VAR	1.0183	0.8957	0.9336	0.9048	0.9369
BVAR	0.9698	0.9367	0.9781	0.9800	0.9660
OLS	1.1114	0.8176	0.9192	0.8094	0.9068
Composite forecast $(1/m)$	0.7796	0.8094	0.8016	0.7423	0.7828
Composite forecast $(1/m^2)$	0.8069	0.8414	0.8256	0.7587	0.8075
Composite forecast (mean)	0.7626	0.8635	0.8277	0.7521	0.8002
Composite forecast (median)	0.8096	0.824	0.7925	0.7310	0.7885

a. The RMSE statistics are presented relative to the RMSE for the AR benchmark. Values greater than unity indicate a higher RMSE than the AR benchmark (with an analogous meaning for values below unity).

b. GM is the geometric mean of the mean square errors for h=1,2,3 and 4.

The results differ, however, for the three-quarter and year ahead forecasts with the various factor approaches resulting in markedly different RMS errors The RMS errors for the factor models are clearly smaller than their VAR and BVAR counterparts for nominal GDP. In contrast, the VAR and BVAR models produce better forecasts than the unweighted factor models for the unemployment variable (with the benchmark AR process also resulting in smaller RMS errors than the unweighted factor models). The RMS errors for the unemployment variable, however, improve greatly when forecasts are generated using weighted factors (being smaller than BVAR errors, and only slightly larger than the VAR model which produces the best three-quarter and year ahead unemployment forecasts). The unweighted factor forecasts (using approach one) for year ahead inflation are poor and produce a significantly higher RMS error than the benchmark AR process. In contrast, the weighted factor models (using approach one) produce better year ahead forecasts than either the VAR or BVAR models or the AR benchmark.

Table 7. RMSE statistics for unemployment forecasts[a]

Model / Forecast steps	h=1	h=2	h=3	h=4	GM[b]
Unweighted PCA (approach 1)	0.9068	0.9408	1.0066	1.0170	0.9667
Unweighted PCA (approach 2)	0.9530	0.9467	1.0165	0.9738	0.9721
Weighted PCA (approach 1)	0.9249	0.8383	0.8406	0.8385	0.8598
Weighted PCA (approach 2)	0.8977	0.8409	0.8706	0.8679	0.8690
AR	1	1	1	1	1
VAR	0.9383	0.7910	0.8164	0.8180	0.8391
BVAR	0.9197	0.8694	0.8772	0.8719	0.8843
OLS	0.8582	3.1863	5.0661	0.8483	1.8515
Composite forecast ($1/m$)	0.8888	0.8187	0.8721	0.9087	0.8714
Composite forecast ($1/m^2$)	0.9180	0.8021	0.7989	0.8093	0.8307
Composite forecast (mean)	1.0180	0.9776	1.0477	1.1125	1.0378
Composite forecast (median)	0.8985	0.9153	1.0156	1.0767	0.9738

a. The RMSE statistics are presented relative to the RMSE for the AR benchmark. Values greater than unity indicate a higher RMSE than the AR benchmark (with an analogous meaning for values below unity).

b. GM is the geometric mean of the mean square errors for h=1,2,3 and 4.

The weighted PCA models tend to produce better forecasts than their unweighted PCA variants as h increases, with the weighted PCA models producing significantly smaller RMS errors at $h = 4$ for inflation and unemployment and similar RMS levels for real and nominal GDP. Forni et al (2005) and Boivin and Ng (2006) also find that forecasts from weighted factors tend to outperform forecasts from their unweighted counterparts. Boivin and Ng's (2006) preference for weighted PCA is, however, restricted to real variables. We fail to observe such a restriction here, instead finding that the RMSE gain associated with weighted PCA is greater for nominal GDP than real GDP.

The weighted PCA forecasts typically result in markedly lower RMS errors relative to the AR benchmark for all variables except real GDP. As such, the results appear consistent with simulation evidence that forecasts of y_t using its own lags are less accurate than forecasts depending on lags of F_t (Boivin and Ng, 2005). In general, the weighted PCA forecasts produce RMS errors of a similar magnitude to the VAR and BVAR models, with the exception of nominal GDP and year ahead inflation forecasts where the weighted factor models produce comparatively lower RMS errors.

