A FURTHER CONSIDERATION OF CAUSAL RELATIONSHIPS BETWEEN WAGES AND PRICES

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I Introduction

The content of this paper represents a contribution to the ongoing debate about the relationships between wages and prices in the Australian context. In particular we seek to determine whether or not simultaneity, feedback or simple one way causality as defined in the Weiner-Granger sense applies between such measured series as Average Weekly Earnings (AWE), the Consumer Price Index (CPI) and the Index of Minimum Wage Rates (MWI), these being three of the series used by Fels and Tran Van Hoa (1981) in their recent study. Their variables measuring demand for labour and strikes were omitted, since the first showed no clear evidence of relevance while the second was considered to be symptomatic rather than causal in its relationships with the three included variables. Thus changes in strikes appear to be explained by changes in AWE and CPI but to have no net relevance in explaining movements in these series.

Perhaps the most interesting finding in their paper was that while movements in AWE seemed to affect the CPI, the CPI movements did not appear to be relevant in explaining changes in either AWE or MWI. This finding was utilized by Gelber (1981) to justify the specification of a single estimating equation for price inflation (CPI) which used AWE (and its lags) as a major explanatory variable. Kirby (1981) however, in estimating an Australian wage equation (for quarterly rate of change in AWE), followed McDonald (1977) and used forecast quarterly rate of price inflation from a Box-Jenkins ARIMA model based on the CPI series as an explanatory variable. He found this variable to be a highly significant explanatory factor. It seems very unlikely that such a predicted series could be

1. Clearly some measure of demand for labour would seem to be desirable but suitable measure seemed to be available for the period of our analysis.

2. This suggests that psychological explanation, that workers react to changes in established relativities. Given the conservatism with respect to other types of change that seems to characterize the Australian industrial labour scene this is at least plausible.
significantly related to changes in AWE without the quarterly change in the CPI series itself also being significantly related. Thus there seems to be a contradiction between the results of Kirby and those of Fels and Tran Van Hoa. The robustness of these findings relative to a different sampling period and a different method of analysing causality is one of the matters investigated in the present paper.

In Section II ARIMA models are developed and presented for each of the three series AWE, CPI and MWI. After discussion of these results, cross correlations between the residual series from the three models are analysed using the Pierce-Haugh (1977) approach. These are presented and discussed in Section III. In the absence of a suitable computer algorithm for estimating multivariate time series models, a pseudo-multivariate approach to estimation was utilized to obtain some guidance as to the structure of the multivariate relationships among the series. The results and some discussion are presented in Section IV. Because of the contemporaneous correlation found between each of the pairs of residual series, a single equation transfer function approach to modelling each of the series is probably inappropriate as a means of identifying structural relationships among the series. Nevertheless it may provide useful forecasting equations for each series. For this reason transfer function results are presented in Section V and then conclusions and suggestions for further research are presented in the final section of the paper.

II ARIMA Models

If one wishes to use economic considerations, in addition to pure time series criteria, in the construction of models of economic processes, as recommended by Zellner (1979), then the appropriate level of differencing to apply to particular series in constructing ARIMA models needs to be considered. More particularly, if one expects to be proceeding to the later construction of
multiple time series models, then consistency of specification across equations becomes an important factor in permitting sensible economic interpretation of the results.

With the CPI series, clearly the level of the series is entirely arbitrary, depending as it does on the choice of base period. The one quarter and annual rates of change of the series are however of great economic and social significance and accordingly these series were modelled by Kirby as part of his study. Kirby also examined quarterly and annual rates of change in the average weekly earnings series as part of his study, while Trivedi and Rayner (1978) used quarterly rate of change of the minimum wage series in their analysis of award wage determination. Kirby also examined quarterly and annual rates of change in the average weekly earnings series as part of his study, while Trivedi and Rayner (1978) used quarterly rate of change of the minimum wage series in their analysis of award wage determination. Kirby also examined quarterly and annual rates of change in the average weekly earnings series as part of his study, while Trivedi and Rayner (1978) used quarterly rate of change of the minimum wage series in their analysis of award wage determination. Fels and Tran Van Hoa, likewise use quarterly rates of change in specifying each of the series concerned.

