LEADING INDEXES - DO THEY?

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* The views expressed herein and any remaining errors are our own and should not be attributed to our employer.

ABSTRACT

The two recently developed Australian indexes of leading indicators have received much attention in the press. Despite this, relatively little is known about their usefulness in forecasting the associated indexes of coincident indicators (i.e., measures of the business cycle) or any activity variables which move with the business cycle. Using the vector autoregression methodology and the related innovation accounting techniques, this paper evaluates the usefulness of the two leading indexes in forecasting these variables. We also examine the intertemporal relationships between the various variables to determine which (if any) of the variables the leading indexes in fact lead. The results indicate that the two leading indexes are quite useful in forecasting their associated indexes of the business cycle. One of the leading indexes is, however, a lagging indicator of its coincident index. The results for individual activity variables are mixed. The evidence suggests that the leading indexes are useful in forecasting GDP, an index of production and employment related variables. They are not useful in forecasting either retail sales or motor vehicle registrations.

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1. Introduction

Two indexes of leading indicators have recently been developed by the Melbourne Institute of Applied Economic and Social Research and the National Institute of Economic and Industry Research. Each is primarily intended as an aid to forecasting future movements in economic activity. Both have received much attention in the Australian press. This is partly due, no doubt, to the fact that both indexes appear to be signalling a downturn in the economy. Despite the attention paid to these indexes, relatively little appears to be known about their reliability or usefulness in forecasting the future path of economic activity.

A study conducted by the Office of the Economic Planning Advisory Council (EPAC) (1985) provides a brief evaluation of the index published by the Melbourne Institute, and of the usefulness of leading indicators in general. The major criticism of the Melbourne Institute's index made by EPAC was that the lead time between turning points in the leading index and turning points in the coincident index (an index that is designed to track the business, or reference, cycle) was highly variable. Moreover, the leading index failed on a number of occasions to pick turning points in the coincident index and occasionally signalled turning points that did not eventuate. These criticisms have also been made with respect to leading indexes in the US (see Ratti (1985) and Vaccara and Zarnowitz (1977)).

The EPAC paper also argued that there were three basic areas in which leading indexes were generally defficient. First, although the leading index may be of some use in forecasting the reference cycle, such a forecast may be of limited use to policy makers who are more concerned with the individual series which make up the reference cycle (e.g., employment and production).[1] Secondly, the leading index provides little or no information on the reasons behind movements. These are of considerable importance for policy makers. Thirdly, the reference cycle, which the leading index is devised to predict, does not contain a number of variables with which policy makers are concerned.

Much of the evaluation of the reliability of leading indexes in the literature has been based on a rather _ad hoc_ decision rule whereby two or three consecutive falls (rises) in the leading index signal a downturn (upturn) in

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1. The leading index may provide, however, a consistency check on forecasts of such series, since a set of forecasts for individual series implies a forecast for the reference cycle which can be compared to that provided by the leading index.

the reference cycle. This approach takes little account of the size of the falls in the index and one could argue that the variable lead times observed may be a result of the ad hoc decision rule rather than the properties of the leading indexes themselves. Neftci (1982) has attempted to formalise the decision rule into a probability framework by assuming that the leading index switches probability distributions prior to a turning point in the reference cycle (relying on the assumption of asymmetric business cycles). By setting a subjective probability threshold, a turning point is signalled when the probability that the leading index has switched distributions reaches this threshold. This technique has, however, received little attention in the literature.[2]

In general, these approaches to evaluating leading indexes assume that the model underlying the economy undergoes a discrete change when turning points occur, and that leading indexes are primarily of use in picking turning points. A more desirable method of evaluating the forecasting usefulness of leading indexes may be to look at the relationship between them and variables representing the business cycle at all points. Such an evaluation would show whether the indexes were valuable for forecasting per se rather than for forecasting turning points only. Of course, if standard forecasting techniques perform badly at turning points, and if leading indexes are useful at picking turning points, then such an analysis should show that leading indexes add to the forecasting power of more traditional techniques. A number of studies along these lines have been conducted for the US leading indicators (see Auerbach (1983), Vaccara and Zarnowitz (1977) and Weller (1979)). The general conclusion is that leading indexes may be useful for forecasting economic activity when these indexes are incorporated into distributed lag regressions.

The recently popularised vector autoregression (VAR) methodology (which may be thought of as a multivariate generalisation of the single equation distributed lag methodology) appears well suited to the evaluation of the forecasting ability of leading indexes.[3] In particular, the innovation accounting

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2. Palashi and Radecki (1985) is the only application of which we are aware. Attempts by a colleague to apply it to Australian data have been unsuccessful.

3. There has been a certain amount of controversy over the usefulness of VARs. In particular, the recent contribution of Cooley and LeRoy (1985) argues that they are of limited usefulness for policy analysis. However, all participants of this debate seem to agree that VARs are useful in the realm of forecasting.

techniques generally applied to VARs (in order to describe them succinctly) provide detailed information on the patterns and degrees of influence among variables in the VAR.

The aim of this paper is to use the VAR methodology to evaluate the forecasting usefulness of the two leading indexes published by the Melbourne and National Institutes. In particular, the ability of the indexes to forecast individual activity variables (e.g., employment and production) is examined to evaluate the EPAC criticism that these indexes are of limited use in forecasting individual activity variables. A number of small unrestricted VARs consisting of a leading index and a variable representing the business cycle, are estimated. Tests of "Granger-causality" (to determine the intertemporal timing relationships between variables) and the innovation accounting techniques are employed to examine the "usefulness" of leading indexes in forecasting future activity and to determine the lead times between movements in the leading index and movements in activity variables.

The paper begins with a brief discussion of the VAR methodology and, in particular, the innovation accounting techniques employed. The usefulness of each leading index in forecasting its own (or related) coincident index is evaluated in Section 3. The following section evaluates the ability of each index to help forecast individual activity series and, where appropriate, compares the two indexes. Finally, in Section 5, a summary of the main results and some concluding remarks are presented.

2. The VAR Methodology

In general we will be concerned with a (nxl) vector of n endogenous variables Y_t containing a leading index and (n-1) variables representing the business cycle, whether these be indexes of the business cycle (e.g., a coincident index) or variables that might be expected to move with the business cycle (e.g., employment). We assume that Y_t is generated by the following m^{th} order vector-autoregression

$$(1) \qquad Y_t = D_t + \sum_{j=1}^{m} B_j Y_{t-j} + \epsilon_t$$

where D_t is a (nxl) vector representing the deterministic component of Y_t (generally a polynomial in time), B_j are (nxn) matrices and ϵ_t is a (nxl) vector of multivariate white noise residuals (or innovations).

Equation (1) is specified and estimated as an "unrestricted reduced form". As is the hallmark of VARs, there are no exclusion restrictions within the B_j matrices. Rather, the B_j's are uniquely determined under the orthogonality conditions $E(\varepsilon_t) = 0$ and $E(Y_{t-j}\varepsilon_t) = 0$, $j=1, \ldots, m$, and are estimated by ordinary least squares. Since, in this paper, it is relatively straightforward to decide what variables should be in Y_t, the only pretesting involved with the fitting of equation (1) is in choosing the appropriate lag length m. In general we choose the smallest m such that ε_t is indistinguishable from a multivariate white noise process.[4]

Tests which are commonly applied to the VAR are tests for Granger-causality which test whether a variable, say Y_{1t} is useful in forecasting another variable, say Y_{2t}. Y_{1t} is said to be useful in forecasting Y_{2t} if the inclusion of lags of Y_{1t} in the equation for Y_{2t} significantly reduces the forecast variance. Thus it tests whether lags of Y_{1t} contain any additional information on Y_{2t} which is not already contained in the lags of Y_{2t} itself.

The model presented in equation (1) is difficult to describe in terms of the B_j coefficients. The best descriptive devices are the innovation accounting techniques suggested in Sims (1980, p.21) and described by Litterman (1979, pp.74-85). The first of these techniques of innovation accounting are the impulse response functions which describe the dynamic response of variables in the VAR to an impulse in one of the variables. To understand these impulse response functions, consider the moving average representation of equation (1), obtained by repeated back substitution for Y_{t-j}

$$(2) \qquad Y_t = D_t^* + \sum_{j=0}^{\infty} M_j \varepsilon_{t-j}$$

where M_j is a (nxn) matrix of moving average coefficients. The response of the i^{th} variable to a unit innovation in the k^{th} variable j periods earlier is given by the ik^{th} element of M_j. In general, however, there is likely to be some contemporaneous correlation among innovations, which is not taken into account in equation (2). By making an assumption about the contemporaneous causal ordering of the variables in Y_t (such that

4. On the basis of tests for within, and across, equation serial correlation. The inverse autocorrelation function (i.e., the autocorrelation function of the dual model) is used to test for non-stationarity of the residuals. (See, for example, Priestley (1981). All of the empirical work is done using the macro facilities of version 5 of SAS.

contemporaneous causality is one way, i.e., recursive) one can obtain orthogonalised innovations u_t where $u_t = G\varepsilon_t$, so that $E(u_t u_t') = \phi$ where ϕ is a diagonal (nxn) matrix. In this paper we always assume that the variable representing the business cycle does not contemporaneously cause the leading index. Thus if we order Y_t such that the leading index is the first variable then G will in general be of the form

$$G = \begin{vmatrix} 1 & 0 \\ -\rho & 1 \end{vmatrix}$$

where ρ is the estimated coefficient in the regression equation

$$\varepsilon_{2t} = \rho\varepsilon_{1t} + u_{2t}$$

ε_{1t} is the innovation in the leading index, ε_{2t} the innovation in the business cycle variable and u_{2t} the orthogonalised innovation in the business cycle variable (in the sense that it is orthogonal to $u_{1t} = \varepsilon_{1t}$).

