Australian Bureau of Statistics

1352.0.55.079

Research Paper

Some Aspects of Turning Point Detection in Seasonally Adjusted and Trend Estimates

New Issue

Research Paper

Some Aspects of Turning Point Detection in Seasonally Adjusted and Trend Estimates

Xichuan (Mark) Zhang, Nicholas von Sanden,

Zuleika Menezes and Craig McLaren

Statistical Services Branch

Methodology Advisory Committee

23 June 2006, Canberra

AUSTRALIAN BUREAU OF STATISTICS

EMBARGO: 11.30 AM (CANBERRA TIME) THU 20 JUL 2006

ABS Catalogue no. 1352.0.55.079
ISBN 0 642 48242 X

Views expressed in this paper are those of the author(s), and do not necessarily represent those of the Australian Bureau of Statistics. Where quoted, they should be attributed clearly to the author(s).

Produced by the Australian Bureau of Statistics

INQUIRIES

The ABS welcomes comments on the research presented in this paper.
For further information, please contact Dr Mark Zhang, Statistical Services Branch on Canberra (02) 6252 5132 or email <mark.zhang@abs.gov.au>.

SOME ASPECTS OF TURNING POINT DETECTION IN SEASONALLY ADJUSTED AND TREND ESTIMATES

Xichuan (Mark) Zhang, Nicholas von Sanden, Zuleika Menezes and Craig McLaren
Australian Bureau of Statistics

EXECUTIVE SUMMARY

The Australian Bureau of Statistics publishes original, seasonally adjusted and trend estimates. Users are often concerned about which estimate is most appropriate for use to accurately determine current and future economic behaviour. In this research we compare the use of the seasonally adjusted and trend estimates in terms of the detection of turning points. It is found that turning points are generally detected in a more timely fashion and with a lower incidence of falsely detected turning points for trend rather than seasonally adjusted estimates when compared with trend and seasonally adjusted benchmarks respectively. Additional information is presented in seasonally adjusted estimates that may be of aid in the detection of turning points. However due to increased clarity, the trend estimates are preferred to identify turning points for low-end users.

QUESTIONS FOR THE METHODOLOGY ADVISORY COMMITTEE

1. Do you believe the discussion presented in this paper will be valuable for users?
2. Is the PAT approach for detecting turning points turning points a reasonable method for detecting turning points in both trend and seasonally adjusted estimates?
3. In this paper we have compared turning points detected in the trend estimates against trend benchmarks and turning points detected in the seasonally adjusted estimates against seasonally adjusted benchmarks. Does this cross-benchmarking approach provide a useful comparison and still lead to relevant results?
4. Are the assessment methods presented in this paper appropriate to the topic of interest?
5. With regards to decomposing the irregular into potentially useful information (irregulars relating to real world events) and nuisance information (volatility in the irregular relating to data estimation issues, e.g. Sampling error) can you suggest any methods to assess and include this information explicitly in the analysis?

CONTENTS

SOME ASPECTS OF TURNING POINT DETECTION IN SEASONALLY ADJUSTED AND TREND ESTIMATES

Xichuan (Mark) Zhang, Nicholas von Sanden, Zuleika Menezes and Craig McLaren
Australian Bureau of Statistics

1. INTRODUCTION

Business cycles refer to economy wide fluctuations in output. Information about business cycles can be used to appropriately manage expansions and contractions in an economy, for example central banks can adapt monetary policy to foster growth in a slowing economy. One of the most important features of business cycle analysis is the dating of turning points for given socioeconomic time series. The timely and accurate detection of turning points is therefore an important issue in economic analysis and policy making.

Different time series estimates, such as the original estimates and the derived seasonally adjusted and trend estimates are available to help assess turning points. The Australian Bureau of Statistics (ABS) regularly publishes original, seasonally adjusted and trend estimates to provide users a complementary suite. In particular, these trend estimates are designed to give the general public a clear picture of the underlying direction of a time series. Trend estimates may then assist policy makers to make informed judgements and policy decisions in a timely fashion.

Although the ABS publishes trend estimates to present a clearer picture of the underlying movement in a time series, analysts may question whether this increased clarity comes at the cost of a loss of information regarding turning points. This paper presents an empirical comparison of turning point detection in monthly ABS trend and seasonally adjusted estimates rather than developing or evaluating turning point detection methods.

This paper is structured as follows. In Section 2, we describe the background of time series decomposition in relation to cycles. Section 3 defines turning points and discusses some common identification methods available in the literature. In Section 4 our experimental design is detailed and the accompanying results are presented in Section 5. Some concluding remarks, discussion and possible directions for future work are then presented in Section 6.