We take issue with all of these specifications as not really addressing directly the measurement of the key variables of economic interest. Because the economy is dynamic rather than static it is not the rate of change of these economic variables which is of major significance but rather the rate of change of the rate of change - in other words the acceleration or deceleration which is occurring. The physical analogy of being a passenger in a car is relevant. As long as the car travels at a steady speed, whatever that speed, the passenger is comfortable and in equilibrium with his/her immediate environment. Sharp changes in speed lead to immediate discomfort for the passenger and are generally causally associated with changes in the larger environment of the vehicle.

The most convenient way to compute a rate of change for a positive economic variable is as a difference of logarithms of the original variable.

3. Trivedi and Rayner also develop a seasonal ARIMA model for price expectations as part of their study which differs significantly in structure from the two models proposed by Fels and Tran Van Hoa.
Obtaining a rate of change of a rate of change then involves a second differencing operation with respect to the relevant reference period. For non-seasonal series the reference period typically relates to the previous rate of change and second differencing of the series is appropriate to obtain the acceleration/deceleration variable involved. For seasonal series such as AWE or unemployment the relevant reference period typically relates to the same season of the previous year and one is interested in the change that has occurred. This implies that one should seasonally difference the rate of change series to obtain the relevant acceleration/deceleration variable involved.

Bearing in mind these considerations, several alternative levels of differencing of the three series of logarithms were examined using a modified version of the time series identification program originally developed by Pagan (1974). The data sample ran from 1948(3) to 1981(2) a total of 132 observations and the results are summarized in Table 1 in terms of the variances of the various differenced series and their apparent stationarity or lack of stationarity. The various differencing filters utilized are summarized in terms of the parameters, \( d \), \( s \) and \( d_s \) these being the orders of non-seasonal differencing, of seasonality and seasonal differencing respectively. Beesley (1981) has shown that acceptable ARIMA models can be developed for the first differences of the \( \ln \) MWI series and

<table>
<thead>
<tr>
<th>Original Series</th>
<th>( \ln ) CPI</th>
<th>( \ln ) MWI</th>
<th>( \ln ) AWE</th>
</tr>
</thead>
<tbody>
<tr>
<td>( d, s, d_s )</td>
<td>1, 0, 0</td>
<td>2, 0, 0</td>
<td>0, 4, 1</td>
</tr>
<tr>
<td>( \ln ) CPI</td>
<td>0.000 203*</td>
<td>0.000 114</td>
<td>0.002 544*</td>
</tr>
<tr>
<td>( \ln ) MWI</td>
<td>0.000 557</td>
<td>0.000 847</td>
<td>0.003 981</td>
</tr>
<tr>
<td>( \ln ) AWE</td>
<td>0.003 560*</td>
<td>0.011 644*</td>
<td>0.002 625*</td>
</tr>
</tbody>
</table>

*The correlogram in each of these cases showed clear evidence of nonstationarity of the relevant differenced series.
the second differences of the \( \ln \) CPI series. However the only level of differencing for which all three series exhibit stationarity involves first and seasonal differencing of each of the original series. There seems in this case to be no sound economic argument for utilizing different levels of differencing for each of the series, such as could arise if one series was already in rate of change form originally.

After analysing the correlogram two basic models seem to be indicated for the CPI series. These are

\[
(1) \quad (1-\phi_1 L)(1-L)(1-L^4) \ln CPI = (1-\Delta_1 L^4-\Delta_2 L^8)u_t
\]

and

\[
(2) \quad (1-L)(1-L^4) \ln CPI = (1-\theta_1 L-\theta_2 L^2-\theta_3 L^3)(1-\Delta_1 L^4-\Delta_2 L^8)u_t
\]

In estimating these models it became necessary to add \( \theta_2 \) and \( \theta_3 \) parameters to equation (1) to clean up the residual correlogram but it still produced a residual sum of squares 6.3 percent larger than that from model (2) when the same estimation period was utilized\(^4\).