In terms of orthogonalised innovations, u_t, the moving average representation is

$$Y_t = D_t^* + \sum_{j=0}^{\infty} M_j G^{-1} u_{t-j}$$

$$(3) \qquad = D_t^* + \sum_{j=0}^{\infty} A_j u_{t-j}$$

where the ikth element of A_j gives the response of variable i to an orthogonalised unit impulse in variable k, j periods earlier. Litterman (1979), however, notes that unit innovations may be difficult to interpret, especially when the standard errors of the innovations are very small. For this reason we calculate a scaled version of equation (3) which gives the response of the system to innovations of one standard error in size. The impulse response functions obtained from this scaled version provide information regarding the length of time it takes for shocks in the leading index to show up in the activity variable. Hence, they provide some idea of the lead time between a movement in the leading index and the associated subsequent movement in activity.

The second device of innovation accounting relates to the decomposition of the k-step ahead forecast variance of each variable in the VAR, into percentages contributed by the innovations in each variable. A variable whose <u>own</u> innovations account for all or most of its own forecast variance would be said to be exogenous (in the Sims sense) to the system. Thus, if the leading indexes are useful in forecasting business cycle variables, then the innovations in the leading index should account for a (subjectively) large percentage of the k-step ahead forecast variance of business cycle variables.

The k-step ahead forecast variance may best be seen by considering the k-step ahead forecast error induced by forecasting Y_t linearly from its own past

(4) $$Y_{t+k} - E_t(Y_{t+k}) = A_0 u_{t+k} + \ldots + A_{k-1} u_{t+1}$$

(in terms of orthogonalised innovations) where $E_t(Y_{t+k})$ is the linear least squares forecast of Y_{t+k} given all information at time t. The k-step ahead forecast variance is

(5) $$E[(Y_{t+k} - E_t(Y_{t+k}))(Y_{t+k} - E_t(Y_{t+k}))'] = A_0 \phi A'_0 + \ldots + A_{k-1} \phi A'_{k-1}$$

Because of the extensive orthogonality conditions built into the model, the k-step ahead forecast variance of each variable will be a weighted sum of the variances of the innovations to each variable. Thus we can obtain the percentage contribution of each variable's innovations to the variance of any other variable. Again, if the leading indexes are useful for forecasting activity variables at horizon k, their innovations will have a large contribution to the k-step ahead forecasting variance of these activity variables.

3. Forecasting the Coincident Indexes

In this section we consider the ability of each leading index to forecast its related coincident index, using the VAR methodology described above. In fitting the VARs in this paper all variables are included in levels.[5] Some adjustments for trends were, therefore, required and this was achieved by including polynomials in time.[6] Also since all the indexes were seasonally adjusted (as are all the other variables used later) no adjustments in terms of seasonal dummies were included. The data supported the absence of a residual seasonal pattern.

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5. VARs using growth rates and first differences were also estimated but gave essentially similar results.

6. At most a quadratic in time was required to induce stationarity in the residuals.

(a) Melbourne Institute's Leading Index (MILI)

The Melbourne Institute (MI) currently publishes three indexes. In addition to its leading index, a coincident index (MICI) and a lagging index (MILA) are also published. The coincident index is intended to track the reference cycle (or business cycle) while the lagging index is intended to confirm and clarify the pattern of recent economic activity.[7] All these indexes are available back to January 1956 on a monthly basis. The VAR relating these three indexes with each other was estimated over the whole period (with some adjustment for the lag length order of the VAR).[8] Fourteen lags (and a quadratic in time) were required to induce white noise residuals in the VAR. Tests for Granger-causality[9] among the variables provide a summary of the interdependence in the VAR and these are presented below in Table 1.

Table 1
Granger-Causal Ordering Test Results
(Marginal Significance Levels)*

Equation	Explanatory Variable		
	MILI	MICI	MILA
MILI	-	.0222	.0091
MICI	.0001	-	.0004
MILA	.0171	.0019	-

* The entries in this table give the marginal significance level of the test of the null hypothesis that the lags of one variable do not assist in predicting movements in another - i.e., each is the (minimum) level of significance that is required to reject the null hypothesis. Hence, a value of .0100 implies that the null hypothesis would be rejected at a level of significance $\geq$ 1%.

7. See, for instance, Boehm and Moore (1984).

8. This study was initiated in January 1986, so the last observation used is that published in January 1986. This corresponds to the October 1985 observation. We are grateful to Ernst Boehm (Melbourne University) for making these data available to us.

9. These are essentially F-tests of the joint hypothesis that the coefficients on all lags of a particular variable in a particular equation are zero. They should be interpreted as testing whether a particular variable is useful in forecasting another variable.

This table reveals a number of things. As could be expected from the definitions of the variables, there is highly significant intertemporal "causality" running from the leading index to the coincident index, and from the coincident index to the lagging index. Less intuitive, however, is the significant feedback from the lagging index into both the leading and coincident indexes. Moore and Shiskin (1978) suggest this might be the case because lagging indicators usually measure signs of excesses and imbalances (resulting from the cycle just experienced), and as such may be the first sign of developments bringing about a reversal in the leading indicators (and index) and hence in the level of activity. Although the tests presented in Table 1 suggest that the MI leading index is useful in forecasting the MI coincident index, a detailed examination of the innovation accounting for the VAR is required to reveal more about the horizon over which it is useful and the lead time between movements in the two indexes.

Variance decompositions for all variables in the VAR may be calculated. However, we are particularly concerned with that for the coincident index since we presume that the main interest in leading indexes is in their ability to forecast business cycle movements.[10] The variance decomposition for the coincident index is summarised in Table 2. Over horizons of eleven months or longer, innovations in the leading index account for more than 50 per cent of the unexpected variation in the coincident index. This again supports the usefulness of the leading index in forecasting the coincident index. Over horizons of 30 months or more, innovations in the lagging index account for 25 per cent of the variation in the coincident index. Since over such long horizons other variables (including the stance of policy) could be presumed to be of importance, the lagging index appears to be of little use in forecasting the coincident index.

Although one can obtain some guide as to the likely lead time between movements in the leading and coincident indexes from the above table, this can more easily be seen by considering the impulse response functions for a one standard error innovation in the leading index. These show the length of time it takes for an innovation in the leading index to feed through to the coincident and lagging indexes and hence provide a measure of the "typical" lead time between changes in the leading index and subsequent changes in the coincident index. Figure 1 shows the response of the system to an innovation

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10. In calculating the variance decompositions and impulse response functions we were required to make assumptions regarding the contemporaneous causal ordering of the three variables. They were recursively ordered as leading index, coincident index, lagging index.

Table 2
Decomposition of K-Step Forecast Variance of MICI

K	K-Step Forecast Variance	Per Cent Due to Innovations in: MILI	MICI	MILA
0	0.20	3.2	96.8	0
1	0.39	6.3	92.6	1.1
2	0.65	9.1	88.1	2.7
3	0.88	11.8	85.6	2.6
4	1.17	14.7	83.0	2.3
5	1.52	20.2	77.6	2.2
6	1.90	27.0	71.2	1.8
7	2.32	33.0	65.4	1.6
8	2.75	37.7	61.0	1.3
9	3.24	43.1	55.7	1.2
10	3.83	48.5	50.3	1.2
11	4.47	53.9	44.6	1.5
12	5.17	58.2	39.1	2.6
18	10.54	69.0	19.7	11.3
24	15.68	68.3	13.4	18.3
30	19.35	63.5	11.6	24.9
36	23.47	57.5	11.9	30.6