Table 8. RMSE statistics for inflation forecasts[a]

Model / Forecast steps	h=1	h=2	h=3	h=4	GM[b]
Unweighted PCA (approach 1)	0.9721	0.9557	1.0179	1.1983	1.0318
Unweighted PCA (approach 2)	0.9576	0.8823	0.9649	1.0229	0.9556
Weighted PCA (approach 1)	0.9657	0.9605	1.0105	0.8717	0.9507
Weighted PCA (approach 2)	0.9309	0.9162	0.9582	0.8894	0.9233
AR	1	1	1	1	1
VAR	0.9485	0.9041	0.9973	0.9681	0.9539
BVAR	0.9717	0.9379	1.0108	1.0047	0.9808
OLS	1.0453	1.0130	0.9374	0.8824	0.9674
Composite forecast ($1/m$)	0.9217	0.8996	0.9215	0.9644	0.9265
Composite forecast ($1/m^2$)	0.9332	0.9257	0.9284	1.1361	0.9770
Composite forecast (mean)	0.9393	0.9155	0.9574	0.9181	0.9324
Composite forecast (median)	0.9311	0.9044	0.9526	0.9054	0.9232

a. The RMSE statistics are presented relative to the RMSE for the AR benchmark. Values greater than unity indicate a higher RMSE than the AR benchmark (with an analogous meaning for values below unity).

b. GM is the geometric mean of the mean square errors for h=1,2,3 and 4.

Neither factor approach (approach (1) which uses X to derive the factors, or approach (2) which uses the augmented X^* to derive the forecasts) appears to dominate where weighted PCA is adopted. The second approach, however, appears to produce more stable unemployment forecasts at $h = 3, 4$ when employing unweighted PCA estimates of the factors.

The composite forecasts tend to produce lower RMS errors than any of the individual models. In this respect, the composite forecast produced by reference to the BIC of the individual forecasting models penalised using $\frac{1}{m}$ never produces a RMSE greater than that of the AR benchmark. Although the composite and factor forecasts depend on the same information set, the composite forecasts tend to produce smaller RMS errors than the unweighted PCA models (the exception being real GDP where the weighted or unweighted PCA and composite forecasts are similar). By comparison, the weighted PCA forecasts produce relatively similar, and in some cases better, forecasts than their composite counterparts. In this respect, the weighted PCA models tend to produce lower RMS errors than the composite forecasts for both year ahead inflation and unemployment. This suggests that the weighted PCA models may be useful for the derivation of longer term forecasts.

The forecasting performance of the diffusion index approach for Australia tends to reflect the results observed for the US and the EU. Stock and Watson (2002a,b) find that the diffusion forecasts typically improve on forecasts obtained from AR models for the US economy. Brisson, Campbell and Galbraith (2003) and Artis, Banerjee, and Marcellino (2006) arrive at similar conclusions for Canada and the UK. The performance improvement observed for Australia, however, appears to be smaller than that observed for the aforementioned economies (especially when using unweighted PCA). Likewise, the typical preference (in terms of MSE values) observed for the diffusion index approaches over the VAR and BVAR forecasts fails to appear in the Australian context. In a number of cases, the AR benchmark also produces similar, or even better, forecasts, than the factor approaches. A possible reason for the weaker performance of the diffusion index approach in this paper may be the number of time-dependent observations, since both the factor estimates F and the loadings β are sensitive to T. Monthly data is employed in the three aforementioned papers, whereas we employ quarterly data and are subject to a smaller T (see, in this respect, Schumacher, 2007).

Another reason for the relatively weaker forecasting performance of the diffusion index approach may be associated with the number of variables N. It is not clear, however, that increasing the number of explanatory variables used to derive the common factors would improve factor-based forecasts. Boivin and Ng (2006) suggest that the forecasting results of factors derived from smaller, pre-screened panels of data are similar to or better than forecasts from larger panels. Since the variables adopted in this paper have effectively been pre-screened by the Australian Treasury as relevant to modelling the Australian economy, the performance of the factor models in this paper is also a good indicator of the performance of factor models constructed using pre-screened data relative to alternative forecasting approaches.

5 Conclusion

This paper examined the forecasting performance of the diffusion index approach for Australian real GDP, nominal GDP, unemployment and inflation. We constructed diffusion index forecasts based on factors estimated using weighted and unweighted principal components from 118 quarterly variables used by the Australian Treasury in their formal model of the Australian economy. The diffusion index forecasts were compared to forecasts derived from a range of alternative approaches, in addition to composite forecasts. The results suggest that diffusion index forecasts tend to improve on benchmark AR forecasts. We found, however, that the size of the forecasting improvement is less marked than previous research, with the diffusion index forecasts typically producing mean square errors of a similar magnitude to the VAR and BVAR approaches.

Significant differences were observed between the forecasts generated using weighted and unweighted principal components, with weighted variants tending to produce smaller forecast errors, especially at greater forecast horizons. Although the composite forecasts errors were typically smaller than their diffusion index counterparts, the weighted principal component forecasts produced relatively similar mean square errors. Overall, composite forecasts derived by reference to the BIC of individual models and weighted such that models with higher BIC statistics are gradually phased out tended to produce the smallest errors and always improved on the AR benchmark.

