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Abstract
This paper investigates the changing pattern of seasonal influences on quarterly Australian data on aggregate working days lost due to industrial disputes per thousand employees for the period 1983:1 to 2004:3. The analysis suggests the presence of (a) a structural break in the stationarity properties of the data around 1992-93 and (b) the presence of seasonality in the data, though this appears to be most significant for the pre-1993 period. It is noted that the break in the stationarity and change in seasonality properties of the data corresponds approximately with the period between the introduction of enterprise bargaining in the Australian Industrial Relations Commission in late 1991 and the introduction of the Industrial Relations Reform Act 1993, which was enacted in early 1994. It is suggested that these and other legislative and socio-economic changes that ushered in the progressive abandonment of centralised wage-fixing practices, may have contributed to the weakening of seasonality in aggregate quarterly strike statistics during the latter part of the period under review.

The last couple of decades have seen major changes in the Australian Industrial relations landscape. Not only have there been remarkable changes in the structure of unions, as identified and analysed in Davis (1990), Griffin (1992), Dabscheck (1995), Chaison (1996), Tomkins (1999) Michelson (2000), Wooden (2000, 2001), Hose and Rimmer (2002) and Hose (2003), among others, but there have also been remarkable changes in the level and pattern of industrial disputes, as identified and analysed in Chapman (1998), Morris and Wilson (1999), Perry and Wilson (2001) and Healy (2002), among others. The question arises: have these changes in the industrial relations landscape had any impact on the seasonality of strikes in Australia, and if so, why? The presence of seasonality in strike data has clear and important short-term implications for management, unions and government in planning for and managing systematic and predictable ups and downs in disputation levels.

To address these issues, this paper uses a number of statistical techniques to...
identify underlying cyclical patterns in the data. In section 1 we review the
treatment of seasonality in past studies of strike data for Australia. In section
2 we analyse the data for breakpoints in the stationarity properties of the
data drawing on the methodology of Zivot and Andrews (1992). In section
3 we employ autocorrelation analysis, spectral analysis and seasonal index
construction analysis to test for the presence of seasonality in the data,
followed in section 4 by a discussion of the implications of the tests. Some
concluding thoughts are offered in section 5.

1. Seasonality in Strikes in Review

Considerable econometric research has been undertaken on various
measures of the strike activity in Australia. Most of this research seeks to
explain strike activity in terms of variables such as inflation and some
measure or other of the underlying demand for labour (e.g. the
unemployment rate), among other variables considered. Seasonality has
been treated as a side issue and not explored as an issue in itself. The earliest
systematic quantitative treatment of seasonality in strikes was made by
Bentley and Hughes (1971). They found a significant increase in the
frequency of strikes (i.e. the number of strikes) in the September quarter
over the period 1952:1 to 1968:4 for strikes in the coal sector and separately
for strikes in the non-coal sector. This seasonality did not quite extend to
the average duration of disputes (i.e. number of working days lost due to
disputes divided by the number of workers involved) however, as none of
the seasonality dummy variables proved to be statistically significant.
Likewise, their employee loss regressions (working days lost in disputes per
employee) have insignificant seasonal dummies (p.165). Phipps (1977)
recognised seasonality in his strike frequency equation for the period 1961:1
to 1972:4. The strike equation itself fits into a 3-equation interdependent
system with equations for strike frequency, nominal wage growth and price
inflation. He seasonally adjusted his strike frequency variable by expressing
it as a 4-quarter moving average value. However, two appended seasonally
unadjusted equations, one within a 2-stage least squares setting, the other
within a 3-stage least squares setting, indicated a significant increase in
unadjusted strike frequency during the September quarter. Beggs and
Chapman (1987) analysed two indicators of strike activity. The first was
union involvement measured by the number of workers involved in disputes
per unionist. The second was an average duration measured by the number
of working days lost due to disputes divided by the number of workers
involved in disputes. For the union involvement variable, the seasonal
dummy variables for the March quarter and the December quarter have
negative coefficients and the September quarter has a positive coefficient.
The ‘t’ statistics appear marginal for March and December and insignificant
for September. For the duration equation, the same coefficient signs are
present as for their first equation, however, they appear to be insignificant.
All of these papers are of course addressing larger issues than seasonality.
And the models themselves - i.e. their conceptual bases, functional forms
and specifications – may have an impact on the sensitivity of seasonal
dummies to seasonal influences on the left- and the right-hand side of the

2 See also Yoder (1938), Griffin (1939), Knowles (1952) Durcan et al. (1983) and Reddy
(1991) for an introduction to earlier and overseas research.
equation. These and other non-seasonal models are summarised, reviewed and compared in Miller and Mulvey (1993).

Finally, Morris and Wilson (1994, 1995, 1999 and 2000) allow for seasonality in their various quarterly models of Australian strike activity. Covering 1959:3 to 1991:4, Morris and Wilson (1994) find a significant seasonal decline in union involvement in disputes for the March and December quarters. They do not find statistically significant seasonality, however, in the duration of strikes. Morris and Wilson (1995) cover the period 1959:3 to 1992:4 and change their dependent variable to the log of time lost (working days lost per employee). Seasonal dummies for the March and December quarters have significant negative coefficients both in the pre-Accord equation and the full-period equation. Morris and Wilson (2000) cover the period 1959:3 to 1996:2. In their ‘final parsimonious model’ (p.195) the March quarter seasonal dummy has a significant negative coefficient. The December quarter coefficient is also negative, but not significant (at the 5 per cent level). Morris and Wilson (1999) cover the period 1959:3 to 1997:4. Here the March quarter seasonal dummy has a significant negative coefficient. September and December quarter dummies are also included, with respectively positive and negative coefficients, however they are both statistically insignificant.

Summarising, the following observations can be made. First, quite a number of different strike rate indicators have been tested over the years. Different rationales have been advanced for using different indicators. The variable that has tended over time to attract the greatest attention has been the time lost per employee indicator (i.e. working days lost per employee). This indicator is the broadest measure, and arguably the most appropriate variable, upon which to focus attention. Second, there has emerged a tendency for March and December quarters to register relatively low disputation levels, while the September quarter has tended to register – though much less convincingly – relatively high levels of disputation. And thirdly, there is something of a suggestion that can be gleaned from the data that as the length of the period of the study extends into the later 1990s the strength of the seasonal influence has tended to weaken. In particular, the presence of negative December quarter seasonality appears to have diminished.

There are two points of departure in this paper from earlier research. First, this paper focuses on the period 1983-2003. This encompasses the period of the Accord 1983-1996 and what might be called the post-Accord period. So it extends the period of analysis of the more recent past research. Also, it has been suggested by Chapman (1998) and Morris and Wilson (1999) that the post-1982 period may have been associated with a permanently transformed industrial relations landscape. In this regard Chapman (1998, p. 637) suggests that ‘... the Accord could have been associated with a landscape or cultural transformation in Australian industrial relations, which would manifest itself in a structural change in the disputation that

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lasts beyond its early influence’. All in all, if these suggestions have merit, then a focus on the post-1982 period is, at the very least, of some interest.