2. BACKGROUND

Assume a multiplicative decomposition model for the original estimates at time t, O_t, which can be decomposed as a combination of the combined seasonal factor S_t, the long-term trend T_t, cycle C_t, and the irregular I_t,

$$O_t = S_t \times T_t \times C_t \times I_t \tag{2.1}$$

The seasonally adjusted estimates ($\widehat{SA}_t$) are derived from the original estimates by estimating and removing the systematic calendar related component according to (2.2) following. Estimates of the seasonal factor ($\hat{S}_t$), trend ($\widehat{T_t \times C_t}$), and irregular ($\hat{I}_t$) components in (2.1) can be produced by a filter based seasonal adjustment approach, for example X12–ARIMA (see Findley *et al.*, 1998).

$$\widehat{SA}_t = \frac{O_t}{\hat{S}_t} = \widehat{T_t \times C_t} \times I_t \tag{2.2}$$

The seasonally adjusted estimate (2.2) above contains the long-term trend, cycle, and irregular components. Movements in the seasonally adjusted estimates will be influenced by the irregular component which can mask the underlying direction of the series. ABS trend estimates contain both the long-term trend and cycle components, $\widehat{T_t \times C_t}$, (hereafter referred to as the trend) and are derived from the seasonally adjusted estimates by smoothing the irregular component through use of the Henderson filter (Henderson, 1916). The trend estimate is an attempt to represent the underlying direction of a time series which is influenced by general changes. Compared to seasonally adjusted estimates, trend estimates are smoother and show gradual movements including all the cycles above approximately eight months.

Seasonal adjustment and trending are processes that 'filter' out certain information from the original time series. The remaining signal in seasonally adjusted or trend estimates may then highlight information useful to the analyst, such as the business cycle. Seasonal adjustment aims to extract non-calender related effects from the original estimate, while trending aims to also filter out irregular fluctuations and one-off outliers in the seasonally adjusted estimates. The irregular is associated with high frequency fluctuations and is generally considered not to be of interest in the analysis of cycles. Trend estimates therefore present a much clearer representation of the underlying direction of a time series, though at the cost of suppressing perceptible irregular information. The removal of the irregular from the trend estimates is of concern to many users as this information is generally considered useful in the detection of turning points. This then raises the question as to whether trend estimates still contain sufficient information regarding turning points.

3. DEFINING A TURNING POINT

A turning point can be defined to have occurred at time t when there is a peak or a trough in the cycle component, C_t . Conceptually this is equivalent to the first derivative of C_t changing sign and hence a turning point can be identified at time t for a continuous time series when

$$\frac{dC_t}{dt} = 0 \tag{3.1}$$

A discretized version of (3.1) is to consider a sequence of monotonic decreases (increases) followed by increases (decreases) over a given number of time periods. This discrete definition is widely used in the literature and is applicable to an unknown cycle, C_t. For example Wecker (1979), Zellner *et al.* (1992), Pfeffermann *et al.* (1992), Knowles and Kenny (1997) apply this definition in the context of trend estimates. This definition, however, is not appropriate to apply to seasonally adjusted estimates because the irregular component can vary considerably between consecutive time periods. Intuitively this means that turning points in the seasonally adjusted estimates may not be found using this definition.

The key issue of identifying turning points in classical/traditional methods[1] is how to decompose long-term trend and irregular components to extract the cycle component, C_t.

One group of methods focuses on estimation of the long-term trend, $\hat{T}_t$, removing it from seasonally adjusted estimates $\widehat{SA}_t$, and then picking up turning points from remaining cycle and irregular components ($\widehat{C_t \times I_t}$). This group of methods includes the widely accepted Phase Average Trend (PAT) approach (Boschan and Ebanks 1978) for identifying turning points, and filter based methods to extract the long-term trend such as the Hodrick–Prescott (HP) filter (Hodrick *et al.,* 1997). A concern with this approach, that has been raised in the literature, is that the turning points may not be independent of the statistical assumptions needed to extract the long-term trend.

Another group of methods focuses on extracting the cycle component, C_t, directly and applies the generic turning point definition (3.1) to directly analyse $\hat{C}_t$. This group of methods includes the band-pass filter method (Baxter and King, 1999) and the state space framework (Harvey, 1989) which directly models C_t. Additional to the long-term trend component extraction (as highlighted in the previous group of methods), smoothing of observations can be applied to reduce the variance and hence reduce the probability of falsely detecting turning points. For example, Öller (1986) use exponential weighting while Hall *et al.* (1995) use kernel estimators for

1 For example, Markov switching models (MSMs) is one non-traditional method which decides the differences between expansion and recession probabilities before determining the turning points.

smoothing. In a Monte Carlo study, Andersson *et al.* (2006) show that smoothing reduces the distinctiveness of the turning points.

It has been found that the PAT is superior to its alternatives in the matter of details (Zarnowitz and Ozyildirim, 2002) although the PAT method has its own weakness. In other words, there is no absolute error-proof method.

In the following we have adopted the PAT approach for identifying turning points, as;

1. The PAT is well recognised and widely accepted by the economic community. For example various versions of PAT have been applied by Eurostat (see Anas and Ferrera, 2002), the National Bureau for Economic Research (NBER) (see Bry and Boschan, 1971), the Organization for Economic and Cultural Development (OECD), the Reserve Bank of Australia (see Gillitzer *et al.*, 2005) and the Melbourne Institute.

2. The PAT approach is a non-parametric and robust technique.

3. The PAT has been designed to identify turning points in seasonally adjusted estimates and is therefore not biased towards the trend.

A description of the PAT approach for identifying turning points can be found in the Appendix. Please refer to Boschan and Ebanks (1978) and Zarnowitz and Ozyildirim (2002) for further details. The PAT algorithm adopted in this paper has been adapted from Watson (1994).