Estimates for model (2) were

\[
(2.1) \quad (1-L)(1-L^4) \ln CPI = (1+0.5261 L+0.5295 L^2+0.4821 L^3)(1-0.3605 L^4-0.4234 L^8) u_t
\]

with a standard error of \( \hat{\sigma} = 0.00909 \) and a Box-Pierce statistic of \( \chi^2 = 14.299 \) over 24 lags of the residual correlogram. The figures in brackets beneath the estimated coefficients are the absolute values of the associated \( t \)-statistics. Over the same estimation period this model is 2.1 percent better in terms of residual sums of squares than the model based on second differences of logarithms which was proposed by Beesley (1981) even though the basic variance

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4. Estimation of these equations was accomplished using a modified version of program AUTO which was developed by Pagan (1974).
of the (1 4 1) differenced series is 57 percent greater (see Table 1).

Turning to the correlogram for the MWI series. A model of the form

\[ (3) \quad (1-L)(1-L^4)\ln MWI = (1-\theta_2L^2)(1-\Delta_1L^4)u_t \]

would appear to be a useful starting point for whitening the series. An additive rather than a multiplicative model with a third parameter to model structure at lag 8 was eventually preferred, this being estimated as

\[ (4) \quad (1-L)(1-L^4)\ln MWI = (1+0.2124L^2-0.5039L^4-0.2836L^8)e_t \]

\[ (2.825) \quad (5.627) \quad (3.084) \]

with a standard error of \( \hat{\sigma} = 0.02229 \) and a Box-Pierce statistic of \( \chi^2 = 29.506 \), over 24 lags of the residual correlogram. Once again this model appears to be equivalent to the alternative model obtained by Beesley for the non-seasonally differenced series since the standard error is of the same magnitude despite the fact that the basic variability in the series is 23.5 percent greater (see Table 1).

Finally, after analysing the correlogram for the AWE series an initial model for the series would appear to be

\[ (5) \quad (1-L)(1-L^4)\ln AWE = (1-\Delta_1L^4-\Delta_2L^8)u_t \]

When this model was fitted further structure appeared in the residuals at lag 2. This seemed to be additive rather than multiplicative with the identified seasonal structure, giving rise to the estimates

\[ (6) \quad (1-L)(1-L^4)\ln AWE = (1+0.2352L^2-0.4137L^4-0.2373L^8)e_t \]

\[ (3.147) \quad (4.514) \quad (2.655) \]

with a standard error of \( \hat{\sigma} = 0.01891 \) and a Box-Pierce statistic of \( \chi^2 = 19.862 \) over 24 lags of the correlogram. Interestingly, the structural pattern
obtained for the ARIMA models (4) and (6) seem very similar, suggesting that very similar factors are involved in the acceleration/deceleration of the rates of change in the two underlying series.

III Cross Correlation Analysis

Because of its symmetric treatment of the series involved, the Haugh (1972) approach to causality analysis is preferred to the approach originally suggested by Box and Jenkins (1970). The latter approach is really only appropriate where one way causality is known to exist between a pair of series. With the Haugh approach one seeks to cross correlate the conceptual white noise innovation series affecting each of the variables of interest, these conceptual innovation series being approximated by the series of residuals from the fitted ARIMA models. Where significant associations are found between a pair of innovation series this is taken to be indicative of a (linear) causal relationship in the Granger (1969, 1980) sense, existing between the two economic variables of interest.

Of course, as in ordinary correlation analysis in a multiple regression framework, it is the partial cross correlations, holding all other relevant variables constant, which are indicative of a genuine relationship between variables. Simple correlations may indicate only that both variables are affected by a third unidentified variable not taken into account by the analyst. Granger recognized this trap in his definition of causality but it has perhaps been given insufficient weight by some subsequent analysts of causal relationships between economic variables. It was knowledge of this difficulty which led Fels and Tran Van Hoa to adopt their multivariate approach to causality analysis.