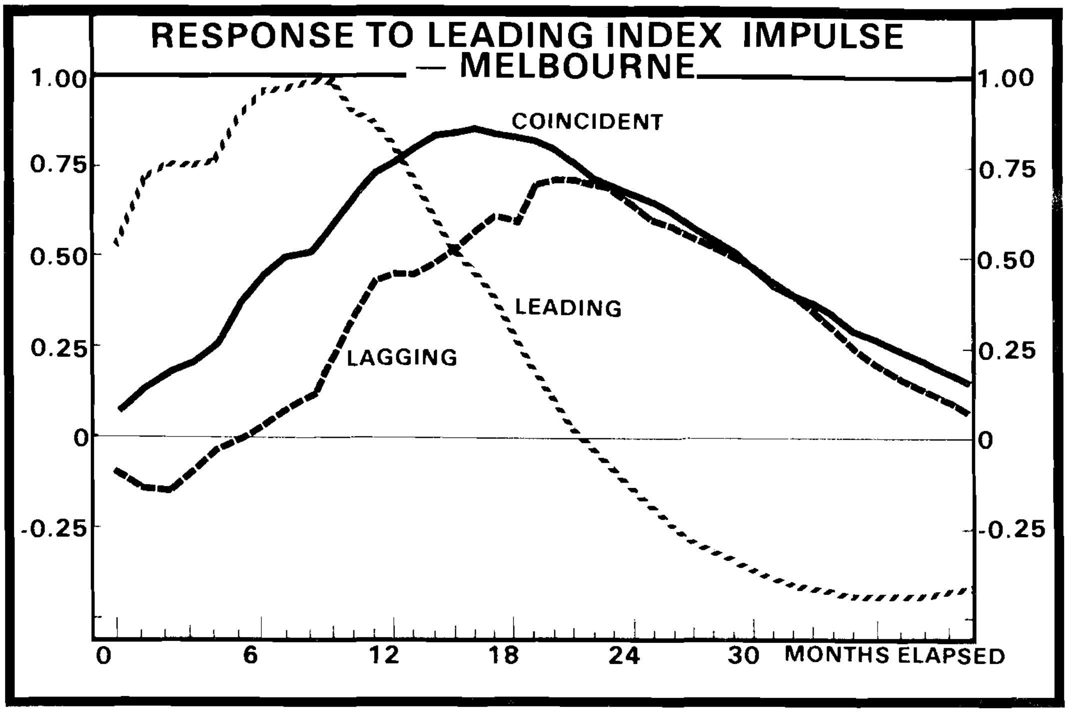

Figure 1. Melbourne Institute Coincident Index

in the leading index. As this figure shows, the turning points in the leading index appear to be roughly eight months prior to those in the coincident index. Hence one could expect an average eight month lead time.[11] However, since there is a three month lag in the publication of these indexes, there is effectively a five month informational lead time. Further, we note that the lagging index does appear to lag the coincident index, by about four to five months. Although not presented here, the other impulse response functions support these measures of the lead and lag relations among the variables.

(b) National Institute's Leading Index (NILI)

The National Institute (NI) currently publishes just two (Australia-wide) indexes. These are the leading index and a coincident index (NILI).[12] The indexes are available from September 1966 till the present, some ten years less data than is available for the MI indexes.[13] Again, the VAR relating these two indexes is estimated over the whole period allowing for initial conditions.

Fewer lags were required in this VAR to induce white noise residuals, than were required for the MI's indexes. The final model has nine lags. No trend terms were required to model the deterministic component since both of these indexes are already calculated as deviations from trend. The results of the tests for Granger-causality are presented in Table 3 below. These indicate that the variables exhibit significant feedback - i.e., each index significantly helps forecast the other.

Table 3
Granger-Causal Ordering Test Results
(Marginal Significance Levels)

Equation	Explanatory Variable	
	NILI	NICI
NILI	-	.0001
NICI	.0001	-

11. Note that here we are not concerned with the variability of the lead time but the typical or average lead time over the observed sample period.

12. The National Institute call their coincident index the "current index".

13. The last observation on the NI leading index was for August 1985 corresponding to a January 1986 publication date. However, since data for the NI coincident index was only available up till September 1984, this was taken as the last observation. We are grateful to Peter Smith (State Bank of Victoria) for making these data available to us.

Unfortunately, publicly available details of the construction of these NI indexes are rather sketchy.[14] It is, therefore, difficult to speculate on the reason for the highly significant feedback from the coincident index into the leading index.

The innovation accounting for this VAR was performed under the assumption that the coincident index does not contemporaneously cause the leading index (as assumed previously). Again we consider only the variance decomposition for the concident index. This is presented below in Table 4. As can be seen, the innovations in the leading index account for 50 per cent of the forecast variance for horizons of just four months and over - considerably less than the ten month horizon of the MI indexes. The largest contribution is at an 11 month horizon where 79 per cent of the variance comes from the leading index. Also notable in Table 4 are the sizes of the forecast variances of the MI coincident index which are considerably larger than for the MI coincident index. This suggests that it is easier to forecast MI's coincident index than NI's coincident index (although the usefulness of this is not clear because of the significant differences in the coincident indexes themselves).

These variance decompositions suggest that the lead time, or time taken for changes in the leading index to appear in the coincident index, may be considerably smaller than for the MI's indexes. This can be examined more clearly by looking at the response of these NI indexes to a one standard error innovation in the leading index. This impulse response function is shown in Figure 2. The length of time between turning points in the leading and coincident indexes is four months and hence considerably shorter than the ten months in the case of the MI index. Because there is a publication lag of five months for the NI's indexes, there is effectively an information lag of one month. That is, the most recently published NI leading index tells what happened to economic activity last month (assuming that the coincident index conveys a general picture of current activity).

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14. The only information that appears to be available is the appendix to a press release dated October 1985. This appendix lists some of the variables used to construct each index. However, it appears that many of the same variables are used in both indexes.

Table 4
Decomposition of K-Step Forecast Variance of NILI

K	K-Step Forecast Variance	Per Cent Due to Innovations in: NILI	NICI
0	9	9.8	90.2
1	20	13.6	86.4
2	36	25.9	74.1
3	44	38.0	62.0
4	56	50.5	49.5
5	70	60.4	39.6
6	86	67.7	32.3
7	105	72.9	27.1
8	120	75.2	24.8
9	133	77.2	22.8
10	143	78.3	21.7
11	153	79.1	20.9
12	163	78.9	21.1
18	221	70.2	29.8
24	251	63.1	36.9
30	281	64.5	35.5
36	317	67.9	32.1

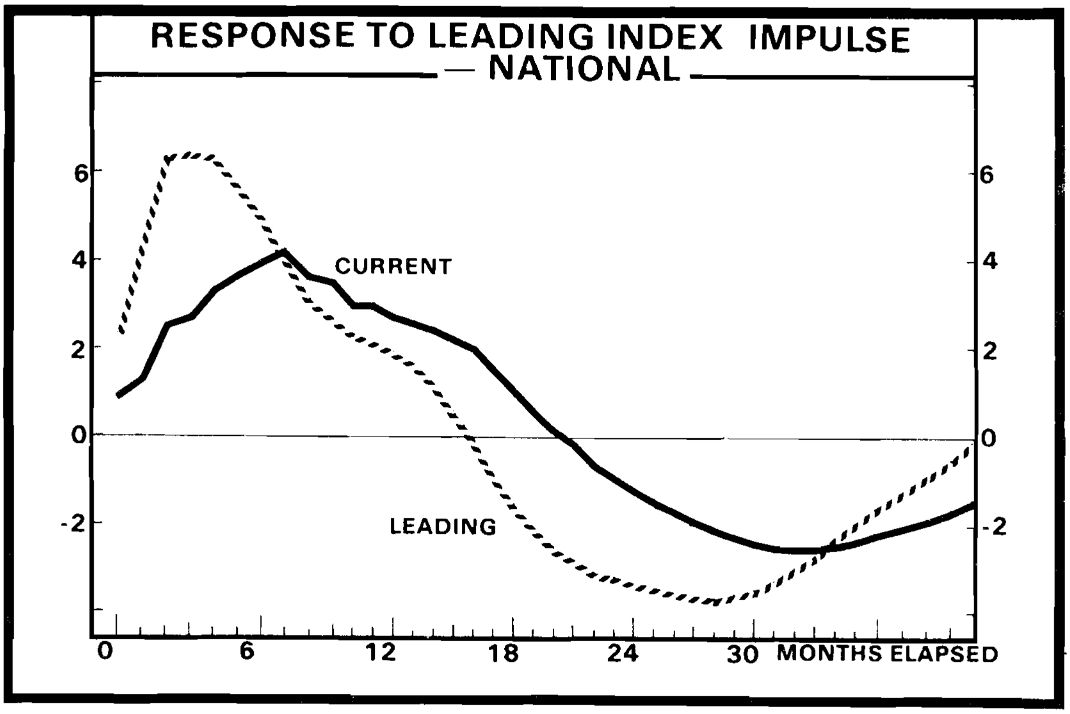

Figure 2. National Institute Current Index

(c) An Inter-Institute Comparison

The above results support the usefulness of each leading index in forecasting its related coincident index. Both the tests for causal ordering and the variance decompositions suggest that knowledge of the leading index can help to significantly reduce the error in forecasting the coincident indexes (below that obtained from using only the past values of the coincident index itself). However, of considerable importance is the timing of the relationships between the indexes. What does today's published movement in the leading index tell us about future business cycle movements? The results in this regard are mixed. On the one hand we find a typical five month information lead for MI's index while on the other we find a typical one month information lag for NI's index.[15]

These results for the National Institute's indexes raise questions about the relative timings of all the indexes. For example, is the shorter lead time for NI's leading index due to different timing of the two leading indexes or due to different timing of the two coincident indexes? Further analysis of VARs containing MI's leading index and NI's coincident index, and then with the converse combination, suggest that the difference is due to the different timing of the coincident indexes themselves. MI's leading index leads the NI's coincident index by four months (and hence there is an information lead of zero months), while for the converse combination (i.e., the NI leading index and MI coincident index) the lead time was eight to nine months. Further, NI's coincident index helps forecast MI's coincident index and appears to lead it by four months.

These results show some of the problems with coincident indexes, or any other measure of a concept as nebulous as the business cycle. Therefore an ability to forecast a coincident index may be of limited usefulness since these coincident indexes appear to be somewhat subjectively defined. Presumably, the leading indexes are only of use if they are able to provide information about the activity variables that move with the business cycle. We address this issue in the next section.