4. COMPARING TURNING POINT DETECTION FOR SEASONALLY ADJUSTED AND TREND ESTIMATES

The results presented in this paper were calculated based on a selection of monthly real and simulated time series. The series selected for this empirical experiment were as follows;

1. All Australian employment and unemployment time series, a total of 50 time series, see (ABS, 2006b);
2. All Australian Short-Term Visitor Arrivals (STVA) time series, this is a total of 34 time series, see (ABS, 2006a);
3. 72 time series simulated according to the following conditions.

Different realisations of monthly time series, Y_t, were simulated using the airline model (Box and Jenkins, 1976),

$$(1-B)(1-B^{12})Y_t = (1-\theta B)(1-\Theta B^{12})\varepsilon_t \tag{4.1}$$

where B is the backshift operator, ε_t is disturbance term following a white noise process with variance σ_ε^2 and moving average parameters $\theta = 0.5$ and $\Theta = 0.7$. The volatility of the disturbance was controlled by the size of σ_ε^2. The airline model with appropriate parameter choice adequately fits a large proportion of ABS time series (approximately 80% – see Zhang and Sutcliffe, 2001). Seasonally adjusted and trend estimates were then calculated using a derivation of the X12–ARIMA method.

4.1 Comparison between trend and seasonally adjusted estimates

To assess the turning points detected using the PAT method, we can compare the turning points derived from the full span of seasonally adjusted and trend estimates respectively. In general it appears that the turning points detected in the trend and seasonally adjusted estimates are broadly consistent. In other words a similar number of turning points are detected at similar times in both the seasonally adjusted and trend estimates, but the exact timing may be different.

This can be seen in table 4.1 following, in which the proportion of turning points found in both the seasonally adjusted and trend estimates is presented for all time series examined in this report.

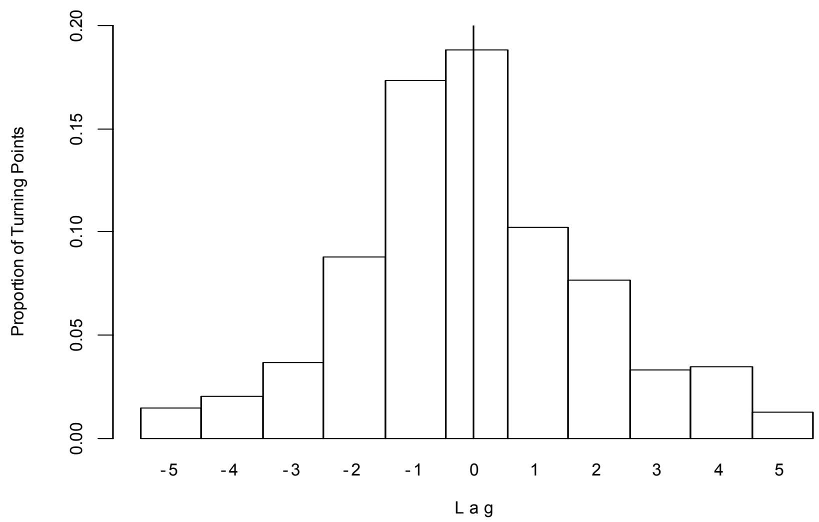
4.1 Percentage of turning points detected in both trend and seasonally adjusted estimates over all time series

	Employment	*Unemployment*	*Short term visitor arrivals to Australia*	*Simulated series*	*All series*
Percentage of turning points detected					
At same time point	22.4	23.5	13.9	19.4	19.3
Within 1 period	42.7	36.9	21.7	28.4	30.9
Within 2 periods	16.8	16.7	15.4	17.4	16.6
No consistent turning points	18.1	22.9	49.0	34.8	33.2
Number of turning points detected	571	765	933	1,082	3,351

For a seasonally adjusted or trend series an equivalent turning point is found (at the same time point, within one or two time points either side, or no turning point is detected is detected within two months – referred to above as there being no consistent turning points)

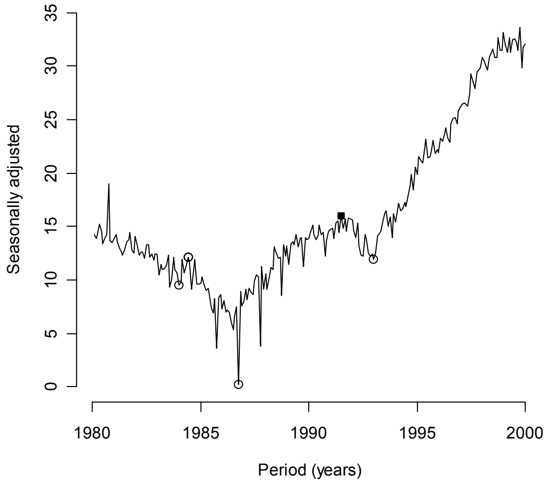
We can see in table 4.1 that only a small proportion (19.3%) of turning points were detected at exactly the same time point in both the trend and the seasonally adjusted estimates. However 66.8% of turning points found in either the seasonally adjusted or the trend estimates appear within two months of an equivalent turning point in either the trend or the seasonally adjusted series. Consequently we can say that approximately two thirds of the turning points appear to be broadly consistent between the trend and seasonally adjusted estimates. This indicates a shift in the timing of turning points detected in the seasonally adjusted and trend estimates. This shift is examined in more detail in figure 4.2 following.