Conceding this caution about interpreting cross correlation analyses in a simple minded fashion, nevertheless, from the original work of Pierce (1977) onward, there seems to have been fairly widespread findings of lack of any
relationships between macroeconomic time series when they are subjected to cross correlation analysis using the procedures proposed by Haugh. A number of papers, of which that by the Hernandez-Iglesias (1981) may be taken as indicative, have been written to show that despite lack of significant cross correlations, nevertheless particular economic series may be causally related. Perhaps another more pragmatic factor of significance is the use of an inappropriate level of differencing when attempting to construct the preliminary ARIMA models. The basic innovation series seem often to be or relatively small magnitude and thus readily swamped in induced variability by inappropriate modelling.

With this background of apparent lack of causal relationships among macroeconomic variables, some positive findings should be welcomed as good news, despite the caution that the analyses are bivariate only and not of the conditional bivariate form in which other factors are held constant. The three residual series from the preceding ARIMA models were cross correlated in pairs using an extended version of the Pagan identification program. The results obtained are presented in Figures 1 to 3 which each contains two parts - one where variable Y lags variable X and the second where variable X lags variable Y.

In Figure 1a the residual series from the MWI equation is lagged against the residual series from the CPI equation. The significant correlation at lag zero indicates that the alternative hypothesis of contemporaneous correlation between the disturbances of the ARIMA models would be accepted. In terms of the classification of causality patterns outlined by Pierce (1977) this finding suggests that instantaneous causality exists between the series. The further finding of significant correlations at lags 1 and 10, with indications of structure at lags 5 and 6, suggests that lagged values of the MWI variable could explain variation in the

5. Note the partial cross correlations were also estimated but are not reported due to space considerations. They are available on request.
current CPI variable. Turning to Figure 1b in which the residual series from the CPI equation is lagged against the residual series from the MWI equation, there is evidence of significant correlation at lag 1, so suggesting that the lagged CPI variable could explain variation in the current MWI variable. Relating the two Figures, the finding of significant correlations in both directions is indicative of a feedback relationship between the variables in the terms of Pierce's classification of causality patterns.

Considering Figure 2 in which the residual series from the CPI model is correlated with the residual series from the AWE model there is an indication once again of instantaneous causality with feedback between the series. At lag 1 in both directions, at lags 6 and 13 in Figure 2a and at lags 10 and 21 in Figure 2b there is evidence of non random structure in the correlograms. Turning to Figure 3 in which the residual series from the MWI is correlated with the residual series from the AWE equation, there seems to be no firm evidence of a relationship running from lagged AWE variables to MWI although a first order autoregressive relationship dying away from lag 0 could be postulated. On the other hand there is strong evidence for a first order lag relationship running from MWI to AWE, of possible structure at lag 17, as well as evidence of instantaneous causality.

In this case there may be an artifactual measurement problem behind the patterns of observed correlations in Figure 3. On logical grounds it is apparent that an increase in minimum award rates of pay must increase average weekly earnings directly through its effect on the lower bound of the distribution. On economic grounds an increase in minimum award rates is
likely to flow on to all workers so that relativities are maintained, and thus lead indirectly to a further increase in average weekly earnings. Institutional friction could lead to some delay in this flow on process so giving rise to the significant lag correlation but generally within an industry the flow on of award increases tends to be immediate.

Another explanation arises form the fact that AWE is essentially a mid quarter measure whereas MWI is an end of quarter measure. Thus adjustments to minimum wage levels which occur in the first half of any quarter should be reflected in the mid quarter average weekly earnings measure as well as the end of quarter minimum wage index. However adjustments to minimum wage levels occurring in the second half of a quarter will be reflected in the end of quarter minimum wage index but not picked up until the following quarter in the average weekly earnings index. Given the virtual equality of the partial cross correlations at lags 0 and 1 in the correlogram of MWI lagging AWE this latter explanation is fairly plausible. A similar explanation may well be appropriate for the one period lag which appears in Figure 1b where CPI lags MWI since the CPI is principally a mid quarter measure also.