4. Forecasting Activity Variables

This section takes up the criticism that leading indexes may not be useful since (at best) they provide forecasts of coincident indexes of the business

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15. The VAR for the Melbourne Institute's indexes was re-estimated over the shorter sample used for the National Institute's indexes, and the lagging index dropped. The results were essentially the same.

cycle while policy makers are more concerned with individual series. We evaluate the validity of this criticism by considering the ability of the two leading indexes to forecast individual activity series. Unfortunately, we are somewhat limited by the availability of series, since we require them to be on a monthly basis in order to get an accurate estimate of the leads and lags involved. The activity variables chosen are retail sales, motor vehicle registrations, the ANZ index of industrial production, total employment and the inverse of the unemployment rate. One would expect all these variables to move contemporaneously with the business cycle.[16]

A number of two variable VARs consisting of a leading index and an activity variable were estimated. Again because the activity variables (and leading indexes) were seasonally adjusted, no adjustment for seasonality was required when fitting the VARs, although some adjustments for trends were made by the inclusion of the appropriately ordered polynomial in time.[17] The characteristics of these estimated VARs are described below. A comparison is also provided, in which both leading indexes and an activity variable are included in a VAR to determine whether either index dominates the other in terms of its contribution to the forecast variance of the activity variable.

(a) Retail Sales and Motor Vehicle Registrations

The results for the leading indexes' ability to forecast these activity variables are fairly similar and thus reported together. In sum, neither leading index helps forecast either retail sales or motor vehicle registrations.[18] That is, any information embodied in the leading indexes which may be relevant to forecasting these variables, is dominated by the information embodied in the lags of the variables themselves. Retail sales is in fact almost perfectly correlated with its own lags, so that the addition of lags of the leading indexes to the equation does not significantly reduce the forecast error variance. Even though motor vehicle registrations was not

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16. Boehm and Moore (1984) identify all these variables as ones that move with the cycle. Variable definitions and data sources are listed in the Appendix B. Appendix A contains the results of an analysis of the ability of the leading indexes to forecast quarterly GDP. These results, however, need to be interpreted with care because of the intertemporal smoothing involved in moving from the monthly leading indexes to quarterly series.

17. A second order, or lower, polynomial.

18. All four VARs required nine lags and a quadratic in time and were estimated over the period September 1966 to September 1984.

highly correlated with its own lags, the leading indexes do not significantly reduce the forecast error variance.[19] This can be seen from Table 5 below, which displays the marginal significance levels for tests of Granger-causality in the four VARs.

Table 5
Granger-Causal Ordering Test Results
(Marginal Significance Levels)

Equation	Explanatory Variables: Retail Sales	Explanatory Variables: MILI	Equation	Explanatory Variables: Retails Sales	Explanatory Variables: NILI
Retail Sales	-	.6472	Retail Sales	-	.2903
MILI	.0003	-	NILI	.3827	-
	Registrations	MILI		Registrations	NILI
Registrations	-	.1890	Registrations	-	.1658
MILI	.5877	-	NILI	.3479	-

One cannot reject the null hypotheses that neither leading index Granger causes either activity variable, at even a 15 per cent level of significance. Although not presented here, the variance decompositions and impulse response functions are in agreement with this result that neither of the two leading indexes is useful in forecasting motor vehicle registrations or retail sales.[20]

(b) ANZ Production Index

The ANZ index is a monthly, seasonally adjusted index of industrial production; data are available back to September 1966. The VAR containing MI's leading index and the ANZ production index required six lags plus a quadratic trend component, while the one involving National's leading index required eight lags and a linear trend component. Table 6 contains the results for the Granger-causality tests in these two VARs.

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19. In fact the equation explaining motor vehicle registrations was quite poor with an R^2 of 0.7 as compared to the R^2's of approximately 1.0 obtained for all other equations in this study.

20. A possible reason for the inability of the leading indexes to forecast retail sales could be due to the fact that only a nominal retail sales series is available; movements in inflation could be masking the cyclical behaviour of real retail sales.

Table 6
Granger-Causal Ordering Test Results
(Marginal Significance Levels)

Equation	Explanatory Variables Production	MILI	Equation	Explanatory Variables Production	NILI
Production	-	.0001	Production	-	.0014
MILI	.1038	-	NILI	.9972	-

The significance levels in Table 6 clearly indicate that there is strong one way Granger-causality running from each leading index to the ANZ index. It appears that this may be slightly stronger in the case of MI's leading index. Therefore, the leading indexes may be useful with respect to forecasting future levels of production (as measured in the ANZ index).

The decompositions of the forecast variances for the production index in the two VARs are presented in Tables 7 and 8. In both cases, for horizons of nine months or more at least 25 per cent of the forecast variance is contributed by innovations in the leading indexes. For slightly longer horizons of thirteen months in the case of MI's leading index and seventeen months for NI's leading index, over 50 per cent of the forecast variance comes from the leading index. Both of these results confirm that the leading indexes help to forecast the production index. One may also compare the relative merits of the two indexes by considering the relative sizes of the forecast variances. Tables 7 and 8 clearly indicate that the forecast variance is considerably lower when using MI's leading index than when NI's index is used. A measure of the lead time in the relationship between each index and the production index can be observed in the impulse response functions (for one standard error innovations in each leading index) presented in Figures 3 and 4. From Figure 3, it can be seen that the lead time for MI's leading index is quite small at about five months.[21] By comparison, Figure 4 indicates that NI's leading index leads the production index by about eleven months. It is also interesting to note that much larger movements are required in the NI index, than in the MI index, to generate a given movement in production.

21. Although it is slightly difficult to judge in the case of the first peak, since the leading index reaches a small turning point before turning completely at about six months after the impulse. The turning point at the trough is better defined.

Table 7
Decomposition of K-Step Forecast Variance of Production
Melbourne Institute

K	K-Step Forecast Variance	Per Cent Due to Innovations in: MILI	Production
0	2.69	1.3	98.7
1	2.94	1.2	98.8
2	3.25	1.8	98.2
3	3.42	1.8	98.2
4	3.62	1.7	98.3
5	3.81	4.9	95.1
6	4.05	10.0	90.0
7	4.38	16.5	83.5
8	4.74	22.8	77.2
9	5.17	29.3	71.7
10	5.72	36.1	73.9
11	6.36	42.3	57.7
12	7.03	47.6	52.4
18	10.50	62.5	37.5
24	11.80	63.7	36.3
30	12.05	63.3	36.7
36	12.87	65.6	34.4

Table 8
Decomposition of K-Step Forecast Variance of Production
National Institute

K	K-Step Forecast Variance	Per Cent Due to Innovations in: MILI	Production
0	3.04	0.2	99.8
1	3.55	0.2	99.8
2	4.20	1.4	98.6
3	4.88	3.2	96.8
4	5.80	5.4	94.6
5	6.60	7.2	92.8
6	7.72	11.0	89.0
7	8.84	16.0	84.0
8	10.13	21.5	78.5
9	11.45	26.1	73.9
10	12.86	30.5	69.5
11	14.34	34.7	65.3
12	15.87	38.5	61.5
18	24.57	53.1	46.9
24	29.88	57.7	42.3
30	31.79	57.9	42.1
36	32.41	57.1	42.9