4.2 Histogram of proportion of turning points detected within a given number of periods over all time series

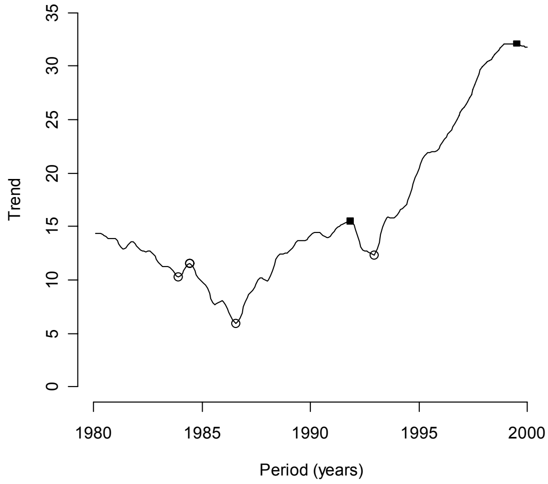


One of main differences between detecting turning points using the trend and the seasonally adjusted estimates is due to the smoothing effect of the trend. This increased clarity comes at a cost, however, as we can see in figure 4.3 that there is a less sharp distinction between consecutive periods to indicate the exact timing of the turning point. It might be argued that smoothing the series can cause a shift in the detected timing of the turning points in the trend. A comparison (see figure 4.2) of the timing of the turning points detected in the seasonally adjusted and trend estimates shows that there is no systematic timing shift in the detected turning points, with a mean shift of –0.05 months across all time series examined in this study.

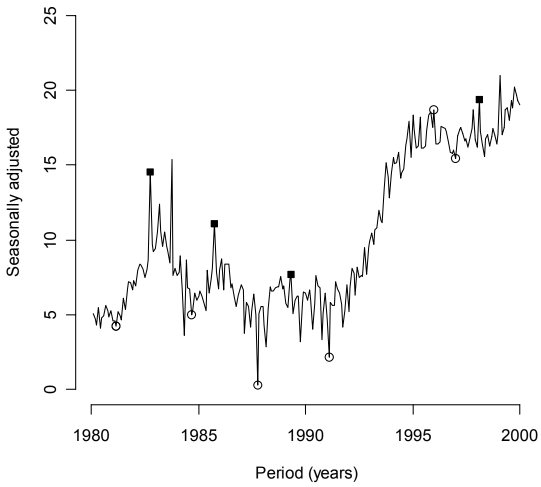
4.3 Turning points detected in both seasonally adjusted and trend estimates (hollow circle) and in either trend or seasonally adjusted for two selected times series examples (filled square)



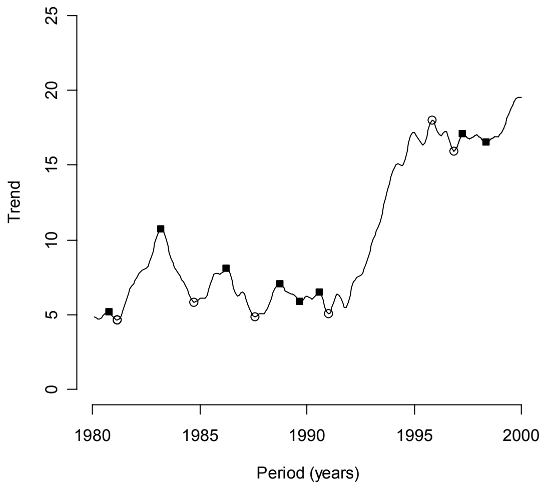
(a) Turning points detected in seasonally adjusted estimates produced from simulated series #1



(b) Turning points detected in trend estimates produced from simulated series #1



(c) Turning points detected in seasonally adjusted estimates produced from simulated series #2



(d) Turning points detected in trend estimates produced from simulated series #2

To illustrate the different turning points detected using the PAT method, we can compare turning points detected from seasonally adjusted and trend estimates. In figure 4.3 we can see that some turning points are detected at the same time point in both the trend and the seasonally adjusted estimates, while others are detected in just one of the seasonally adjusted and trend series. In many cases, however, the detected turning points still appear to be broadly consistent between the trend and the seasonally adjusted series. We can also see that the smoothing process applied to produce the trend estimates occasionally leads to altered timing for the detected turning points. An example of this is the 1983 turning point in figure 4.3d. This turning point is detected in late 1982 in the equivalent seasonally adjusted series (figure 4.3c) due to a large irregular in that month.

The seasonally adjusted series (figures 4.3a and 4.3c) contains irregular information that has been smoothed from the trend estimates (figures 4.3b and 4.3d). The irregular may contain information that is relevant to the detection of turning points but it can also contain information irrelevant to the cycle that may obscure the turning points. From the examples we have seen in figure 4.3 above we can see that there are some different turning points detected in both the trend and the seasonally adjusted estimates, but we are unable to determine whether this difference is due to the presence of information remaining in the seasonally adjusted estimates relating to the cycle.

In general the irregular component will be influenced by both

a. Real world issues, related to short-term variation in the irregular component.

b. Factors affecting the data estimation process. This may be caused by data collection, survey and estimation errors, and will lead to volatility in the irregular component.