The second point of departure in this paper is the employment of a number of techniques well suited to identify and/or measure seasonality. Perhaps principal among these techniques is spectral analysis, which is specifically designed to identify any cyclical regularities in the data. Spectral analysis departs from the practice – perfectly legitimate, of course – of explaining strike activity in terms of other economic variables. These explanatory economic variables include, for example, inflation, the unemployment rate (or similar proxy) and various other variables. Spectral analysis does not directly link strikes to any other variables. Rather, it simply identifies cyclical patterns in time series data that may be hidden from view. In this regard we will be particularly interested in identifying any consistent pattern in seasonality of data, as well as any other regularities.

2. Stationarity Tests

The data series we are interested in exploring is the number of working days lost per thousand employees. This is the broadest measure of disputation, incorporating all three elements of strike activity: the frequency of strikes (i.e. the number of strikes per employee), involvement in strikes (i.e. the average number of workers involved in each dispute) and the average duration of strikes (i.e. the average number of working days lost in strikes per worker involved). We initiate our analysis of the data by testing the stationarity of the series for the full period 1983:1 to 2003:3. Table 1 indicates the data are not stationary. In this table we were not constrained by a model type, i.e. we have presented the results for models incorporating a constant, a constant and trend and neither. The important point here is that, irrespective of the model type adopted, conventional ADF tests indicate that the series are first-difference stationary. It is worth commenting on the lag structure adopted. Had we adopted AIC or SC lag structure criteria the indicated number of lags would be less than the eight lags adopted. For consistency the lag structure adopted here was based on the lag structure that evolved from the Zivot and Andrews (1992) modelling process discussed below. According to Peron (1989) a larger lag structure does not harm the unit root testing process in that “… including too many extra regressors of lagged first-differences does not affect the size of the (unit root) test but only decreases its power”. The Perron (1989) and the Zivot and Andrews (1992) procedures included up to the last significant lag. This ensured no autocorrelated errors. It was the work of these authors that showed the presence of structural breaks in the data series can yield misleading results from conventional ADF unit root tests. For example, conventional unit root tests may incorrectly indicate a non-stationary series when, in fact, the series may be trend stationary around a break.

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4 See, for example, Forchheimer (1948).
Table 1 Conventional ADF Unit Root Tests on Strike Rate Series without Breakpoints

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Levels Test Statistics</th>
<th>Lags</th>
<th>1st Differences Test Statistic</th>
<th>Lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Constant</td>
<td>-0.95</td>
<td>8</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(2) Constant and Trend</td>
<td>-2.64</td>
<td>8</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(3) None</td>
<td>-1.83</td>
<td>8</td>
<td>-3.91</td>
<td>8</td>
</tr>
</tbody>
</table>

Critical Value (5% CV): (1) ‘t’ = -2.90; (2) ‘t’ = -3.47; (3) ‘t’ = -1.95

So, the possibility of a break in the series also warrants attention since a casual visual inspection of figure 1 is suggestive of a potential break. The presence of a structural break (or breaks) is indicative of a change (or changes) in the underlying forces generating the series. To explore this possibility we employ the technique developed by Zivot and Andrews (1992) – henceforth Z-A – which endogenises the potential break i.e. it lets the data determine where potential break/s may occur.5

We apply a Z-A unit root test to, in this instance, the original (un-logged) data.6 The Z-A procedure sequentially tests the data for a unit root in a series with an unknown breakpoint. The null hypothesis is that the series contains a unit root (i.e. is non-stationary) against the alternative hypothesis that the series is trend stationary about a structural break. Z-A followed the nomenclature of Perron (1989) in allowing for three model types: break in trend, change in trend slope and both – referred to as models A, B and C (the specific models tested are presented in Appendix 1).

Table 2 contains the key results from the Z-A test for a unit root in the series in the presence of an unknown break for each of the models A, B and C. While Model B did not produce any significant results at the 5 per cent level (although it did at the 10 per cent level) we see that Model A indicates the data are trend stationary about a level shift in the trend in the December quarter of 1993 and model C indicates the data are trend stationary about a trend break and change in slope around the September quarter, 1992. That is, in each case the calculated ‘t’ statistic exceeded (in absolute value) both the asymptotic and (available) finite sample critical values. Following Z-A, once a break is identified, the testing procedure is re-run from the identified breakpoint. As explained in the Appendix, the Z-A procedure loses 30 per cent of the data in the testing process and, due to these circumstances, there were an insufficient number of degrees of freedom to test for further potential breaks in the series7.

5 It is important to note that the Zivot and Andrews technique was developed to test for a unit root in the presence of a potential break. However, a fortunate flow-over effect from the process is the determination of statistically significant break/s in the series. See also Perron (1989) and Perron and Vogelsang (1992).

6 The logged data are marginally different in that they suggest a break in the B model (though not the A or C models) during 1988 at the 5 per cent level. Since we find the strength of the 1992-93 break in the un-logged series more significant and since also the un-logged series do not reveal a significant (5 per cent level) break in 1988, we have not applied a 1988 break generally in our analytics.

7 From the Z-A Monte Carlo simulations the lowest number of observations for which critical values were available was 62 – well short of the available observations post break after the loss of 30 per cent due to the procedure.
Table 2  Z-A Unit Root Test in Presence of Unknown Breakpoint(s) in the Series

<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inf ‘t’</td>
<td>-5.61</td>
<td>not significant</td>
<td>-8.04</td>
</tr>
<tr>
<td>Period</td>
<td>Dec 93</td>
<td>Sept 92</td>
<td></td>
</tr>
<tr>
<td>Lag</td>
<td>8</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>5% CV*</td>
<td>-4.80</td>
<td>-4.42</td>
<td>-5.08</td>
</tr>
<tr>
<td>Asymptotic</td>
<td>-5.12 to -5.38</td>
<td>-4.42 to -4.84</td>
<td>-5.63 to -5.68</td>
</tr>
<tr>
<td>Finite Sample**</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*CV= Critical Value  
** where n ranged from 62 to 111.  
There were insufficient df to test beyond first break.

Overall, these results suggest the presence of a break in the series somewhere around the period 1992-93. As indicated earlier, this evidence of a break in the series is also suggested by a visual inspection of the strike rate chart presented in figure 1. Up until, say, the December quarter of 1992 the strike rate data appear to be relatively high and volatile. During the subsequent period the strike rate is both lower on average and less volatile. The Z-A test is picking up this apparent structural change in the series. We will return to what may lie behind the break in the series after we explore the cyclical properties of the series.