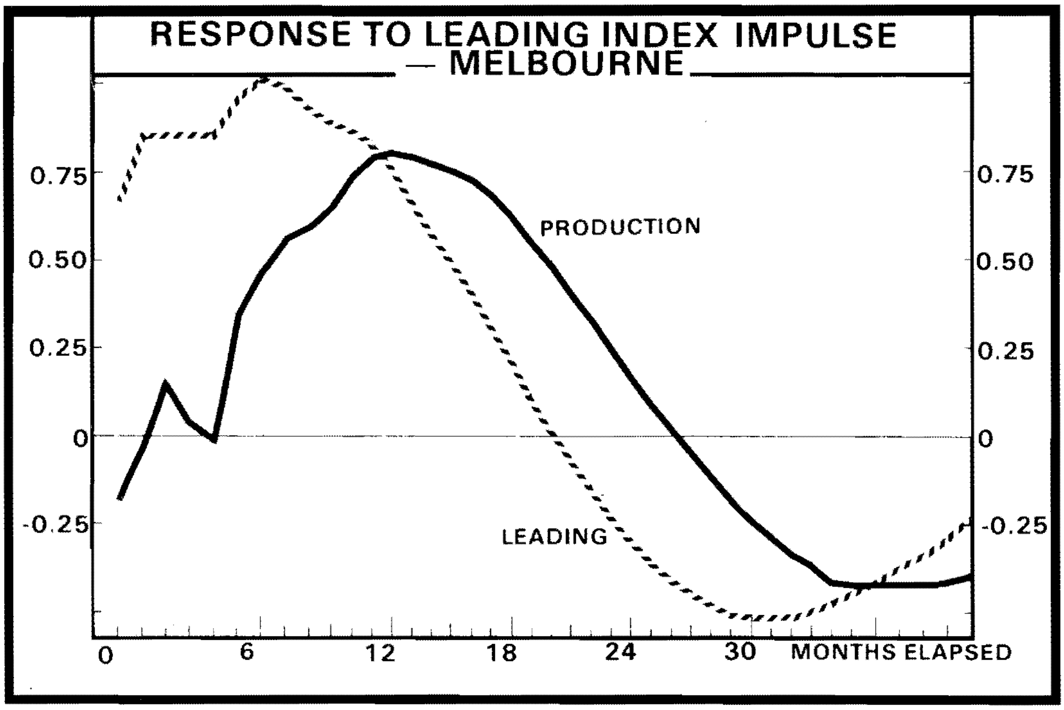

Figure 3. Production Index - Melbourne

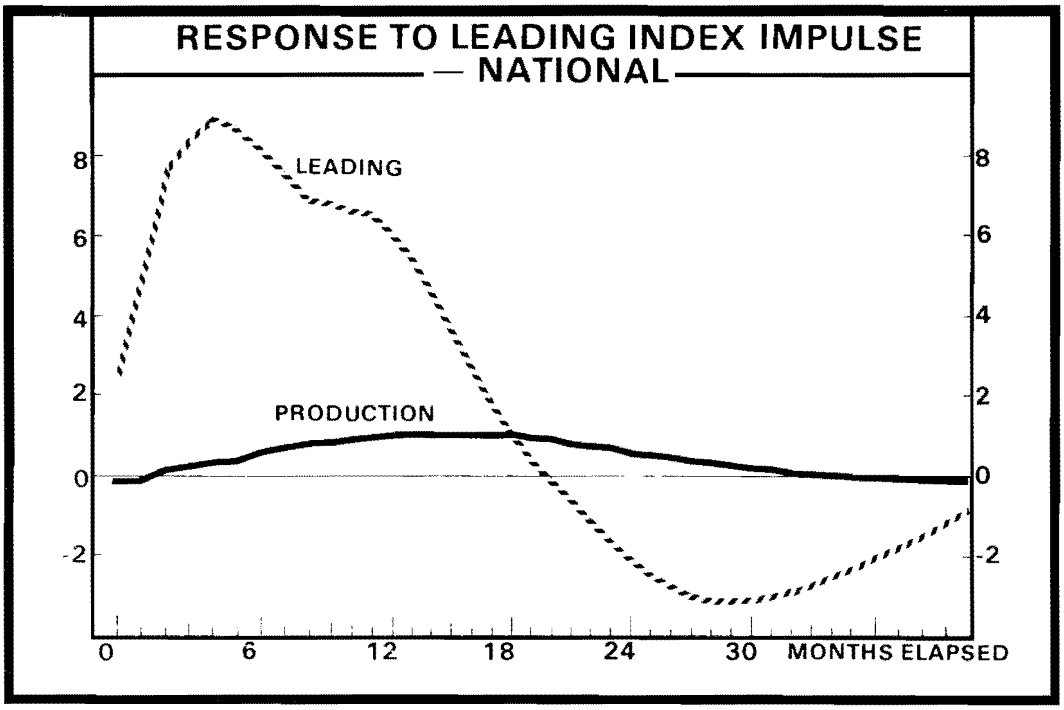

Figure 4. Production Index - National

In terms of the informational lead times, these results indicate a two month informational lead time in the case of MI's index, and a six month informational lead for the NI's index.

(c) Employment and the Unemployment Rate

The final two activity variables we consider are employment and the inverse of the unemployment rate - it is inverted to obtain a procyclical variable.[22] Because the publication of these data has been on a monthly basis only since February 1978, the sample size used for the VARs containing these variables and the leading indexes is considerably smaller than previously. Before allowance is made for initial conditions, there are 80 observations compared with the 217 observations used for the previous three activity variables. Hence, the results using these employment variables should be viewed more cautiously.

In fitting these VARs only three or four lags and a linear trend were required to produce multivariate, white-noise residuals. Results for Granger-causal ordering tests for all four estimated VARs are presented in Table 9. These indicate that each leading index is useful in forecasting each employment related variable in the sense that each leading index significantly Granger-causes them. Further, there is evidence of feedback from each employment related variable into each leading index.

Table 9
Granger-Causal Ordering Test Results
(Marginal Significance Levels)

Equation	Explanatory Variables		Equation	Explanatory Variables	
	Unemployment	MILI		Unemployment	NILI
Unemployment	-	.0005	Unemployment	-	.0001
MILI	.0001	-	NILI	.0069	-
	Employment	MILI		Employment	NILI
Employment	-	.0001	Employment	-	.0001
MILI	.0005	-	NILI	.0084	-

22. Note that we have scaled these variables. Employment is in units of one hundred thousand while the inverse of the unemployment rate has been multiplied by one hundred.

The variance decompositions for the forecast variance in the employment related variables are presented in Tables 10 through 13. They show the strength of the intertemporal causality from the leading indexes to the employment variables. In all cases, 50 per cent of the forecast variance in the employment variables comes from innovations in the leading indexes for horizons of one year and longer. With respect to both employment variables, the leading index published by the NI appears to yield a marginally lower forecast variance. This suggests that this leading index may provide more information on the future movements in employment than MI's index provides.

The impulse response functions (for one standard error impulses in the leading indexes) presented in Figures 5 through 8 indicate a lead time of approximately one year for each of the four VARs estimated. Thus, there is approximately a seven month informational lead time for the employment variables provided by the NI leading index, while the MI leading index yields a nine month informational lead time. Note again, however, that much larger movements in the NI index, than in the MI index, are required to induce a given movement in these employment variables.

(d) An Inter-Institute Comparison

We have demonstrated thus far that the leading indexes appear to be useful with respect to forecasting some activity variables that are coincident with the business cycle (the ANZ production index, employment and the unemployment rate inverted) and not very useful for others (motor vehicle registrations and retail sales). A comparison of the relative sizes of the forecast variance (in the activity variables) each index produced suggested that neither index was uniformly superior to the other. A more formal comparison of the two indexes may be obtained by nesting them in a composite VAR. This consists of both leading indexes and the relevant activity variable to determine which one dominates the other in terms of the Granger-causal ordering tests or the percentage contributions to the forecast variance of the activity variables.[23]

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23. These results should, however, be viewed with some caution. These tests may lack power due to multicollinearity of the two leading indexes.

Table 10
Decomposition of K-Step Forecast Variance of Unemployment
Melbourne Institute

K	K-Step Forecast Variance	Per Cent Due to Innovations in: MILI	Unemployment
0	0.14	1.9	98.1
1	0.24	2.5	97.5
2	0.31	3.0	97.0
3	0.39	5.1	94.9
4	0.46	8.8	91.2
5	0.53	13.2	86.8
6	0.61	18.0	82.0
7	0.68	23.1	76.9
8	0.75	28.4	71.6
9	0.83	33.6	66.4
10	0.90	38.5	61.5
11	0.97	43.0	57.0
12	1.04	47.0	53.0
18	1.47	58.4	41.6
24	1.81	53.8	46.2
30	2.05	48.3	51.7
36	2.26	49.9	50.1

Table 11
Decomposition of K-Step Forecast Variance of Unemployment
National Institute

K	K-Step Forecast Variance	Per Cent Due to Innovations in: MILI	Unemployment
0	0.13	0.4	99.6
1	0.20	1.5	98.5
2	0.24	2.0	98.0
3	0.27	3.3	96.7
4	0.31	4.9	95.1
5	0.34	8.0	92.0
6	0.38	12.7	87.3
7	0.42	18.9	81.1
8	0.46	25.9	74.1
9	0.52	33.0	67.0
10	0.58	39.7	60.3
11	0.64	45.6	54.4
12	0.71	50.6	49.4
18	1.15	62.6	37.4
24	1.51	57.3	42.7
30	1.68	52.0	48.0
36	1.85	54.6	45.4

Table 12
Decomposition of K-Step Forecast Variance of Employment
Melbourne Institute

K	K-Step Forecast Variance	Per Cent Due to Innovations in: MILI	Employment
0	.035	0.7	99.3
1	.049	0.9	99.1
2	.064	0.7	99.3
3	.077	1.8	98.2
4	.091	4.9	95.1
5	.105	9.5	90.5
6	.119	15.3	84.7
7	.135	21.9	78.1
8	.152	28.9	71.1
9	.171	35.8	64.2
10	.191	42.3	57.7
11	.212	48.1	51.9
12	.235	53.1	46.9
18	.375	66.8	33.2
24	.469	63.5	36.5
30	.513	58.8	41.2
36	.560	60.4	39.6

Table 13
Decomposition of K-Step Forecast Variance of Employment
National Institute

K	K-Step Forecast Variance	Per Cent Due to Innovations in: MILI	Employment
0	.030	3.0	97.0
1	.037	4.0	96.0
2	.043	5.6	94.4
3	.045	5.7	94.3
4	.050	5.2	94.8
5	.055	6.9	93.1
6	.061	11.8	88.2
7	.070	19.6	80.8
8	.081	28.2	71.8
9	.094	36.8	63.2
10	.109	44.5	55.5
11	.124	51.3	48.7
12	.141	57.0	43.0
18	.256	75.1	24.9
24	.331	75.6	24.4
30	.357	71.9	28.1
36	.400	72.5	27.5