In practice it is very hard to distinguish either real world or data estimation contributions to the irregular. If short-term variations relating to real world factors dominate the irregular it may provide information highlighting the exact timing of turning points. This information is usually smoothed out of the trend estimates, potentially leading to mistimed detection of turning points. On the other hand, if data estimation induced volatility dominates the irregular it will not provide any useful information about turning points. Furthermore it may increase the probability of falsely detecting turning points. In this case the trend estimates will provide more reliable turning point information.

In summary, we have seen in figure 4.3 that the distinctiveness of the turning points is reduced in the trend as compared with the seasonally adjusted estimates. This is a similar result to that presented in Andersson *et al*. (2006) and reflects a strong assumption that the irregular component is comprised solely of real world variations.

In practice this assumption is unlikely to hold and therefore we might expect trend estimates to provide reliable turning point information. At this point we believe it is premature to make a quantified assessment of turning points without knowing the composition of the irregular component.

4.2 Quantifying differences between seasonally adjusted and trend estimates

Based on the inconclusive results described in the last section, two sets of benchmark turning points were produced for the seasonally adjusted and trend estimates respectively. These benchmarks were produced by applying the PAT approach to the full span time series. An empirical experiment was then performed in which trend and seasonally adjusted estimates were prepared based on the first seven years of the original series. The turning points detected in this sub-span were then compared with those detected in the respective benchmarks. This experiment was then repeated with additional original estimates sequentially added until three years from the end of the full length time series. The seasonally adjusted and trend estimates face revision as additional original estimates are added which can result in turning points being lost and found.

In this paper we consider the following issues for both the seasonally adjusted and trend estimates:

a. Clarity. Refers to how easily the statistical output (seasonally adjusted and trend) can be interpreted with regards to the turning points, see discussion in Section 4.1.

b. Timeliness. Refers to the number of elapsed data points required to detect a turning point. It can be measured by the number of periods before a turning point is first detected.

c. Accuracy. Refers to the accuracy of a detected turning point compared with the ‘true’ turning point. It can be measured by the rate of correctly or incorrectly identified turning points as determined by comparison with the benchmark turning points. All time points can be considered to fall into one of four categories:

   - T|T. There is a turning point detected in both the time series and there is a corresponding benchmark turning point.
   - T|F. There is a turning point detected in the time series but there is no corresponding benchmark turning point.
   - F|T. There is no turning point detected in the time series but there is a corresponding benchmark turning point.

- F|F. There is no turning point detected in the time series and there is also no corresponding benchmark turning point.

Revision occurs to seasonally adjusted and trend estimates as more time points become available and a more appropriate estimate of the seasonal pattern can be made. The magnitude of these revisions generally die down and the estimates can be considered to be stable after approximately three years. Hence the proportion of points that fall into each of these four categories will be dominated by F|F and T|T if it is calculated over the entire data span. To provide meaningful comparisons the proportion of false turning points in each of the four categories above has been calculated for a three year window after each benchmark turning point.

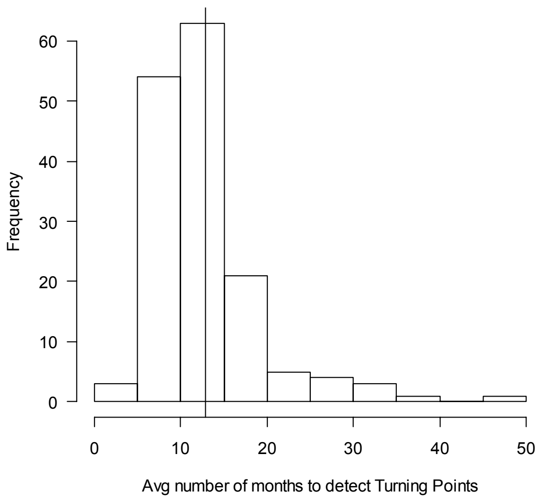
Based on the above framework an empirical experiment was set up to compare the timeliness and proportion of false turning points detected in a selection of real and simulated time series through incremental comparison of the trend and seasonally adjusted estimates with their associated benchmarks. As we have seen in Section 4.1 that smoothing can lead to altered timing in the detection of turning points, we have considered turning points detected within one month of the benchmark turning point to be the same turning point. The following section describes results based on real and simulated data.

5. RESULTS

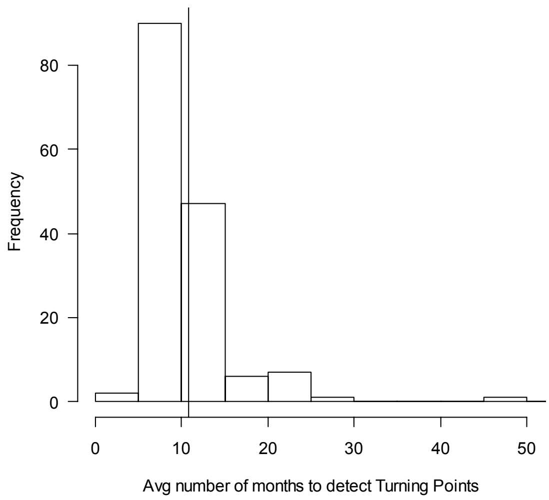
5.1 Timeliness of turning point detection

Figure 5.1 compares the mean time required to detect turning points in the trend and seasonally adjusted example series. The trend benchmark turning points are used to calculate the mean time to detect turning points in the trend series (figure 5.1b) while the seasonally adjusted benchmark is used to calculate the mean time to detect turning points in the seasonally adjusted series (figure 5.1a). In each case 90% of turning points were detected within 20 months, with the mean time to detect turning points in the seasonally adjusted series being 12.9 months and 10.9 months for the trend estimates.