3. Three Tests for Seasonality

Having noted the stationarity properties of the series and, in particular, the presence of a breakpoint in the series around 1992-93, we now move on to the central issue of this paper, that of the presence or absence of seasonality in the data.

* The respective means for the early and later periods are 54 and 18 working days lost each quarter per 1000 employees. The respective standard deviations are 27 and 10. Thus while the volatility has declined in absolute terms during the later period, it has marginally increased relative to the mean during the later period (from .50 to .56).
Autocorrelation Analysis
To commence, we examine the autocorrelation function of the first difference of the raw strike rate series, reproduced in figure 2. Near identical results are generated from either the natural log of the strike rate or the raw strike rate data.

Figure 2  Autocorrelation Function of the First-Differenced Raw Strike Rate

Autocorrelation analysis is a common procedure to ascertain the likely existence of seasonality in a (stationary) data set. This involves testing the autocorrelation function using either confidence bounds or with a Box-Pierce portmanteau test. Using the first approach, the confidence limits for the autocorrelation coefficients are given by $r_k \pm z_{\alpha} \text{se}_{r_k}$ where $r_k$ is the $k^{th}$ autocorrelation coefficient, $z_{\alpha}$ is the chosen confidence limit and $\text{se}_{r_k}$ is the standard error of $r_k$ and is usually calculated as $1/\sqrt{n}$, where $n$ is the sample size. Using the second approach the Box-Pierce $Q$ statistic is given by:

$$Q = n \sum_{k=1}^{m} r_k^2$$

where $m$ is the maximum lag being considered and $Q$ is distributed as a chi-square.

Figure 2 plots the autocorrelation coefficients along with the upper and lower 95 per cent confidence bounds. Here it can be seen that the autocorrelation coefficient falls outside the bounds at lags of 4, 8 and 20, which supports a belief that there is a seasonal pattern in these quarterly data. The Box-Pierce $Q$ statistic was applied to thirty six lags with a resulting $Q$ statistic of 72.5 clearly indicating that the set of autocorrelation coefficients is significantly different from a null set at the 1 per cent level, reinforcing a belief that there is a seasonal pattern in these quarterly data.

Given the evidence of a break point in the data around 1992-93, we next split the sample data into pre-break and post-break periods. The pre-break period, referred to as the ‘early period’, is set from 1983:1 to 1992:4. The post-break period, referred to as the ‘later period’, is set from 1993:1 to...
2003:3. These tests indicated that the seasonality noted for the entire period was apparent for the early period (with the tell-tale spikes at lags of 4 and 8 periods in the autocorrelation function), but not for the later-period data.9

**Spectral Analysis and Seasonal Cycles**

Another common procedure to isolate seasonality, as well as the possible existence of longer cycles in a data series, is through the use of spectral analysis. In the physical sciences the use of spectral analysis often presumes the existence of fixed length cycles. In the social sciences it is unlikely that there are any perfectly cyclical patterns where human endeavour is involved, i.e. fixed length cycles are unlikely to exist. In spite of this, while few if any cycles in economics series have a fixed length, the literature conventionally refers to cycles of a specific duration of, say, \( t \) periods. For instance, the literature refers to economic cycles of three years and nine years duration (Sargent, 1987, p.261, Dauten and Valentine, 1974, p.288), building cycles of 18 years duration (Long, 1940, p.159) and even long economic cycles of 50 years duration (Kondratieff, 1935). This is not to imply that these cycles are fixed at these lengths but that the average duration for the given cycle is about \( t \) periods.

Spectral techniques have found a great deal of effectiveness in identifying the approximate length of cycles in data, which have non-periodic cycles. Nerlov (1964) and Granger (1966, 1969) pioneered the application of spectral and cross-spectral techniques to economic time series in the search for preliminary information on the nature of short and long cycles in such series, and in an examination of the nature of any relationship that may exist between the time series in terms of their respective frequency contents. Since this pioneering work there has been a long research history on the use of spectral techniques in cyclical analysis of economics time series (cf. Hannan (1965, 1967), Engle (1974), Praetz (1979)). In an Australian context, Layton (1987) used spectral techniques in a study on indices of cyclical economic growth and Wilson and Perry (2004) have used it for short-term unemployment forecasting.

In spectral analysis the focus of a search for cyclical patterns in time series is changed from an amplitude-time domain to an amplitude-frequency domain. Changing the manner in which the time series is represented does not change the information content of the series; it merely permits another way of extracting this information. Thus spectral analysis commences with the assumption that any series, \( \{Y_t\} \), can be transformed into a set of sine and cosine waves such as:

\[
Y_t = \mu + \sum_{i=1}^{n} [A_i \cos(\omega_i) + B_i \sin(\omega_i)]
\]

where \( \mu \) is the mean of the series, \( \omega_i \) refers to a given frequency, \( i \) ranges from 1 to \( n \) where \( n = T/2 \) and \( T \) is the number of periods for which we have observations.

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9 In the interest of brevity we do not include the sub-period autocorrelation figures. The authors will supply them on request.
Thus the series \{Y_t\} may contain many cycles of different frequencies and amplitudes and it can be demonstrated that such combinations of frequencies and amplitudes may yield cyclical patterns which appear non-periodic with irregular amplitude (cf. Wilson and Perry, 2004). Spectral analysis may be used to identify these cycles and ‘extract’ approximate dominant cycles from the data. To be able to extract such dominant cycles we first have to estimate a periodogram (or sample spectrum). Since the sine and cosine functions in equation 2 are orthogonal we may sum the squared coefficients for each frequency to obtain the sample spectrum (cf. Hamilton, 1994) e.g.

\[
\hat{s}_y(\omega) = \left[ \frac{T}{8\pi} \right] (A_i^2 + B_i^2)
\]

where \(\hat{s}_y(\omega)\) is the periodogram value at frequency \(\omega\), \(A_i\) and \(B_i\) are the sine and cosine coefficients from equation 2 and \(T\) is the overall series length.

The search for periodicity in a series makes use of the fact that the spectrum is the Fourier cosine transform of the autocovariance of the series. That is, the periodogram values can be interpreted in terms of variance (sums of squares) of the data at the respective frequency or period. Periodogram values may be plotted against either the frequencies (the most common approach) or the periods. Therefore, if we estimate the sample spectrum then the area under this periodogram in some given small frequency range approximates the proportion of the variance of the series in that frequency range. Consequently these peaks in the sample spectrum indicate peaks in the variance of the series in the given frequency ranges, which may be indicative of cyclical patterns in the data.