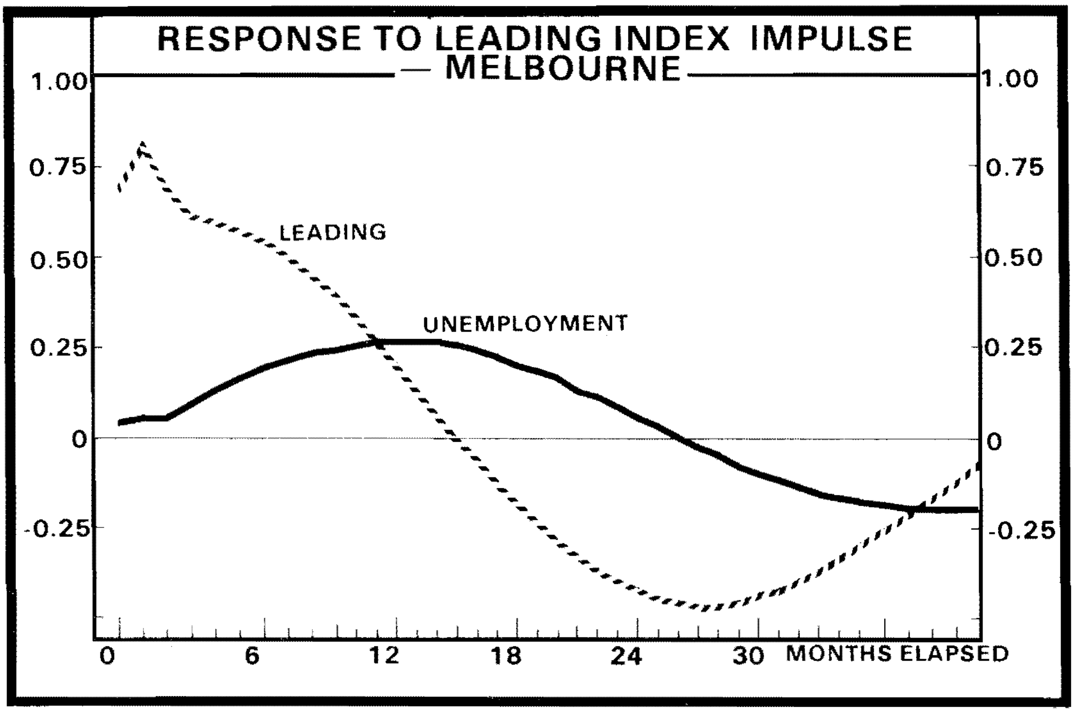

Figure 5. Unemployment - Melbourne

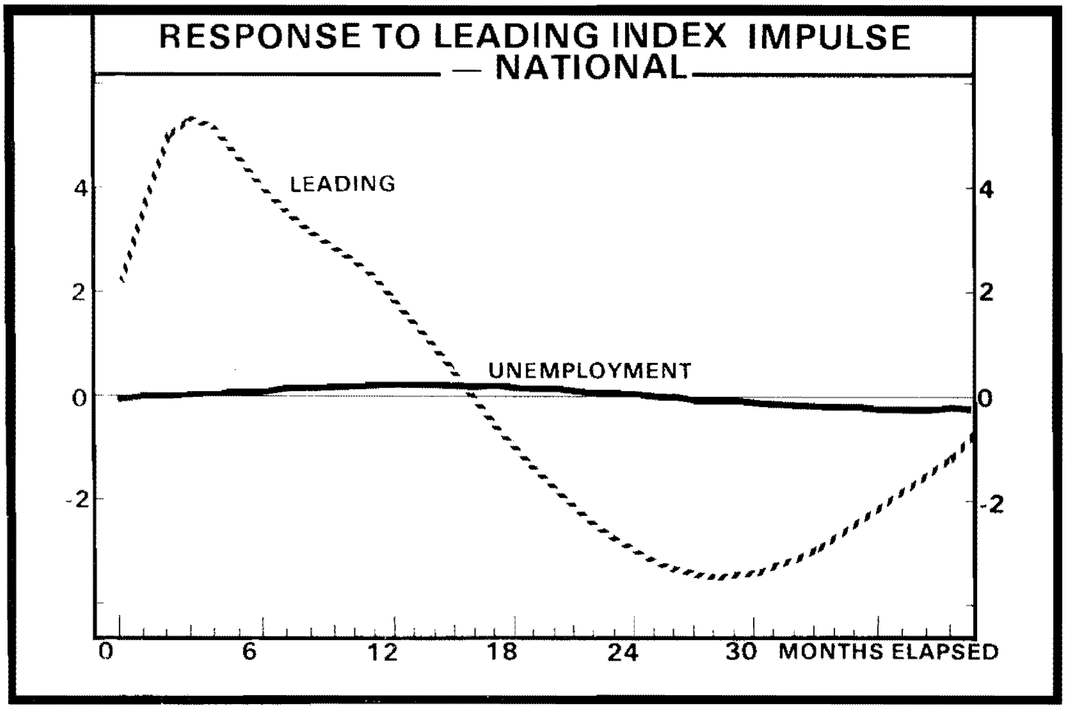

Figure 6. Unemployment - National

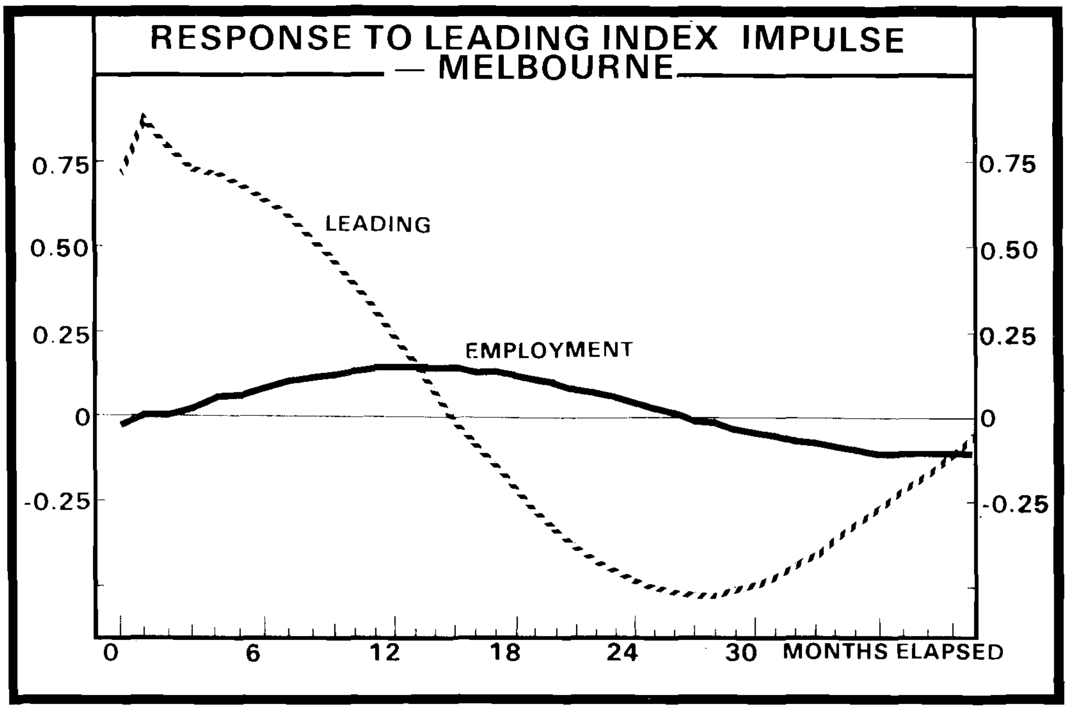

Figure 7. Employment - Melbourne

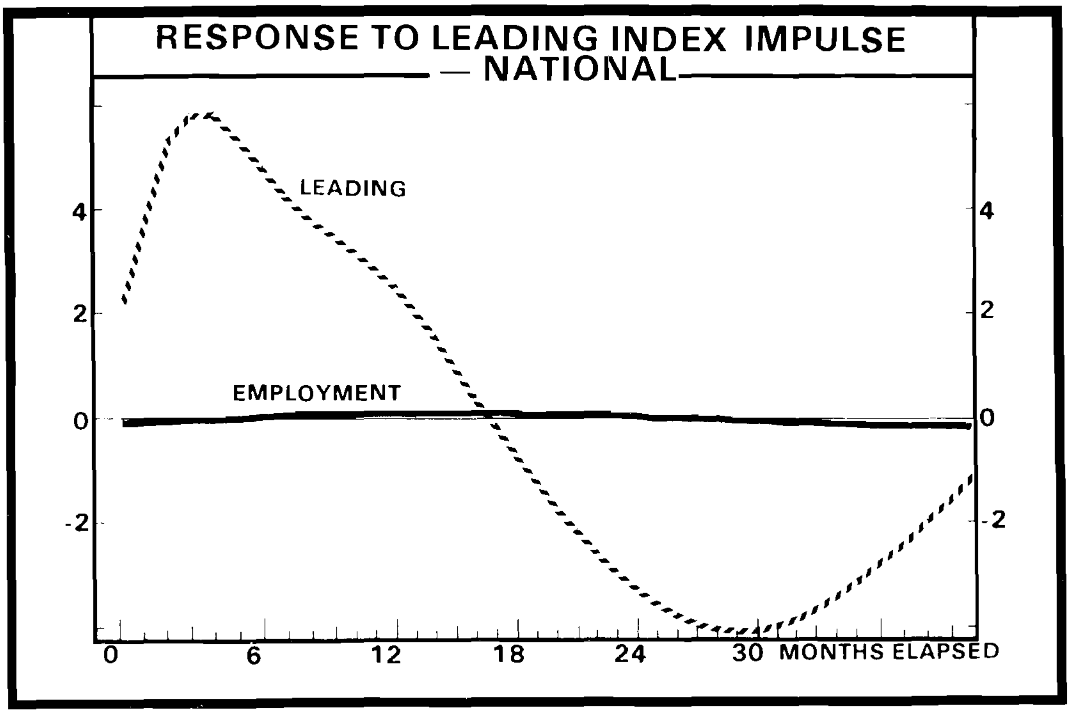

Figure 8. Employment - National

We only consider the three variable VARs for those activity variables that the leading indexes were found to be useful in forecasting - the ANZ production index, employment and the unemployment rate (inverted). For the ANZ production index eight lags and a quadratic trend component was required. The results of the Granger-causal ordering tests are provided below in Table 14.