In summary, the additional data incorporated in large factor models, even where the data are preselected as relevant to a particular economy, does not necessarily lead to forecast improvements relative to less data intensive approaches.

To improve the forecasting performance of the diffusion index approach, further research is needed regarding the construction of straightforward methods for filtering large datasets in a manner conducive to obtaining forecast improvements.

6 Appendix: Data

This appendix lists the data used in this paper. The diffusion indices are constructed using all variables. The variables are available from the Modellers' Database released by the Australian Bureau of Statistics on a quarterly basis. This database contains variables used by the Australian Treasury's TRYM model of the Australian economy and is available at www.abs.gov.au. The transformations in column four are: 0 = no transformation; 1 = first difference of logarithms; 2 = first difference; 3 = percentage difference (in decimal points).

Number	Code	Units	Trans.	Description
Dwelling sector				
1	gdw	cvm, $million/qtr	1	Dwelling-sector gross value added
2	ddm	cvm, $million/qtr	1	Dwelling-sector intermediate inputs
3	idw	cvm, $million/qtr	1	Dwelling investment
4	iret	cvm, $million/qtr	1	Real-estate transfer expenses (o'ship transfer costs)
5	kdw	cvm, $million	1	Dwelling capital stock
6	kvacd	Fraction	2	Rental vacancy rate
7	pcre	Deflator, base = 1	1	Market price of rental consumption
8	pcret	Deflator	1	Trend market price of rental consumption
9	pddm	Deflator, base = 1	1	Trend mkt price of dwelling-sector intermediate inputs
10	piret	Deflator, base = 1	1	Market price of real-estate transfer expenses
Enterprise sector				
11	genc	cvm, $million/qtr	1	Enterprise sector non-commodity output
12	ib	cvm, $million/qtr	1	Private business investment
13	ie	cvm, $million/qtr	1	Enterprise sector investment
14	ige	cvm, $million/qtr	1	General enterprise investment
15	ke	cvm, $million	1	Enterprise sector capital stock
16	nee	thousand persons	1	Enterprise sector employment
17	need	thousand persons	1	Enterpise sector labour demand
Financial market				
18	fie	Percentage points/yr	2	Long-run expected inflation
19	fiex	Percentage points/yr	2	Full-information long-run expected inflation
20	qval	Ratio	1	Government securities valuation ratio
21	resdr	Index of $F/$A, base=1	1	SDR exchange-rate index
22	retwi	Index of $F/$A, base=1	1	Export-weighted exchange-rate index
23	retwim	Index of $F/$A, base=1	1	Import-weighted exchange-rate index
24	ri90	Percentage points/yr	2	Domestic 90-day bill rate
25	rigl	Percentage points/yr	2	Domestic 10-year bond rate
26	wfie	Percentage points/yr	2	World inflationary expectations
27	wri90	Percentage points/yr	2	Weighted average of G7 90-day bill rates
28	wrigl	Percentage points/yr	2	Weighted average of G7 10-year bond rates
29	N/A	Index, base = 100	3	Inflation
General government				
30	dgf	cvm, $million/qtr	1	General government final demand
31	dgm	cvm, $million/qtr	1	General government market demand
32	ggk	cvm, $million/qtr	1	General-government production from capital
33	ggn	cvm, $million/qtr	1	General-government production from labour
34	gtlsz	current prices, $million/qtr	1	Taxes on products (GST, sales taxes, etc)
35	igg	cvm, $million/qtr	1	General government investment
36	rtav	Fraction	2	Average tax rate on supply to the dom goods market
37	rtcnr	Fraction	2	Rate of tax on non-rental consumption
38	rtcre	Fraction	2	Rate of tax on rental consumption
39	rtddm	Fraction	2	Rate of tax on dwelling sector intermediate inputs
40	rtdgm	Fraction	2	Rate of tax on government market demand
41	rtge	Fraction	2	Rate of tax on enterprise sector output
42	rtgenc	Fraction	2	Rate of tax on ent sector non-commodity output
43	rtidw	Fraction	2	Rate of tax on dwelling investment
44	rtie	Fraction	2	Rate of tax on enterprise sector investment