However a difficulty here is that the periodogram fluctuates violently about the theoretical spectrum, so that there are many messy periodogram spikes. This is because, in practice, what often happens is that the given frequency will “leak” into adjacent frequencies. For example, one may find large periodogram values for two adjacent frequencies, when, in fact, there is only one strong underlying sine or cosine function at a frequency that falls in-between those implied by the length of the series. This problem can be circumvented by smoothing the periodogram and in doing so one may identify the general frequency “regions” (or spectral densities) that significantly contribute to the cyclical behaviour of the series. That is, we identify the frequency regions, consisting of many adjacent frequencies that contribute most to the overall periodic behaviour of the series.10

We have noted above that the original strike rate series appeared to be non-stationary in levels (that is, an I(1) series) but first difference stationary, as shown in table 1. However, when the possibility of a structural break in the series was taken into account, the results from the Z-A analysis, as shown in table 2, clearly indicate that the series was trend stationary around a

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10 In the present analysis the periodogram was smoothed using a Tukey-Hamming window of width 5 and the Statistica software. As with most smoothers the weight functions will assign the greatest weight to the observation being smoothed in the centre of the window, and increasingly smaller weights to values that are further away from the centre. Conventionally the weights are standardised so that they sum to 1.
break in the trend. Given that spectral analysis can only proceed with stationary series, and given that we will not make any presumptions on the nature of stationarity, we examine four standard transformations of the original series. The transformations are:

(a) Demeaned and detrended original strike rate data
(b) Demeaned and detrended logged strike rate data
(c) First differenced original strike rate data and
(d) First differenced logged strike rate data.

The first two transformations involve generating new series that are essentially deviations about the trend in the data: hence the descriptor ‘demeaned and detrended’. These transformations presuppose that an underlying deterministic trend mechanism is generating the realised values of the strike rate variable over the timeframe of the analysis. Since the earlier Z-A analysis supports trend stationarity around a break in the series, these two transformations take on particular importance in this analysis, as it is likely that the underlying data generating process contains a deterministic trend. The last two transformations are quarterly changes in, respectively, the original strike rate variable and the natural log of the strike rate variable. These last two transformations presuppose an underlying stochastic trend mechanism is generating outcomes. These have been included for completeness since we are not making any assumptions on the underlying data generation process. Therefore whether, for the period under review, these quarterly data have an underlying deterministic or stochastic trend component, is not an issue in this paper. Rather, our concern is to investigate the presence or otherwise of cyclical regularities in the series allowing for the possibility that either of the mechanisms may be operative.

Let us now proceed to the outcomes of our tests. Figure 3 charts the spectral density function against frequency for the transformation (a) mentioned above, i.e. for demeaned and detrended original strike rate data. The frequency ranges from zero, which effectively reflects the long term trend in the series (i.e. no cycles), to 0.5, which is the Nyquist frequency. As Bloomfield (1976) explained, this is the highest frequency that can be observed, and it is one half the sampling rate.\(^{11}\) So, if the sampling rate is 1 observation per unit time (as it is here), the Nyquist frequency is 0.5. Intuitively when we read the spectral density graphs we are looking for the frequency range in which the largest number of full cycles will be completed, as this will tell us what the dominant cyclical pattern will be.

\(^{11}\) The Nyquist frequency is also called the folding frequency, since higher frequencies are effectively folded down into the interval determined by a zero frequency and the Nyquist frequency endpoint (Bloomfield 1976). Consider this as explained by Bloomfield. Suppose the sampling interval is \(\Delta\) so that the \(t\)th observation is made at time \(t\Delta\). Let us suppose the data consist of a pure cosine wave at frequency \(\omega\), in that case the \(t\)th observations will be \(Y_t = \cos \omega t \Delta\). If the frequency \(\omega\) is increased from zero this wave oscillates more and more rapidly until at \(\omega = \pi / \Delta\) we have \(Y_t = \cos \pi\), which is the most rapid oscillation we can observe. The Nyquist frequency is \(\pi / \Delta\) radians per unit time. In cycles per unit time it is \(1 / (2 \Delta)\). Since the sampling interval is \(\Delta\) the sampling rate is \(1 / \Delta\) observations per unit time. Hence the Nyquist frequency is one half the sampling rate i.e. there are two samples per cycle of the Nyquist frequency, the highest frequency that can be observed. If the sampling interval is a unit of time, as in our analysis, then \(\Delta = 1\). Hence the Nyquist frequency in cycles per unit time is \(\pi / \Delta\) and all frequencies lie in the interval \([0,0.5]\).
So, for example, if we were hoping to find ten year cycles in a quarterly data set then we would be looking for peaks in the spectral density at about the $1/40^{th}$ frequency (ten years of quarterly data) i.e. at frequency 0.025. On the other hand, if we looking for seasonal patterns in quarterly data then we would look for peaks in the spectral density function at about the $1/4^{th}$ frequency (i.e. every $4^{th}$ quarter) i.e. frequency 0.25 and so on.

The sizable spike in the spectral density function around the frequency 0.25 suggests that there are seasonal – i.e. four quarter cyclical - regularities in the series. The spike at the Nyquist frequency is indicative of a considerable quarter-to-quarter cyclical change. In other words, it is indicative of an up-down-up-down, quarter-by-quarter pattern in the series. While this pattern may represent the machinations of some underlying very short-term cyclical process, it may also incorporate a considerable amount of noise.

Figure 4 measures spectral density against the periodicity of a possible cycle. Thus period 4 (say) represents a 4-quarter cycle, while period 16 (say) represents a four year (i.e. 16-quarter) cycle. Figure 4 thus represents another way of visualising the results charted in Figure 3. The seasonality of the data is reflected in the spike in the chart at period 4. The spike at period 2 may represent noise or it may represent some other underlying pattern that may be worth future investigation. There are also minor spikes at about two, four and ten years that also may be the subject of future investigation.

Figures 5 and 6 are analogous to figures 3 and 4 respectively, however the latter figures measure demeaned and detrended logged strike rate data (category (b) above). We see that the log transformation results in an increase in the relative importance of the two year and ten year cycles along with the possible noise factor. More importantly, there continues to be strong evidence of seasonality in the data series.

Figures 7 and 8 are analogous to figures 3 and 4 respectively, however the latter figures measure first differenced original strike rate data (category (c) above). Here we see that while four-quarter seasonality is still strongly evident, the first differencing transformation has resulted in an increase in the relative importance of 2-period cycles. In view of the earlier Z-A analysis we are placing less emphasis on the first differencing transformation. Nevertheless the analysis continues to be supportive of seasonality.

Figures 9 and 10 (also analogous to figures 3 and 4 respectively) measure first differenced logged strike rate data (category (d) above). While seasonality is still evident the 2-period cycle is even more pronounced. Again, for the same reasons as given earlier, we are placing less weight on the differenced data.