IV Pseudo Multiple Time Series Models

Given the finding of contemporaneous correlation between all three series of residuals an appropriate modelling procedure at this point would be the development and estimation of a multivariate stochastic time series model (Jenkins and Alavi, 1981). The information presented in Figures 1 to 3 provides the basis for the initial identification of such models. Given the somewhat isolated nature of the individual structural elements in the Figures, a multivariate moving average model was selected for initial investigation. This has the general form
Figure 1a: Cross Correlogram between the Residuals from the Models for CPI and MWI with MWI lagging CPI

Figure 1b: Cross Correlogram between the Residuals from the Models for CPI and MWI with CPI lagging MWI
Figure 2a Cross Correlation between the Residuals from the Models for CPI and AWE with AWE lagging CPI

Figure 2b Cross Correlation between the Residuals from the Models for CPI and AWE with CPI lagging AWE
Figure 3a Cross Correlation Between the Residuals from the Models for MWI and AWE with MWI lagging AWE

Figure 3b Cross Correlation Between the Residuals from the Models for MWI and AWE with MWI lagging AWE
where the vector $w_t$ contains one observation on each of the three series of first and fourth differenced logarithms of CPI, MWI and AWE. The vector $a_t$ is assumed to be drawn from a time independent trivariate normal distribution, while the matrix $\Theta(L)$ contains individual moving average lag operators for each variable in each equation. The diagonal operators have a leading term of unity while the off diagonal operators omit this term.

Identification of the structure of the $\Theta(L)$ matrix is based on first identifying the structure of the matrix $\theta^*(L)$ in

\[
\begin{bmatrix}
w_{1t} \\
\vdots \\
w_{3t}
\end{bmatrix}
= \begin{bmatrix}
\theta_{11}(L) & \theta_{12}(L) & \theta_{13}(L) \\
\theta_{21}(L) & \theta_{22}(L) & \theta_{23}(L) \\
\theta_{31}(L) & \theta_{32}(L) & \theta_{33}(L)
\end{bmatrix}
\begin{bmatrix}
a_{1t} \\
\vdots \\
a_{3t}
\end{bmatrix}
\]

for $t=1,\ldots,T$;

where the vector $e_t$ contains one observation on each of the residual series from equations (2.1), (4) and (6). As Jenkins and Alavi point out, in situations where (i) the standard errors of the three ARIMA equations differ significantly, or (ii) there is evidence of significant contemporaneous correlation among the residual series from the preliminary ARIMA models, it is not necessarily valid to assume that $\theta^*_{11}(L) = \theta^*_{22}(L) = \theta^*_{33}(L) = 1$ in (8). However, for "quick and dirty" initial estimates of the parameters in equation (8), they suggest making this assumption and then estimating the parameters $\theta_{ij,k}^{(L)}$ associated with $L^k$ in the $(i,j)$ position as equal to the negative of $r_{ji}(k)$ from the relevant cross correlogram. This latter proposal is a
straightforward extension of a corresponding "quick and dirty" approach to obtaining initial estimates of MA parameters in ARIMA modelling. Naturally, if such an approach is used, the possibility of finding additional structure from unidentified parameters in residual correlograms needs to be borne in mind when estimation of the identified model is attempted.

In the present instance these assumptions were adopted for lack of a better alternative, except that impulse response function coefficients were used in place of the $r_{ji}(k)$ values to adjust for the differing standard errors of the three residual series. Jenkins and Alavi indicate that no suitable algorithm for obtaining better preliminary estimates has yet been developed for other than very simple models. Using this approach the three equations in (8) were initialized in a perhaps rather over-parameterized form as

\begin{align}
(8.1) \quad e_{1t} &= a_{1t} + (-\theta_{12,1}L-\theta_{12,5}L^5-\theta_{12,6}L^6-\theta_{12,10}L^{10})a_{2t} \\
&\quad + (-\theta_{13,1}L-\theta_{13,6}L^6-\theta_{13,13}L^{13})a_{3t}
\end{align}

\begin{align}
(8.2) \quad e_{2t} &= (-\theta_{21,1}L-\theta_{21,4}L^4)a_{1t} + a_{2t} + (-\theta_{23,1}L-\theta_{23,6}L^6)a_{3t}
\end{align}

\begin{align}
(8.3) \quad e_{3t} &= (-\theta_{31,1}L-\theta_{31,10}L^{10}-\theta_{31,21}L^{21})a_{1t} + (-\theta_{32,1}L)a_{2t} + a_{3t}
\end{align}

where equations (8.1) to (8.3) relate to residuals from the CPI, MWI and AWE models respectively.