Table 14
Granger-Causal Ordering Test Results
(Marginal Significance Levels)

Equation	Explanatory Variable		
	Production	MILI	NILI
Production	-	.0019	.8023
MILI	.9787	-	.1180
NILI	.2199	.0023	-

Since we are most concerned with forecasting production, the figures in the first row are the most important. They clearly indicate that MI's index dominates NI's in terms of Granger-causing the ANZ index. Indeed, once the information contained in the lags of the production index and the MI leading index has been utilised, there is no role for the information contained in the lags of the NI leading index.

In considering the decomposition of the forecast variance of the production index into contributions made by innovations in the two leading indexes, we are faced with the problem of choosing which leading index contemporaneously causes the other.[24] To overcome this, we present the variance decompositions obtained under each of the two possibilities. These are presented in Table 15. In both cases MI's leading index contributes a greater percentage of the forecast variance of production. Thus, on the basis of these results (and the earlier ones obtained from the two variable VARs), it would seem that MI's index is superior to the NI index for forecasting industrial production.

For the employment related variables both three variable VARs required four lags and a linear trend component. The results of Granger-causal ordering tests are presented for both models in Table 16 below.

24. This problem did not occur previously because of the natural assumption that the leading index was contemporaneously exogenous to the activity variable.

Table 15
Decomposition of K-Step Forecast Variance of Production

		Percent Due to innovations in:				
		Ordering 1		Ordering 2		
K	K-Step Forecast Variance	MILI	NILI	NILI	MILI	Production
0	2.62	1.2	0.1	0.2	1.1	98.7
1	2.87	1.4	0.7	0.9	1.2	97.9
2	3.15	1.5	1.0	1.3	1.2	97.5
3	3.30	1.5	1.2	1.4	1.2	97.3
4	3.50	1.6	1.4	1.6	1.5	97.0
5	3.63	2.9	1.8	2.2	2.5	95.3
6	3.87	6.3	3.4	4.5	5.2	90.2
7	4.17	10.7	5.3	7.2	8.7	84.0
8	4.53	15.0	7.7	10.6	12.0	77.3
9	4.96	19.5	9.9	13.8	15.6	70.6
10	5.51	24.5	11.9	16.8	19.7	63.5
11	6.14	29.4	13.6	19.3	23.6	57.1
12	6.81	33.4	15.0	21.5	26.9	51.6
18	10.25	44.0	20.2	28.9	35.3	35.8
24	11.53	44.4	21.6	30.6	35.4	34.0
30	11.75	44.4	21.5	30.4	35.4	34.3
36	12.51	46.4	21.4	30.6	37.3	32.1

Table 16
Granger-Causal Ordering Test Results
(Marginal Significance Levels)

Equation	Explanatory Variable		
	Unemployment	MILI	NILI
Unemployment	-	.7086	.0652
MILI	.0038	-	.0131
NILI	.1370	.0201	-
	Employment	MILI	NILI
Employment	-	.4017	.0464
MILI	.0096	-	.0026
NILI	.0559	.2924	-

The figures in the first rows of the two sections of the table indicate the dominance of NI's leading index. However, this dominion is not as pronounced as the dominion by MI's index for the production index. The variance decompositions for the employment variables (again produced for both possible directions of contemporaneous causation between the leading indexes) presented in Tables 17 and 18 also show the dominance of NI's index. Innovations in the NI's index contribute a much higher percentage of the forecast variance for

Table 17
Decomposition of K-Step Forecast Variance of Unemployment

K	K-Step Forecast Variance	Percent Due to innovations in: Ordering 1 MILI	NILI	Ordering 2 NILI	MILI	Unemployment
0	.125	0.2	0.6	0.4	0.3	99.3
1	.191	0.2	2.5	2.2	0.5	97.3
2	.234	0.6	3.7	3.0	1.4	95.6
3	.267	0.6	5.6	4.7	1.6	93.7
4	.299	0.6	7.9	7.0	1.5	91.6
5	.334	0.5	11.4	10.5	1.4	88.1
6	.370	0.5	16.0	15.1	1.4	83.5
7	.410	0.5	21.7	20.9	1.4	77.8
8	.453	0.7	27.7	27.1	1.3	71.6
9	.499	1.1	33.4	33.3	1.1	65.5
10	.545	1.6	38.3	38.9	1.1	60.0
11	.591	2.4	42.3	43.6	1.1	55.3
12	.638	3.2	45.3	47.3	1.2	51.5
18	.933	9.2	47.0	52.4	3.8	43.8
24	1.228	12.0	37.6	42.9	6.6	50.5
30	1.456	11.2	34.5	38.4	7.3	54.3
36	1.642	10.3	39.5	43.1	6.6	50.3

Table 18
Decomposition of K-Step Forecast Variance of Employment

K	K-Step Forecast Variance	Percent Due to innovations in: Ordering 1 MILI	NILI	Ordering 2 NILI	MILI	Employment
0	.028	6.7	1.7	3.5	4.9	91.6
1	.034	8.8	3.1	5.7	6.1	88.1
2	.040	12.5	3.8	7.4	8.9	83.7
3	.045	17.5	3.6	7.7	13.4	78.9
4	.051	17.4	3.3	6.9	13.8	79.3
5	.054	16.3	5.0	8.2	13.1	78.7
6	.059	15.2	9.0	12.0	12.1	75.9
7	.065	13.8	14.9	17.6	11.1	71.3
8	.073	12.5	21.2	23.8	10.0	66.3
9	.082	11.7	28.0	30.9	8.8	66.3
10	.092	11.7	34.2	37.9	8.0	54.1
11	.104	12.1	39.7	44.4	7.4	48.2
12	.117	12.9	44.1	49.9	7.1	43.0
18	.210	20.2	54.7	66.0	8.9	25.1
24	.282	24.9	51.4	64.4	11.9	23.7
30	.311	25.2	47.5	59.7	13.0	27.3
36	.345	23.5	50.0	61.5	11.9	26.6

unemployment at all horizons than the contribution of MI's index. Again, this agrees with the earlier observation that the NI's index produced a lower forecast variance for this variable than did MI's index. However, for forecasting employment, the NI leading index only dominates the MI leading index at horizons longer than six months.

5. Conclusion

In this paper we have attempted to evaluate the usefulness, for forecasting the business cycle and related variables, of the leading indexes published by the Melbourne and National Institutes. The methodology involved the estimation of a number of small unrestricted vector autoregression models and the use of the related innovation accounting techniques.

The results indicate that each leading index contains information that is useful for forecasting its own or related coincident index, in the sense of significantly reducing the forecast variance. Large differences in the lead times were observed, with the Melbourne Institute's leading index leading its coincident index by ten months and the National Institute's leading index leading its coincident index by just four months. Lags in the publication of these two leading indexes reduce the informational or effective lead times by three or five months. In the case of the National Institute's leading index this results in an informational lag of one month - i.e., the leading index they publish this month tells us about the business cycle last month. It was argued on the basis of further results, however, that this was due more to differences in the two coincident indexes rather than in the leading indexes themselves.

Partly because of this, and partly because of the nebulous nature of any single measure of the business cycle, we also considered whether the leading indexes were useful for forecasting individual activity variables that move procyclically. The results indicate that the leading indexes may be of some use in forecasting these individual activity series. Both leading indexes help forecast the ANZ index of industrial production, employment and (the inverse of) unemployment; although neither helps forecast motor vehicle registrations or retail sales.

However, there did not appear to be a consistent lead time between either leading index and each activity variable. This, along with the different timings of the coincident indexes, highlight the difficulties one faces in trying to obtain a single measure of the business cycle and, therefore, a single measure of future movements in this cycle.

The results of a comparison of the two leading indexes offered no firm support for the dominance of one index over the other. The Melbourne Institute's index greatly outperformed the National Institute's index with regard to forecasting the production index[25] while the reverse was true (in a weaker form) for the employment related variables. The one constant factor, however, was that a given movement in these activity variables is associated with a much larger movement in today's National Institute leading index, than in today's Melbourne Institute leading index.[26]

Finally, a word of caution. All of these results have been in terms of the extent to which the information in the lags of a leading index is a useful supplement to the information incorporated in the lags of variable being forecast. However, whether the leading indexes provide additional information over and above that which is normally used to provide forecasts is an open question. Further work involving _ex-ante_ forecasting with leading indexes compared to traditional forecasts and actual outcomes may be able to shed some light on this issue.

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25. The results for quarterly non-farm GDP, presented in Appendix A, are similar to those for the production index.

26. These results probably reflect the different methodologies the two institutes use in constructing their leading and coincident indexes. Unfortunately not enough details of these methodologies are available to enable a comparison to be made.

APPENDIX A

FORECASTING GROSS DOMESTIC PRODUCT

The above analysis of the leading indexes ability to predict activity variables has been restricted to monthly variables that are coincident with the business cycle. Clearly, the one variable that most would regard as the best univariate measure of the business cycle is real (non-farm) gross domestic product (GDP).[27] Unfortunately, this variable is available only on a quarterly basis. Since the leading indexes are monthly series, some assumptions on the intertemporal movements of one of the variables must be made in order to use the leading indexes to forecast GDP. One possibility involves the use of an interpolative procedure to produce a monthly GDP series. However, this requires fairly strong assumptions on the within quarter pattern of GDP. Our preferred procedure is to aggregate the monthly leading index series into quarterly series. Since we regard these leading indexes as flow variables, the appropriate aggregation method is to sum the values of the three months within each quarter.