It goes beyond the scope of this paper to explore this apparent 2-quarter cyclical pattern, given our principal interest is in seasonal patterns. However, one possible partial explanation may be that strikes have a tendency to cluster in terms of frequency and/or involvement and/or duration because of a demonstration effect. Once the bulk of these disputes are resolved, this may lead to a temporary ‘clustered retreat’ from action until the next quarter. This explanation, however, begs the question why does clustering occur on such a short-term basis?
Figure 3 Full Period 1983-2004: Spectral Density by Frequency Demeaned and Detrended Original Strike Rate Data (STRKALL)

Spectral analysis: STRKALL
No. of cases: 82, Hamming weights: .0357 .2411 .4464 .2411 .0357

Figure 4 Full Period 1983-2004: Spectral Density by Period Demeaned and Detrended Original Strike Rate Data (STRKALL)

Spectral analysis: STRKALL
No. of cases: 82, Hamming weights: .0357 .2411 .4464 .2411 .0357
Figure 5  Full Period 1983-2004: Spectral Density by Frequency Demeaned and Detrended Logged Strike Rate Data (LNSTRKAL)

Spectral analysis: LNSTRKAL
No. of cases: 82, Hamming weights: .0357 .2411 .4464 .2411 .0357

Figure 6  Full Period 1983-2004: Spectral Density by Period Demeaned and Detrended Logged Strike Rate Data (LNSTRKAL)

Spectral analysis: LNSTRKAL
No. of cases: 82, Hamming weights: .0357 .2411 .4464 .2411 .0357
Figure 7 Full Period 1983-2004: Spectral Density by Frequency First
Differenced Original Strike Rate Data (DSTRKAL)

Spectral analysis: DSTRKALL
No. of cases: 82, Hamming weights: .0357 .2411 .4464 .2411 .0357

Figure 8 Full Period 1983-2004: Spectral Density by Period First
Differenced Original Strike Rate Data (DSTRKAL)

Spectral analysis: DSTRKALL
No. of cases: 82, Hamming weights: .0357 .2411 .4464 .2411 .0357
Data Split

Given the evidence of a break point in the data around 1992-93, we again split the sample data into pre-break and post-break periods. Recall that the pre-break period, referred to as the ‘early period’, is set from 1983:1 to 1992:4; and the post-break period, referred to as the ‘later period’, is set from 1993:1 to 2003:3. The early period results for the various transformed variables are similar to the results for the full period insofar as there is evidence of seasonality. In the interest of brevity we report on one set of results, namely...
for the demeaned and detrended strike rate (for the reasons given earlier). These results, in figures 11 and 12, are representative of the results for all of the transformations as in our earlier discussion. We note in figures 11 and 12 that the evidence of seasonality is marginally stronger in that the spectral density peak is higher in the 0.25/4-quarter frequency range. For the later period, as figures 13 and 14 show, the four-quarter seasonal pattern has completely disappeared. Instead a relatively strong spike has emerged suggesting a cycle at about two years (7 to 8 quarters). A spike at 8 quarters might be seen as attenuated evidence of a seasonal pattern, to the extent that a four-quarter seasonal cycle may be registering as an eight-quarter cycle. However, there can be little doubt that the later period shows far less evidence of seasonality than the earlier period.

Figure 11 Early Period 1983-1992: Spectral Density by Frequency Demeaned and Detrended Strike Rate Data (STRKALL)

![Figure 11](image1.png)

Figure 12 Early Period 1983-1992: Spectral Density by Period Demeaned and Detrended Strike Rate Data (STRKALL)

![Figure 12](image2.png)
Table 3 summarises the overall results with respect to the spectral analysis of seasonality. For the full period, there is evidence of seasonality in all of the stationary transformations of the strike rate variable. For the early period, there is similarly evidence of seasonality. However, for the later period the evidence of seasonality is much more attenuated.\textsuperscript{13} All in all these results suggest that the time series properties of this strike rate series changed during the post-break period such that, not only did the mean

\textsuperscript{13} The differenced transformations showed strongly reduced rather than totally eliminated seasonality. Since the Z-A analysis indicated trend stationarity we are placing more weight on the demeaned/detrended transformation.
value and the volatility of the index fall, but also the series lost much if not all of its seasonality.

Table 3 Summary Table for Evidence of Seasonality

<table>
<thead>
<tr>
<th>Period</th>
<th>Detrended, demeaned</th>
<th>Logged, detrended, demeaned</th>
<th>First differenced</th>
<th>Logged and first differenced</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Period:</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>1983:1 to 2003:3</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Early Period:</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>1983:1 to 1992:4</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Later Period</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>1993:1 to 2003:3</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
</tbody>
</table>

3. Seasonal Indicator Analysis

We now come to our final approach to gauging seasonality, namely seasonal indicator analysis. This approach has been employed for many years, and basically revolves around various techniques for deseasonalising data. The process of deseasonalising data involves implicitly the recognition of a seasonal element in the data. Our purpose here is to construct a deseasonalised series, from which we can infer the dimensions, if any, of the seasonal component in the data.

Pindyck and Rubinfeld (1998, p.482) note that ‘Seasonal adjustment techniques are basically ad hoc methods of computing seasonal indices …’ and go on to comment on some of the more unusual deseasonalising procedures that have been used in the USA. We employ two approaches to measuring the seasonality of strike data. The first approach measures the difference between a modified 5-quarter centred moving average with the original series - see table 4. The second approach constructs an index based on a conventional ratio-to-moving average method with a centred 4-quarter moving average\textsuperscript{14} - see table 5.

\textsuperscript{14} Conventionally, seasonal variations refer to the almost identical patterns that a time series may follow during corresponding periods of successive years. One way of measuring the magnitude of such variation is to construct a seasonal index number series. There are a variety of methods available to construct such a seasonal index and, perhaps, the most common is the ratio to moving average technique. This method first isolates the trend-cycle of the data by calculating a moving average whose number of terms is equal to the length of seasonality (a 4-quarter moving average in this case) and which is centred on the respective quarter. A moving average of this length contains no seasonal effects and little or no randomness. The original data series is then divided by this moving average (this is the ratio part and it contains only trend and cyclical components) and expressed as a percentage. The result of this division contains only seasonal and erratic components. Percentages for corresponding quarters are then averaged through the entire sample to eliminate the erratic component and give the required index. Some further adjustment may be necessary to ensure the series averages 100 per cent i.e. sums to 400 for the four quarters. Thus the ratio values vary around 100 indicating the effects of seasonality on the average deseasonalised values (they are deseasonalised since we divided by the moving average). So, for example, if the seasonal index number is 120 this suggests that the actual values are 20 per cent higher than would be expected in the absence of a seasonal pattern.
Table 4  Seasonality Comparisons: Days Lost Each Quarter per Thousand Employees*

<table>
<thead>
<tr>
<th>Quarter</th>
<th>Full Period**</th>
<th>Early Period**</th>
<th>Later Period**</th>
</tr>
</thead>
<tbody>
<tr>
<td>March Quarter</td>
<td>-12.9</td>
<td>-30.8</td>
<td>-23.0</td>
</tr>
<tr>
<td>June Quarter</td>
<td>2.1</td>
<td>3.6</td>
<td>4.3</td>
</tr>
<tr>
<td>September Quarter</td>
<td>4.0</td>
<td>7.5</td>
<td>6.0</td>
</tr>
<tr>
<td>December Quarter</td>
<td>6.4</td>
<td>14.1</td>
<td>12.5</td>
</tr>
</tbody>
</table>

* Seasonality is measured as the average level of dispersion from the centred 5-quarter moving average strike rate. The 5-quarter moving average for variable $X_t$ is $[(0.5)X_{t-2} + X_{t-1} + X_t + X_{t+1} + (0.5)X_{t+2}]/4$. Subscripts refer to quarter periods.