5.1 Comparison of mean time to detect turning points for all trend and seasonally adjusted series



(a) Histogram of mean time to detect turning points across all seasonally adjusted series



(b) Histogram of mean time to detect turning points across all trend series

In figure 5.1 we can see that turning points are generally detected faster in the trend than the seasonally adjusted series with 90% of turning points detected in the trend estimates after 15.3 months while it took 19.5 months for 90% of the turning points to be detected in the seasonally adjusted estimates. This is a positive for the timely detection of turning points from trend estimates but does not tell us whether the increased timeliness of detection comes at the cost of detection quality. This will be examined in the following section in which we consider the proportion of false turning points detected.

5.2 False and true detection of turning points

It is desirable to minimise how often a time point is incorrectly detected as a turning point. We have compared the same type of estimate (seasonally adjusted and trend) for both detection and the benchmark. This analysis is useful to gain an understanding of how each time series estimate performs.

Table 5.2 gives a comparison of the percentage of turning points detected and not detected in the seasonally adjusted and trend estimates when compared against the respective benchmark. See Section 4.2 for a discussion of the four conditions of turning point detection, T|T, F|T, T|F, F|F. We can see that for all desirable properties, i.e. high levels of positive detection for turning points in the benchmark (T|T) and high levels of positive rejection of turning points not in the benchmark (F|F) the trend estimates outperform the seasonally adjusted estimates across all groups of series.

5.2 Summary of percentage of turning points detected in all trend and seasonally adjusted series

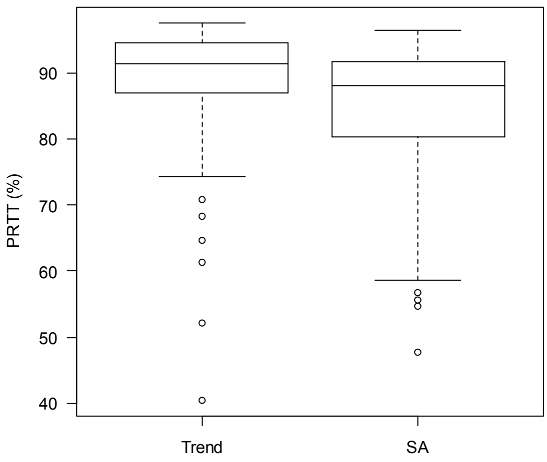
	% T | T		*% F | T*		*% F | F*		*% T | F*	
Series	*SA*	*Trend*	*SA*	*Trend*	*SA*	*Trend*	*SA*	*Trend*
Employed persons (mean)	91.0	93.9	9.0	6.1	99.7	99.8	0.3	0.2
Unemployed persons (mean)	92.6	95.2	7.4	4.8	99.6	99.8	0.4	0.2
Short term visitor arrivals (mean)	86.9	92.9	13.1	7.1	99.3	99.7	0.7	0.3
Simulated (mean)	78.1	83.5	21.9	16.6	98.9	99.2	1.1	0.8
Total (all series mean)	84.4	89.0	15.6	11.0	99.3	99.5	0.7	0.5

The percentage of time points which are detected as turning points in detection series and are also in benchmark (detection | benchmark) where F = False detection and T = true detection for seasonally adjusted (SA) and trend estimates.

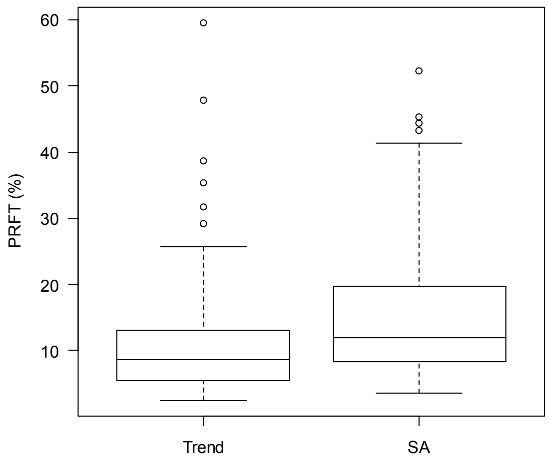
The consistent story in favour of the trend estimates presented across all columns in table 5.2, could potentially be exaggerated by a number of series with unusual properties influencing the results. Figure 5.3 following presents box-plots of the proportion of T|T, F|T, T|F and F|F turning point detected in the trend and seasonally adjusted series.

In figure 5.3 we can see that, barring a few exceptional series, there are generally fewer false turning points in the trend estimates than the seasonally adjusted estimates. We can also see that turning points that were detected in the benchmark series were also more frequently detected in the corresponding trend estimates rather than the seasonally adjusted estimates.