Translating from equations (8.1)-(8.3) to equation (7) requires the multiplication of both sides of each of these equations by the relevant moving average operator from the respective fitted ARIMA models. When this
16.

rather tedious piece of algebra is completed and initial estimates are
substituted for the resulting sets of parameters the off diagonal lag
operators simplify considerably in terms of resulting coefficients with
prospects of statistical significance. Consequently the initial forms
selected for each of the equations were

\begin{equation}
(7.1) \quad w_{1t} = (1 - \theta_{111} L - \theta_{112} L^2 - \theta_{113} L^3)(1 - \Delta_{14} L^4 - \Delta_{18} L^8) a_{1t}
+ (-\theta_{121} L - \theta_{125} L^5 - \theta_{12,10} L^{10}) a_{2t} + (-\theta_{131} L - \theta_{136} L^6) a_{3t}
\end{equation}

\begin{equation}
(7.2) \quad w_{2t} + (\theta_{211} L - \theta_{214} L^4) a_{1t} + (1 - \theta_{222} L^2 - \theta_{224} L^4 - \theta_{228} L^8) a_{2t}
+ (-\theta_{231} L - \theta_{236} L^6) a_{3t}
\end{equation}

and

\begin{equation}
(7.3) \quad w_{3t} = (-\theta_{311} L - \theta_{31,10} L^{10} - \theta_{31,21} L^{21}) a_{1t} + (-\theta_{321} L) a_{2t}
+ (1 - \theta_{332} L^2 - \theta_{334} L^4 - \theta_{338} L^8) a_{3t}
\end{equation}

this once again probably being somewhat over parameterized.

Because no suitable software to estimate such a model as (7.1) to (7.3)
exists in Australia, to our knowledge, it was decided to estimate the model
on a single equation basis to try and obtain approximate results. This was
done by estimating in place of equations (7.1) to (7.3) the equations

\begin{equation}
(9.1) \quad w_{1t} = (1 - \theta_{111} L - \theta_{112} L^2 - \theta_{113} L^3)(1 - \Delta_{14} L^4 - \Delta_{18} L^8) a_{1t}
+ (-\theta_{121} L^9 - \theta_{125} L^5 - \theta_{12,10} L^{10}) e_{2t} + (-\theta_{131} L - \theta_{136} L^6) e_{3t}
\end{equation}
(9.2) \[ w_{2t} = (-\theta_{211} L^{-2} - \theta_{214} L^4) e_{1t} + (1-\theta_{222} L^2 - \theta_{224} L^4 - \theta_{228} L^8) a^*_{2t} \]
\[ + (-\theta_{231} L^{-2} - \theta_{236} L^6) e_{3t} \]

(9.3) \[ w_{3t} = (-\theta_{311} L^{-3} - \theta_{310} L^0 - \theta_{312} L^2) e_{1t} + (-\theta_{321} L) e_{2t} \]
\[ + (1-\theta_{332} L^2 - \theta_{334} L^4 - \theta_{338} L^8) a^*_{3t} \]

and thus utilizing the ARIMA residual series directly in the model. The sorts of heinous sins this involves may be seen by substituting for the residual series in (9) in terms of (8). It is then apparent that a very considerable amount of additional structure is being imposed on the multivariate system which will bias estimates of some of the coefficients - perhaps enough to change their level of significance. Additionally of course, the estimation method is inefficient relative to the correct procedure which properly accounts for contemporaneous covariance. For these reasons the following results should be treated as indicative rather than definitive.