Table 5  Seasonal Index Numbers*

<table>
<thead>
<tr>
<th>Quarter</th>
<th>Full Period</th>
<th>Early Period</th>
<th>Later Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>March Quarter</td>
<td>71.0</td>
<td>57.0</td>
<td>80.6</td>
</tr>
<tr>
<td>June Quarter</td>
<td>106.1</td>
<td>107.6</td>
<td>112.8</td>
</tr>
<tr>
<td>September Quarter</td>
<td>111.4</td>
<td>122.3</td>
<td>105.1</td>
</tr>
<tr>
<td>December Quarter</td>
<td>111.5</td>
<td>113.2</td>
<td>101.6</td>
</tr>
</tbody>
</table>

* Ratio to Moving Average Method

Table 6  International Strike Rate Trend Comparisons: 1983-92 versus 1993-2002

<table>
<thead>
<tr>
<th>Country</th>
<th>Per cent change in mean value of strike rate</th>
<th>Per cent change in standard deviation of strike rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>-67</td>
<td>-62</td>
</tr>
<tr>
<td>USA</td>
<td>-49</td>
<td>-31</td>
</tr>
<tr>
<td>Japan</td>
<td>-77</td>
<td>-82</td>
</tr>
<tr>
<td>UK</td>
<td>-89</td>
<td>-93</td>
</tr>
<tr>
<td>NZ</td>
<td>-93</td>
<td>-95</td>
</tr>
<tr>
<td>Canada</td>
<td>-49</td>
<td>-40</td>
</tr>
<tr>
<td>Average* (O/S)**</td>
<td>-71</td>
<td>-68</td>
</tr>
</tbody>
</table>

* Average refers to the simple average for all of the above countries excluding Australia
** O/S refers to overseas
Table 4 measures seasonality by comparing the actual strike rate series with a deseasonalised strike rate series. The deseasonalised series is a modified 5-quarter centred moving average measure of strikes for which further details are provided beneath table 4.\footnote{Five periods enable the centred moving average (i.e. deseasonalised) series to be \textit{centred} on the quarter in question. The modified 5-quarter centred moving average for variable $X_k$ is $[(0.5)X_{k-2} + X_{k-1} + X_k + X_{k+1} + (0.5)X_{k+2}]/4$. Subscripts refer to quarter periods. The most ‘distant’ quarters are multiplied by 0.5 so as to attenuate for the presence of that quarter twice in the calculation. The advantage of this deseasonalising method is that it is more sensitive to data that exhibit an underlying upward or downward trend than say a conventional centred 4-period moving average which will either be weighted with two lead periods or one. If the series is systematically declining, a 2-period lead will tend to understate the deseasonalised series, while a 1-period lead will tend to overstate the deseasonalised series. Given the downward trend in the data, it seems not unreasonable to apply this modified 5-quarter centred moving average method in addition to the conventional 4-period method.} Table 4 indicates that the seasonal pattern is most pronounced in the early period and less pronounced in the later period. Also it suggests that strikes activity tended to be relatively high in the December quarter, at least for the early period, and relatively low in the March quarter. As mentioned, during the later period the seasonality of the data appears to be less pronounced than in the earlier period. This applies particularly to December quarter data, which appear to lose their seasonality. The March quarter seasonality appears to be present throughout the period of the study, but it is much less pronounced both in absolute terms as well as in percentage terms. The negative seasonality of the March quarter is consistent broadly with the findings of earlier studies. However the earlier period positive seasonality for the December quarter is contrary to the findings in earlier papers. The Seasonal Index Numbers in table 5 were constructed using a conventional ratio-to-moving average method with a centred 4-quarter moving average. For the early period it would appear that the strike rate is relatively more pronounced in the September and December quarters – where the strike activity is respectively 22 per cent and 13 per cent above what would be expected in the absence of any seasonal pattern. Conversely strike activity is relatively low in the March quarter – where it is about 43 per cent lower than would be expected in the absence of a seasonal pattern. In the later period the seasonal index numbers are far less supportive of seasonality other than a reduced activity in the March quarter (about 20 per cent below what we would expect in the absence of seasonality) and an increased activity in the June Quarter (about 13 per cent above what we would expect). Both tables 5 and 6 point in much the same direction, i.e. sizable seasonality in the earlier period and much weaker evidence of seasonality in the later period.

All in all, our three sets of tests point in the same direction. During the early period (1983:1 to 1992:4), there is quite strong evidence of seasonality in the data. Strikes tend to be relatively severe in the September and December quarters and relatively subdued in the March quarter. On the other hand, during the later (post-break) period (1993:1 to 2003:3), the evidence for seasonality is much weaker. While March quarter strikes are still relatively smaller than the seasonally-adjusted average, the difference is much less pronounced; and September and December quarter strikes are unexceptional during the later period. If there is any seasonality in the later-period data, it is very minor indeed.
4. Interpreting Results
What to make of these results that, in particular, (a) there is evidence of a break in the aggregated quarterly strike rate series and (b) during the post break period, direct evidence of seasonality is virtually absent?

The break point in the series occurs around the time of the installation of enterprise bargaining into the Australian industrial relations environment. This was a radical departure from the previous system of centralised conciliation and arbitration. The then Prime Minister, Keating, commented to an international industrial-relations gathering in 1992 that:

‘Not only is the old system finished, but we are rapidly replacing its replacement, and we have now begun to do things in a new way … Bargaining is the [new] way’ Quoted from Dabscheck, (1996, p.104)

Around the time of the introduction and embedding of enterprise bargaining into the industrial relations system, there were a number of specific developments worth mentioning.

First, in October 1991 enterprise bargaining was promulgated by the Australian Industrial Relations Commission (AIRC). Mulvey (1997, p. 231) refers to this as a ‘... key date in the development of enterprise bargaining’, though he notes that its full impact was not immediately felt. The Australian Bureau of Statistics (ABS, 2001, p. 118) observes that the introduction of the enterprise bargaining principle by the AIRC in 1991 ‘... provided a framework for decentralised bargaining and workplace reform’.