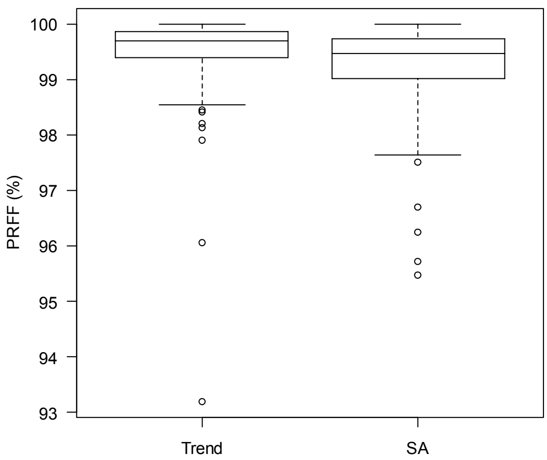
5.3 Boxplots of percentage of turning points detected in all trend and seasonally adjusted series



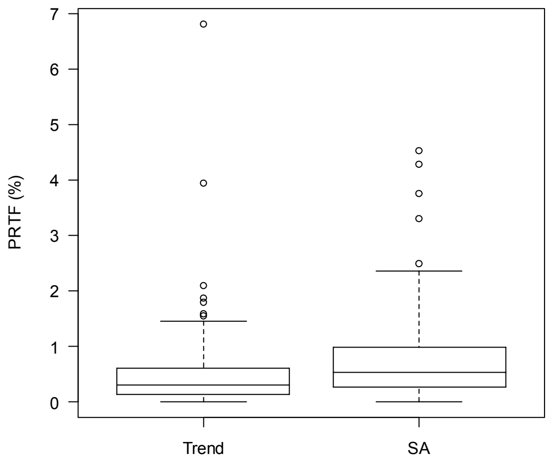
(a) Percentage of turning points detected in benchmark also detected in trend and seasonally adjusted



(b) Percentage of turning points detected in benchmark not being detected in trend and seasonally adjusted



(c) Percentage of turning points not detected in benchmark also not detected in trend and seasonally adjusted



(d) Percentage of turning points not detected in benchmark detected in trend and seasonally adjusted

6. COMMENTS

Users of official statistics can choose the original, seasonally adjusted or trend estimates either individually or in combination to aid in the decision making process. Users need to be aware of the limitations of all available time series estimates and make an appropriate and informed choice regarding which estimate to use. This report presents an empirical study comparing turning point detection in ABS trend and seasonally adjusted monthly estimates. It is found that turning points are generally detected in a more timely fashion and with a lower incidence of falsely detected turning points for trend rather than seasonally adjusted estimates when compared with trend and seasonally adjusted benchmarks respectively.

Trend estimates are derived by smoothing the irregular component from the seasonally adjusted estimates. The irregular may contain information relevant to the turning points when it is dominated by short-term real world variations. Although smoothing out this information can result in a shift in the timing of detected turning points, it may still be desirable to reduce false turning points when the irregular component is dominated by estimation induced volatility. In practice we cannot make conclusive statements about the appropriateness of detected turning points without knowing the nature or composition of the irregular component.

Trend estimates present a clearer picture of the underlying direction of a time series and present timely turning point information which is easily interpretable for the general public. Due to this trend estimates are the preferred primary analytical product for turning point detection for low-end users. Trend estimation, however, can also reduce the distinctiveness of turning point features and introduce auto-correlation. Thus we do not recommend trend estimates for sophisticated analytical applications.

This has been an initial study to compare the detection of turning points in trend and seasonally adjusted estimates. Further work could be applied to examine the characteristics of turning points that are detected in both the seasonally adjusted and trend estimates. An examination of the characteristics of time series which relate to turning point detection and the inclusion of estimation induced volatility as a influential factor may also provide further insight. We recognise that most economic variables exhibit idiosyncratic cycles which are not necessary connected to the general business cycle although their turning points may be of interest in their own rights. For this reason, future work should place increased emphasis on economic variables and survey indicators relevant to business cycle analysis.

7. REFERENCES

Anas, J. and Ferrara, L. (2002) 'Detecting Cyclical Turning Points: the ABCD Approach and Two Probabilistic Indicators', Composite and Leading Indicators Session, 26th CIRET Conference, Taipai, October 2002.

Australian Bureau of Statistics (2006a) *Overseas Arrivals and Departures, Australia*, cat. no. 3401.0, ABS, Canberra.

Australian Bureau of Statistics (2006b) *Labour Force, Australia*, cat. no. 6202.0, ABS, Canberra.

Andersson, E., Bock, D. and Frisen, M. (2006) 'Some Statistical Aspects on Methods for Detection of Turning Points in Business Cycles', *Journal of Applied Statistics*, 33(3), pp. 257–278.

Baxter, M. and King, R.G. (1999) 'Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series', *Review of Economics and Statistics*, 81(4), pp. 575–593.

Boschan, C. and Ebanks, W.W. (1978) 'The Phase-Average Trend: A New Way of Measuring Economic Growth', *Proceedings of the Business and Economic Statistics Section*, American Statistical Association, Washington, DC.

Box, G.E.P. and Jenkins, G.M. (1976) *Time Series Analysis: Forecasting and Control* (revised edition), Holden–Day Inc., San Francisco.

Bry, G. and Boschan, C. (1971) 'Cyclical Analysis of Time Series: Selected Procedures and Computer Programs', National Bureau of Economic Research, New York.