The resulting quarterly leading indexes were then incorporated into VAR's with real non-farm gross domestic product (seasonally adjusted) for the period 1966IV - 1984III. The VAR containing M1's leading index required three (quarterly) lags and a linear time trend, while the one involving the NI's leading index required four (quarterly) lags and no time trend. Table A1 contains the Granger-causality tests in these two VAR's.

Table A1
Granger-Causal Ordering Test Results
(Marginal Significance Levels)

Equation	Explanatory Variable		Equation	Explanatory Variable	
	GDP	M1LI		GDP	NILI
GDP	-	.0781	GDP	-	.0268
M1LI	.5506	-	NILI	.0276	-

The significance levels clearly indicate one way Granger-causality running from the M1 leading index to GDP and feedback effects between the N1 leading index and GDP. Hence these two leading indexes help predict GDP.

27. Real (non-farm) GDP has been scaled to be in units of billions of dollars.

The extent of this assistance may be gauged from the decompositions of the forecast variances for GDP presented in Tables A2 and A3. In both cases the forecast variances are of a similar magnitude. However, the MI leading index clearly out-performs the NI leading index in terms of explanatory power. For horizons of three quarters (i.e., nine months) or more, the Melbourne index explains over thirty per cent of the forecast variance of GDP. The National index accounts for just over ten per cent of the forecast variance over horizons of a year or more.

The impulse response functions are presented in Figures A1 and A2. These suggest that movements in the MI index lead movements in GDP by one to two quarters, while the lead time for the NI index is about three quarters. The implied informational lead times are hence a quarter or less for the MI index and one to two quarters for the NI index. As could be expected from the previous results, a given movement in GDP is associated with a much larger prior movement in the National index than in the Melbourne index.

While these results need to be interpreted with caution due to the intertemporal assumptions required, they do serve to re-enforce the earlier result that the Melbourne index is superior to the National index in forecasting movements in production.

Table A.1

Decomposition of K-Step Forecast Variance of GDP

Melbourne Institute

K	K-Step Forecast Variance	Per Cent Due to Innovations in: MILI	GDP
0	.07	15.5	84.5
3	.12	27.6	72.4
6	.16	32.4	67.6
9	.20	37.7	62.3
12	.24	41.8	58.2
18	.30	46.8	53.2
24	.33	48.5	51.5
30	.34	48.6	51.4
36	.34	48.3	51.7

Table A.2

Decomposition of K-Step Forecast Variance of GDP

National Institute

K	K-Step Forecast Variance	Per Cent Due to Innovations in: NILI	GDP
0	.07	.3	99.7
3	.12	2.4	97.6
6	.15	5.0	95.0
9	.19	8.5	91.5
12	.22	13.1	86.0
18	.29	16.4	83.6
24	.33	16.0	84.0
30	.37	14.3	85.7
36	.42	12.9	87.1

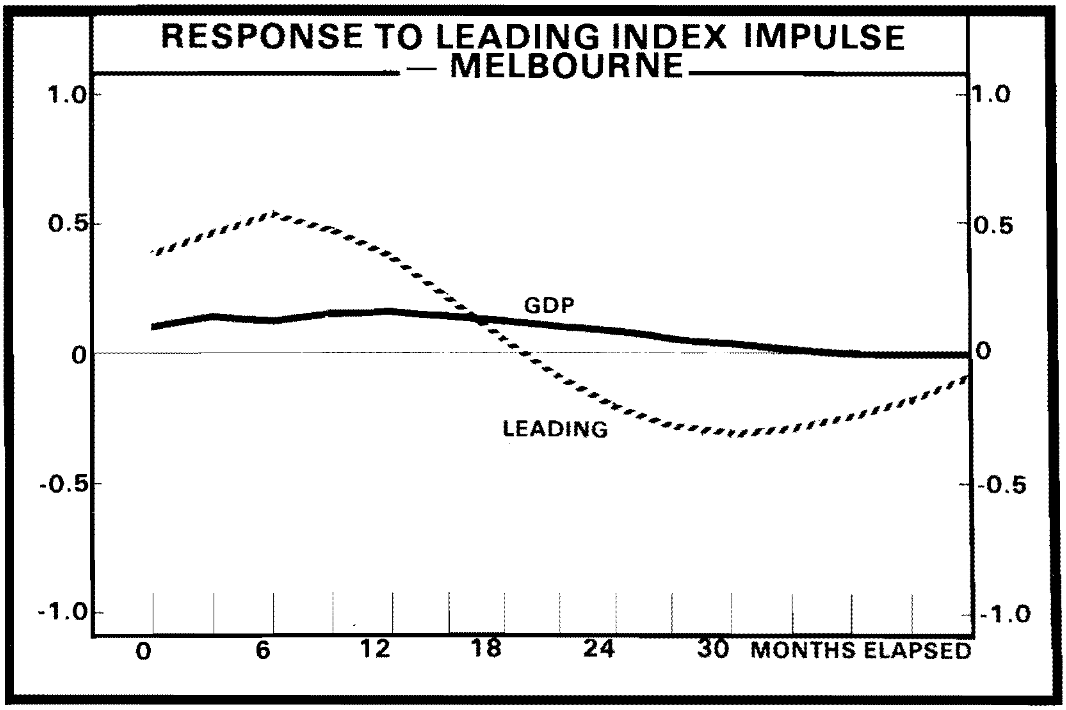

Figure A1. Gross Domestic Product - Melbourne

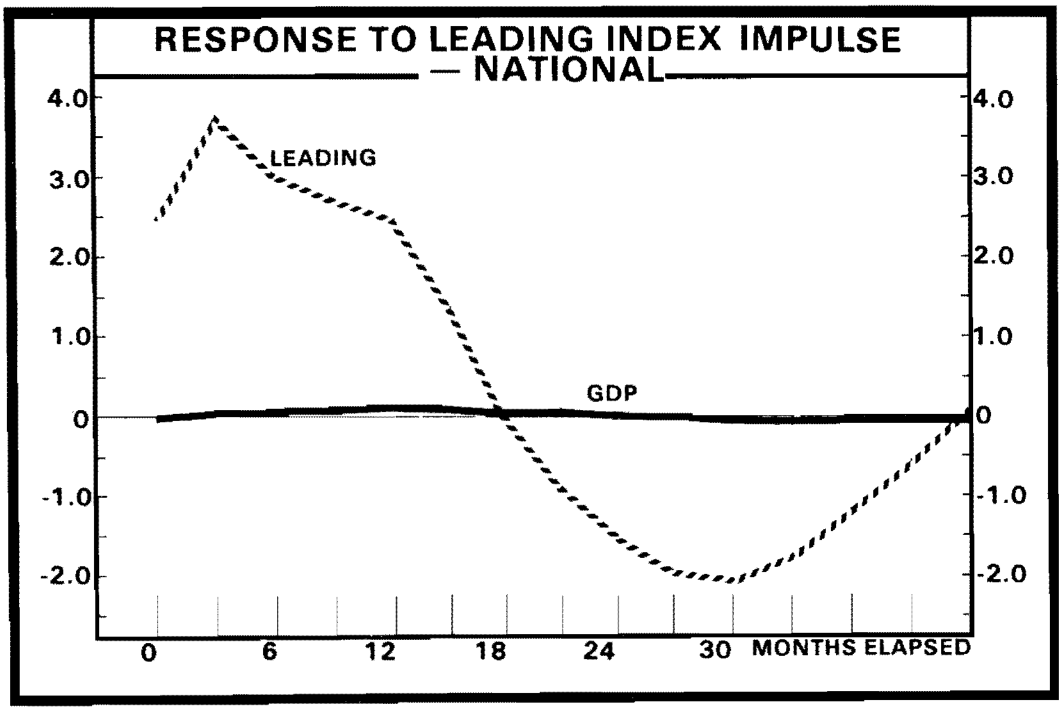

Figure A2. Gross Domestic Product - National

APPENDIX B

DATA SOURCES

MILI	=	Melbourne Institute's index of leading indicators obtained from Ernst Boehm.
MICI	=	Melbourne Institute's index of coincident indicators obtained from Ernst Boehm.
MILA	=	Melbourne Institute's index of lagging indicators obtained from Ernst Boehm.
NILI	=	National Institute's index of leading indicators obtained from Peter Smith.
NICI	=	National Institute's index of coincident indicators obtained from Peter Smith.
Registrations	=	Registrations of new motor vehicles (total) obtained from ABS publication No. 9303.0. (Seasonally adjusted).
Retail Sales	=	Retail Sales, all items (excl. motor vehicles, etc.) in current prices obtained from ABS publication No. 8501.0. (Seasonally adjusted).
Employment	=	Total civilian employed persons obtained from ABS publication No. 6203.0. (Seasonally adjusted).
Unemployment Rate	=	Unemployment rate obtained from ABS publication No. 6203.0. (Seasonally adjusted).
Production	=	ANZ's index of industrial production obtained from ANZ Bank, Business indicators (various issues). (Seasonally adjusted).
GDP	=	Real non-farm gross domestic product obtained from ABS publication No. 5207.0. (Seasonally adjusted).

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