Wooden (2000, p. 7) notes that:

‘Between October 1991 and March 1999 ... almost 25,000 federal agreements were formalised by the AIRC, with the number of employees estimated to be covered by these agreements reaching … by September 1998 ... about 75 per cent of employees covered by the federal award system’.

The growth of employee coverage of these enterprise awards was particularly sharp during the December quarter 1992. Recall that this is the last quarter of the first period of our two-period split. The number of employees covered by federal enterprise wage agreements (specifically those containing a wage increase) more than doubled during the December quarter of 1992.16 By the June quarter of 1994, the number had roughly doubled again (to 800,000); and by June 1999, the number was around 1,400,000.

A second and related development in the industrial relations environment involved the enactment of the Labor government’s Industrial Relations Reform Act 1993 to be followed a few years later by the introduction of the Workplace Relations and Other Legislation Act 1996 and the Workplace Relations Act 1996 by the new Howard Coalition government. The Australian Bureau of Statistics (ABS, 2001, p.118) described the 1993 Act as encompassing:

16 See Wooden (2000) Figure 2.1, p. 8, where the numbers rose from approximately 120,000 employees to around 400,000.
‘...provisions to better allow enterprise bargaining in non-unionised workplaces. The opening up of collective bargaining to workers not represented by unions meant that wages and employment conditions could be changed without unions being directly involved in negotiations’.

The ABS described the *Workplace Relations Act 1996* as allowing:

‘...the development of individual worker agreements (Australian Workplace Agreements) as well as continuing collective worker agreements (Certified Agreements) and prohibited intervention in non-union agreements’ (ABS, 2001, p. 118).

A third development in the industrial relations environment involved changes in the structure and operations of trade unions. These changes occurred in parallel with the aforementioned administrative and legislative changes designed to develop enterprise bargaining. In essence unions were radically restructured in an attempt to make them more industry oriented and less occupationally oriented (Svenson, *et al.* 1999; Kirsch, 2003). Although many mergers took place, the goal of having a small number of industry-oriented unions was not achieved.\(^{17}\)

According to Hose (2003, p.177), the changes in union structure were ‘...on a scale unparalleled’ in the history of the Australian union movement. She points out that: ‘Change was especially rapid between 1991 and 1994 when the number of unions fell from 275 to 157’ [emphasis added]\(^{18}\) Svensen, *et al.* (1999, p.5-6) similarly point out that during the 1991-94 period: ‘Nothing remotely approaching this number of mergers [of unions] has occurred previously in Australia ... or indeed in other industrialised countries’.

A forth development worth noting is that 1993 saw the end of the AIRC’s national wage decisions (Norris *et al.*, 2004), in which across-the-board wage changes had customarily been announced for workers on federal awards and other awards thereto linked. Instead, national wage decisions became safety net rulings affecting workers on minimum wage rates. The end of the national wage decisions arguably marked the end of the era of centralised wage determination in Australia; decentralised enterprise bargaining had finally replaced many decades of centralised wage determination.

All in all, the changes of the early 1990s ushered in a new era of enterprise bargaining, decentralised wage fixing and individual agreements. Wooden (2001, p. 247) sums up the new industrial relations environment as one where: ‘Bargaining, and more specifically, enterprise bargaining, has ... supplanted arbitration as the dominant industrial relations paradigm... [and where] national and industry-wide considerations are much more likely to

\(^{17}\) Kirsch (2003, p. 12) like others points out that ‘... despite massive restructuring, Australia is not dominated by industry unionism’.

\(^{18}\) See also Dabscheck (1995), Chaison (1996) and Tomkins (1999), among others, for discussion of union mergers during the late 1980s and early 1990s.
be subordinate to the needs of enterprises and workplaces ... ’ He further argues that the underlying sources of change have been ‘overwhelmingly of economic and social origin’. (p. 248) He categorises these influences as (i) changing values (for example, the rise of individualism), (ii) increased competition (brought about by progressive tariff reductions and faster communications, for example) and (iii) new technologies.

To the above list of factors contributing to change in the Australian industrial relations environment, we would specifically add international forces. While it is true that international influences are often incorporated into the discussion of various other influences, it can be argued that the influence of worldwide developments, and in turn those factors that drive the worldwide developments, tends to be underreported and underplayed. Thus while it may appear that local experience is being driven by, say, local legislation and local socio-economic variables, behind these seemingly locally-only factors are often powerful worldwide forces. The links between the Australian economy and the outside world, but especially between Australia and its major trading partners, include of course the direct trading links of goods and services and financial assets being traded between one place and another. But there are many other more subtle links between Australia and the outside world that tend, perhaps, to go somewhat unnoticed because they tend to be taken for granted. Ideas, fashions, intellectual movements, knowledge and technology, popular culture and so on are all speedily transmitted from one place to another. Ideas and fashions in managerial practices, including human relations management practices, are similarly quickly transmitted from one place to another. The citizenry of all countries learn, both consciously and unconsciously, from the experience of others. Humans have evolved to be imitators, as well as being highly competitive. If some managerial practice, for example, is seen to be successful and leads to a rival establishing a competitive advantage, there is a strong likelihood that the rival will be imitated.

Decision makers are, typically, constantly making international comparisons. A direct example of international influences affecting union behaviour is the Australian Council of Trade Unions’ (ACTU) decision to embrace enterprise bargaining and restructure (i.e. reduce) the number of unions in the workplace. Svensen et al. (1999, p.6) note that:

‘The first formal union recommendation for mergers followed a joint ACTU/Trade Development Council fact-finding mission to Western Europe. Two resultant strategy documents (ACTU 1987; ACTU/TDC 1987) advocated the adoption of a model of “strategic unionism”, to be achieved chiefly by transferring most of the members of the then existing 326 mainly occupationally-based unions into 20 mainly industry-based “super-unions”’

Governments are similarly very conscious of international practices when framing policy. Consider the comments, for example, of the former Minister for Employment, Workplace Relations and Small Business, when he (or his departmental scriptwriters) observed that:
'The reduction in disputes that occurred in Australia over the course of the 1980s and early 1990s ... has largely reflected international trends. Despite the decline, when the performance of our major trading partners is considered, Australia has not done as well as it could have...' Reith (1999, p. 2)

The above ministerial observation, among others, subsequently led the minister to observe that:

'Australia must continue to look for lessons learnt by other countries to draw on international workplace relations experience. We need to re-examine our system for the betterment of all Australians' Reith (1999, p. 12)

It is beyond the scope of this paper to develop this theme more fully, but to give a further sense of the importance of the international industrial relations environment, let us compare the previously noted decline in the mean value of the strike rate and the volatility of the strike rate in Australia with a that of a selection of significant trading partners.19

Table 6 does exactly this. It compares the mean and standard deviation of the strike rate for the early pre-break period of 1983:1 to 1992:4 with (most of) the later period of 1993:1 to 2002:4. Between these two periods the mean value of the strike rate for Australia decreased by 67 per cent and the standard deviation decreased by 62 per cent. Similar declines occurred for the selected trading partners. In the case of the USA and Canada the declines were somewhat smaller. In the case of New Zealand, the UK and Japan, the declines were somewhat larger. Overall, the changes reported in Table 6 suggest a noteworthy degree of comparability of experience for Australia and its trading partners, despite the observations above by former minister Reith. The comparability of experience, in turn, is consistent with a view that worldwide and broadly common influences are affecting local and overseas strike rates in rather similar ways.20

Let us finally return to the issue of seasonality: its presence in the early period, its near-absence in the later period.