In estimating the equations (9) several of the parameters were found to be not significant, hence they were dropped and the equations re-estimated. The results arrived at following this process for the CPI equation were

(10.1) \[ w_{1t} = (1+0.5179L + 0.5641L^2 + 0.5661L^3)(1-0.2895L^4 - 0.4431L^8)a^*_{1t} \]
\[ (6.305) (6.904) (6.470) (3.054) (5.177) \]
\[ + (+0.0938L - 0.1199L^5)e_{2t} \]
\[ \hat{\sigma} = 0.0086, \quad \chi^2 = 20.940 \]
\[ (3.218) (3.942) \]

In this case \( \hat{\theta}_{112} \) and \( \hat{\theta}_{113} \) seem to have changed values somewhat, but otherwise there is no real change in the initially identified ARIMA model. The addition of the two terms involving lagged errors from the MWI equation results in a significant fall in the residual sum of squares from the fitted model, with
$F_{120}^2 = 9.33$. None of the suggested parameters for the AWE residuals were significantly different from zero in this trivariate context despite the strong bivariate correlation at lag 1 in Figure 2.

In the case of the MWI equation none of the additional parameters included in equation (9.2) turned out to be significant despite the strong lag 1 correlation which was apparent in the bivariate cross correlogram with CPI (Figure 1b). Thus the best model obtained for this series was simply the ARIMA model of equation (4). The results for equation (9.3) varied the most from expectations. Only lag 1 parameter estimates were significant for the added error series but additional structure which became apparent in the resulting residual correlogram indicated the presence of two additional parameters for the AWE own structure. Neither of these terms arose at lags which should have been affected by bias from the utilization of the error series from the other ARIMA equations.

The estimated model was

$$w_{3t} = (+0.5092L)e_{1t} + (+0.2335L)e_{2t}$$  
$$+ (1+0.2497L^2 - 0.4163L^4 - 0.3754L^5 - 0.2320L^8 + 0.2473L^{17})a_{3t}$$

Thus it would appear that innovations in both the CPI and MWI contexts have very significant effects on the acceleration/deceleration of the rate of change in AWE with a one quarter lag. This result is probably not really surprising to any economist familiar with the Australian industrial relations scene. The long lags, in full adjustment to innovations in the AWE series itself, which the fitted model also suggests, may be related to the problem of maintenance of relativities across industries. Diffusion of information about over award payments is probably much slower than diffusion of information about new awards since it is not publically announced in the same fashion.
V Estimated Transfer Function Models

Since there is evidence of contemporaneous correlation and feedback between all three series under consideration, transfer function modelling of the individual series may be deemed inappropriate since simultaneous equations bias will affect the estimation and the transfer functions obtained will be complex mixtures of the forward and backward transfer functions between the series concerned. These are very real considerations for structural coefficient estimation but if the primary interest is on forecasting then such models, warts and all, may still be very useful. Because of the timing of the measurements however, it would be illogical to use the current MWI variable in transfer functions for CPI and AWE so this has been avoided. Development of the transfer function models necessarily proceeded on something of a "cut and try" basis, since the correlations between the two explanatory variables in each transfer function meant that the bivariate impulse response functions were not necessarily a good guide to the forms of the partial impulse response functions.

The equation for the CPI was estimated over observations 19 to 132 with the following results:

\[
W_{1t} = \left( -0.1142L^2 + 0.1193L^4 + 0.0903L^6 - 0.0789L^8 + 0.0525L^{10} \right)w_{2t} \\
+ \left( 0.1597L^0 + 0.3525L^1 + 0.2567L^2 \right)w_{3t} + \left( 1+0.2232L^1 - 0.8199L^4 \right) \epsilon_{1t} \\
- 0.4276L^5 - 0.3521L^8 - 0.2911L^{10} + 0.5760L^{12} - 0.3532L^{16} \epsilon_{1t}
\]

with \( \hat{\sigma} = 0.00589 \) and Box-Pierce statistic of \( \chi^2 = 9.246 \) over 24 lags. With a similar caveat to that in situations where OLS is used to estimate a simultaneous equation, these results suggest a very strong impact of changes in the rate of change of AWE on corresponding changes in CPI, with about 77
percent of the effect being directly translated within two quarters. The effect of changes in the rate of change of MWI is equivocal in aggregate - about 7 percent after ten lags but clearly of some importance at individual lags. The rather complex noise structure may arise in part from external interventions in the CPI series since, at this stage, no adjustments have been made for even such obvious and well known effects as the Medibank changes.