45	rtk	Fraction	2	Rate of tax on capital income
46	rtmgs	Fraction	2	Rate of tax on imports
47	rtn	Fraction	2	Rate of tax on labour income
48	rtogdw	Fraction	2	Rate of tax on production of the dwelling sector
49	rtoge	Fraction	2	Rate of tax on production of the enterprise sector
50	rtpre	Fraction	2	Rate of tax on ent sector lab inputs (payroll tax, FBT)
51	rtxc	Fraction	2	Rate of tax on commodity exports
52	rtxnc	Fraction	2	Rate of tax on non-commodity exports
53	rvdgt	Ratio, $/($/yr)	2	Ratio of government debt to annual GDP
54	ykz	current prices, $million/qtr	1	Capital income tax base
Household sector				
55	cnr	cvm, $million/qtr	1	Non-rental consumption
56	con	cvm, $million/qtr	1	Private consumption
57	vmz	Current prices, $million	1	Private wealth
58	ynz	current prices, $million/qtr	1	Labour income tax base
Import and export				
59	bcaz	current prices, $million/qtr	3	Current-account balance
60	ddmgs	cvm, $million/qtr	1	Weighted demand for imports
61	mgs	cvm, $million/qtr	1	Imports of goods and services
62	pmgs	Deflator, base = 1	1	Price of imports
63	pxc	Deflator, base = 1	1	Final price of commodity exports
64	pxnc	Deflator, base = 1	1	Final price of non-commodity exports
65	wip	Price index, base=1	1	Export-weighted index of world industrial production
66	wmtp	Price index, base=1	1	Export-weighted index of world GDP
67	wnpop	Price index, base=1	1	Export-weighted index of world population
68	wpcon	Price index, base=1	1	Export-weighted index of world consumption prices
69	wpmgs	Price index, base=1	1	Import-weighted index of world GDP deflators
70	wpmpe	Price index, base=1	1	SDR index of oil prices
71	wpmtp	Price index, base=1	1	Export-weighted index of world GDP deflators
72	wpxc	Deflator, base = 1	1	Reserve Bank SDR commodity price index
73	xc	cvm, $million/qtr	1	Commodity exports
74	xgs	cvm, $million/qtr	1	Exports of goods and services
75	xnc	cvm, $million/qtr	1	Non-commodity exports
Inventories				
76	ddsnn	cvm, $million/qtr	1	Weighted demand for non-farm inventories
77	ksfm	cvm, $million	1	Farm inventories
78	ksn	cvm, $million	1	Non-farm inventories
79	pksn	Deflator, base = 1	1	Price of non-farm inventories
80	sfm	cvm, $million/qtr	0	Change in farm inventories
81	snn	cvm, $million/qtr	0	Change in non-farm inventories
Labour market				
82	nairu	Percentage points	2	NAIRU
83	net	thousand persons	1	Civilian employment
84	nlf	thousand persons	1	Civilian labour force
85	npada	thousand persons	1	Working age population (15-64)
86	nv	thousand persons	1	Job vacancies
87	rnu	Percentage points	0	Unemployment rate
88	rnust	Percentage points	2	Unemployment rate at which un rate equals vac rate
89	rwehz	Current prices	1	Hourly enterprise wage
90	rweph	Price ratio	1	Hourly real producer wage
91	rwtz	Current prices	1	Average wage per employee
National Accounts				
92	dise	cvm, $million/qtr	0	Statistical discrepancy in GDP(E)
93	disez	current prices, $million/qtr	0	Statistical discrepancy in nominal GDP(E)
94	gdpa	cvm, $million/qtr	1	GDP(A)
95	gdpaz	current prices, $million/qtr	1	Nominal GDP(A)
96	ge	cvm, $million/qtr	1	Enterprise sector output
97	gnea	cvm, $million/qtr	1	GNE
98	gneaz	current prices, $million/qtr	1	Nominal GNE
99	pgdpa	Deflator, base = 1	1	Market price deflator of GDP
100	pgnea	Deflator, base = 1	1	Market price deflator of GNE
Net lending				
101	beopz	current prices, $million/qtr	2	Private equity investment to overseas
102	bepoz	current prices, $million/qtr	2	Private equity investment from overseas
103	bgpz	current prices, $million/qtr	3	Government borrowing from private sector (net)
104	boraz	current prices, $million/qtr	3	Change in Official Reserve Assets
105	npim	thousand persons	3	Net immigration
106	vdoraz	Current prices, $million	1	Official Reserve Assets
107	vdpoaz	Current prices, $million	1	Net private sector $A debt held by overseas sector
108	vdpofz	Current prices, $million	1	Net private sector foreign-currency debt held by o/s
109	vnflz	Current prices, $million	1	Net foreign liabilities
110	ydgoz	current prices, $million/qtr	1	Government net interest payments on overseas debt
111	ydgpz	current prices, $million/qtr	1	Government net interest payments to private sector
112	ydoraz	current prices, $million/qtr	1	Interest received on Official Reserve Assets

113	ydpoz	current prices, $million/qtr	1	Private net interest payments on overseas debt
114	yeopz	current prices, $million/qtr	1	Dividends and remitted profits received from overseas
115	yepoz	current prices, $million/qtr	1	Dividends and remitted profits paid to overseas
Relative prices				
116	pcnr	Deflator, base = 1	1	Market price of non-rental consumption
117	pidw	Deflator, base = 1	1	Market price of dwelling investment
118	pie	Deflator, base = 1	1	Market price of enterprise sector investment

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