Findley, D.F., Monsell, B.C., Bell, W.R., Otto M.C. and Chen, B.C. (1998) 'New Capabilities and Methods of the X-12–ARIMA Seasonal-Adjustment Program', *Journal of Business and Economic Statistics*, 16(2), pp. 127–177. http://www.census.gov/ts/papers/jbes98.pdf

Gillitzer, C., Kearns, J. and Richards, A. (2005) 'The Australian Business Cycle: A Coincident Indicator Approach', Reserve Bank of Australia Research Discussion Paper No. 2005-07.

Hall, P., Marron, J.S. and Titterington, D.M. (1995) 'On Partial Local Smoothing Rules for Curve Estimation', *Biometrika*, 82, pp. 575–587.

Harvey, A.C. (1989) *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, Cambridge.

Henderson, R. (1916) 'Note on Graduation by Adjusted Average', *Transactions of the American Society of Actuaries*, 17, pp. 43-48

Hodrick, R.J. and Prescott, E.C. (1997) 'Postwar U.S. Business Cycles: An Empirical Investigation', *Journal of Money, Credit and Banking*, 29(1), pp. 1–16.

Knowles, J. and Kenny, P. (1997) 'An Investigation of Trend Estimation Methods', Working Paper MQ 043, Office for National Statistics, London.

Öller, L.-E. (1986) 'A Note on Exponentially Smoothed Seasonal Differences', *Journal of Business and Economic Statistics*, 4, pp. 485-489.

Pfeffermann, D. And Bleuer, S.R. (1992) 'Probabilistic Detection of Non-seasonal Turning Points in Economic Time Series estimated from Sample Surveys', Internal report to the Methodology Branch, Statistics Canada, Ottawa.

Watson, M. (1994) 'Business Cycle Durations and Postwar Stabilization of the U.S. Economy', *American Economic Review*, 84(1), pp. 24–46.

Wecker, W.E. (1979) 'Predicting the Turning Points of a Time Series', *Journal of Business*, 52(1), pp. 35–50.

Zarnowitz, V. and Ozyildirim, A. (2002) 'Time Series Decomposition and Measurement of Business Cycles, Trends and Growth Cycles', NBER Working Paper #8736, National Bureau of Economic Research.

Zellner, A., Hong, C. and Min, C. (1991) 'Forecasting Turning Points in International Output Growth Rates Using Bayesian Exponentially Weighted Autoregression, Time-Varying Parameter, and Pooling Techniques', *Journal of Econometrics*, 49(1–2), pp. 275–304.

Zhang, M. and Sutcliffe, A. (2001) 'Use of ARIMA Models for Improving the Revisions of X–11 Seasonal Adjustment', Paper presented to the Australian Bureau of Statistics Methodology Advisory Committee, Canberra, November 2001, cat. no. 1352.0.55.042, ABS, Canberra.

APPENDIX

A. PHASE AVERAGE TREND (PAT)

The conventional NBER algorithm to estimate the secular trend and identify the growth cycles is called the Phase Average Trend (PAT) method (Boschan and Ebanks 1978). The PAT is an algorithm that follows the following basic steps

1. A 75-month moving average is applied to a given time series O_t to produce an initial approximation of a deseasonalized time series, Z_t.
2. The deviation between the time series O_t and the deseasonalized time series, Z_t, is then calculated.
3. This deviations series is then broken up into a number of 'phases'. Phases are determined to have occurred between each peak and trough in the deviation series.
4. 'Phase averages' are calculated by taking the mean of the time series, Z_t, during each phase.
5. The series of 'phase averages' are smoothed into a series of 'triplets' through use of a three term moving average.
6. The midpoints of the 'triplets' are connected and this connected level series is further adjusted to match the level of the original time series.
7. A 12-month moving average of this adjusted series yields the estimated secular trend.

Deviations of the deseasonalized time series, Z_t, from the Phase Average Trend (PAT) estimated in step 7 above can then be used to identify growth cycles. This approach can be considered to mimic the NBER Business Cycle Dating Bureau's Committee methods for the determination of turning points in business cycles (Anas and Ferrara 2002). For more detail regarding the PAT please refer to Zarnowitz and Ozyildirim (2002).

FOR MORE INFORMATION . . .

INTERNET **www.abs.gov.au** the ABS web site is the best place for data from our publications and information about the ABS.

LIBRARY A range of ABS publications are available from public and tertiary libraries Australia wide. Contact your nearest library to determine whether it has the ABS statistics you require, or visit our web site for a list of libraries.

INFORMATION AND REFERRAL SERVICE

Our consultants can help you access the full range of information published by the ABS that is available free of charge from our web site, or purchase a hard copy publication. Information tailored to your needs can also be requested as a 'user pays' service. Specialists are on hand to help you with analytical or methodological advice.

PHONE 1300 135 070

EMAIL client.services@abs.gov.au

FAX 1300 135 211

POST Client Services, ABS, GPO Box 796, Sydney NSW 2001

FREE ACCESS TO STATISTICS

All ABS statistics can be downloaded free of charge from the ABS web site.

WEB ADDRESS www.abs.gov.au

2000001541616
ISBN 0 642 48242 X

RRP $11.00