The equation for the MWI was estimated over observations 14 to 132 with the following results:

\[
(12) \quad w_{2t} = \left(0.1439L^4\right)w_{1t} + \left(0.7949L^0 - 0.3142L^7 + 0.1782L^8\right)w_{3t}
\]

\[
+ \left(1-0.6697L^1 - 0.3768L^4 + 0.3278L^5 + 0.4365L^7 - 0.3412L^{15}\right)e_{2t}
\]

where \(\sigma^2=0.01682\) and the Box-Pierce statistic was \(\chi^2=16.808\) over 20 lags. This suggests that the CPI has a marginal effect on MWI and that AWE is the variable of critical importance for changes in MWI. This is in line with the findings of Trivedi and Rayner, though because of the logical contemporaneous feedback from MWI to AWE the causality involved is rather dubious. The fairly complex noise structure in the equation is to be expected given the domino effect of changes in specific awards on later judgements relating to other awards but it could also be an artifact of interventions in the series. An intervention analysis for this series, not reported here, gave very much better results in terms of standard error than did equation (12), but is has not yet been fully analysed. It indicates that institutional factors do seem to be important in impeding/facilitating the flow through of economic forces to Minimum Wage Awards.

Finally, the equation for AWE was estimated over observations 9 to 132 producing the equation
21.

(13) \[ w_{3t} = (0.3585L^0)w_{1t} + (0.5463L^1 - 0.1021L^3)w_{2t} \\
     + (1-0.5146L - 0.5445L^4 - 0.2474L^{12} + 0.3341L^{13})e_{3t} \]

\[
(4.447) \quad (8.643) \quad (2.014) \\
(7.389) \quad (7.256) \quad (2.938) \quad (4.009) 
\]

with \( \hat{\sigma} = 0.01381 \) and a Box-Pierce statistic of \( \chi^2 = 12.770 \) over 20 lags. The CPI variable seems only to have a contemporaneous effect, a result consistent with optimal extrapolation or national expectations on the part of wage earners about price changes. The lag 1 effect of MWI on AWE is expected given the logical relationships between the measurements of these series. The noise structure is again somewhat complex and requires further analysis for anomalous interventions that may have occurred.

VI CONCLUSION

This paper has proposed certain changes in the level of differences to be applied to time series, if causality effects between economic time series are to be properly isolated. The suggested approach was adopted in the research reported in the paper. It produced adequate ARIMA models for each of the series concerned and the resulting cross correlograms indicated the existence of contemporaneous correlation between all three series and widespread evidence of feedback between the series at this bivariate level of analysis. The multivariate stochastic equations, although not estimated in a fully appropriate manner, indicated a feedback from innovations in MWI to CPI. No feedbacks seemed to be present from innovations in CPI or AWE to MWI, but both CPI and MWI innovations seemed to feedback to AWE.

In transfer function analysis therefore, MWI lags should be exogenous relative to both the CPI and AWE functions and AWE lags should be exogenous relative to the CPI function. While allowing that simultaneous equations bias may be affecting the results, the transfer function for CPI seems to be strongly influenced by movements in AWE both contemporaneously and for the
two most recent quarters. The effects of MWI on CPI were much more equivocal. Apart from a very strong contemporaneous effect with AWE both CPI and AWE lags seemed to be of some significance in explaining movements in MWI. Contemporaneous CPI and lagged MWI were involved in the AWE equation. These findings as to the effects of CPI on MWI and AWE are more consistent with Fels and Tran Van Hoa's disaggregated Table 1 results than their Table 2 summary. It seems fairly clear that Gelbers results must suffer from simultaneous equations bias. Equation (13) concurs with Kirby on the importance of the current/expected CPI variable in the AWE equation.

Clearly these results require further refinement both as to estimation method and with respect to intervention analysis. Additional series of prices such as export prices, import prices and wholesale prices need to be considered as well as an appropriate unemployment variable. At least in our view, the venture into further research along these lines looks promising.
REFERENCES


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2.