We suggest that the system of enterprise bargaining itself may have acted all but to eliminate seasonality in industrial dispute data. Factors directly contributing to this may include the setting of different contractual periods within different individual enterprises, with and without union involvement. This, in turn, may have acted to distribute more evenly the timing of negotiations over wages and conditions. The earlier centralised system of setting, at times, sector-wide and economy-wide awards would have been more likely to result in a bunching-up of wage determination

19 The selection of trading partners includes those major trading partners for which quarterly and recent strike rate data are available.
20 For further analysis of international influences see Perry and Wilson (2001, 2003). See also Chaison (1996) for further discussion of the similarities and differences in the contextual changes in the industrial relations environments for the English-speaking countries in table 6.
decisions and the posturings (strikes, lockouts, work-to-rules etc.) that precede and sometimes follow a decision.

More generally, the ongoing decline in union density and the development of individual non-union contracts may have acted to reduce the importance and impact of a ‘traditional’ (say) wages campaign put into action at that time of the year when it is going to be strategically most effective. Such campaigns would not be very effective during a summer vacation period (mainly late December and January) when many factories, union offices and legal offices are closed. Thus, in the past, when the system was more accommodating to union aspirations and methods, we might have expected to see more pronounced seasonality in aggregate strike rates. In addition, the significant structural changes in the economy associated with the continuing decline in the relative importance of the manufacturing sector and the concomitant rise in relative importance of the tertiary and information sectors will have likely reinforced the expunging of seasonality from aggregate strike statistics. Thus holiday season closures and winding-down in the manufacturing sector, though present, may have become less important in aggregate; and while some manufacturers may at times cease or severely curtail production over the holiday period, banks, hotels and real estate agents are likely to be operational during most of the break.21

5. Concluding Comments
This paper has examined the seasonality pattern of strikes in Australia over the last couple of decades. It has found that the first half of the period under review displays quite strong evidence of seasonality in aggregate strike data. Essentially the analysis suggests that the March quarter has experienced a discernible relative decline in strike activity. This we attribute to the holiday period. The September and December quarters, on the other hand, display relatively heightened activity. For the second half of the period, we find that the strength of the seasonality of these data is substantially reduced. There is still some evidence of an attenuated negative seasonality during the March quarter, but the seasonal impact of the other periods, and in particular the December quarter is much weaker. Spectral analysis of the data confirms the weakening of seasonality in the later-period data. Indeed spectral analysis suggests the elimination of seasonality during the later period. We suggest the changes in the industrial relations environment, in particular the installation of enterprise bargaining in the early 1990s, plus structural changes in employment have contributed to the virtual elimination of seasonality in the data.

Appendix
The Zivot and Andrews (1992) methodology followed Perron (1989) in considering three possible types of structural break in a series. These breaks

21 The leisure industry, an increasingly important sector, will of course be geared up for action during the holiday season. Direct data on strikes in this sector are unavailable. During the pre-enterprise bargaining period the manufacturing sector accounted for 32 per cent of strikes on average. During the enterprise bargaining period it accounted for 28 per cent of strikes. These changes are roughly in line with the decline in the relative importance of manufacturing as a source of employment. A detailed sectoral analysis of disputes goes beyond the scope of the current paper.
were simply designated by Perron as Models A (a ‘crash’ model with no change in growth), B (change in growth, but no change in level), and C (the most general model permitting both occurrences). In the Z-A approach the null hypothesis is that the data series of interest \( \{y_t\} \) is integrated without an exogenous structural break against the alternative that the series \( \{y_t\} \) can be represented by a trend-stationary process with a once only breakpoint occurring at some unknown time. The aim of the Z-A procedure is to sequentially test breakpoint candidates and select that which gives the most weight to the trend-stationary alternative. That is, the breakpoint \( DU_t \) is chosen as the minimum \( t \)-value on \( \alpha^i \) \((i = A, B, C)\) for sequential tests of the breakpoint occurring at time \( 1 < T_B < T \) in the following augmented regressions:

**Model A**

\[
y_t = \mu^A + \theta^A DU_t(\lambda) + \beta^A t + \xi^A y_{t-1} + \sum_{j=1}^{k} \gamma^A_j \Delta y_{t-j} + \epsilon_t
\]

**Model B**

\[
y_t = \mu^B + \theta^B t + \gamma^B DT_t(\lambda) + \xi^B y_{t-1} + \sum_{j=1}^{k} \gamma^B_j \Delta y_{t-j} + \epsilon_t
\]

**Model C**

\[
y_t = \mu^C + \theta^C DU_t(\lambda) + \beta^C t + \gamma^C DT_t(\lambda) + \xi^C y_{t-1} + \sum_{j=1}^{k} \gamma^C_j \Delta y_{t-j} + \epsilon_t
\]

where \( \lambda \) is the break fraction; \( DU_t(\lambda) = 1 \) if \( t > T_B \lambda \), and 0 otherwise; \( DT_t(\lambda) = t - T_B \lambda \) if \( t > T_B \lambda \) and 0 otherwise. Because the Z-Andrews methodology is not conditional on the prior selection of the breakpoint (all points are considered potential breakpoints) the critical values are larger (in an absolute sense) than the conventional ADF critical values. Consequently, it is more difficult to reject the null hypothesis of a unit root.

**Data Sources**

The strike rate is defined the number of working days lost due to strikes per 1000 employees. Sources: Australian Bureau of Statistics (ABS) *Industrial Disputes*, Cat. No. 6321.0 various issues, ABS *Labour Force Australia*, Cat. No. 6202.0 various issues and AusStat related spreadsheets, OECD, *Main Economic Indicators* and *Economic Outlook*. Certain refinements and updates were communicated directly to the authors via direct correspondence with respective national statistical collection agencies.

**References**


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22 We emphasise again that the Zivot and Andrews procedure was not aimed at testing for structural change per se, but rather was oriented towards the issue of testing for a unit root in the presence of an unknown structural break.
ACTU/TDC (1987), *Australia Restructured*, Canberra, AGPS.


