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Persistence in the short and long term tourist arrivals to Australia

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ABSTRACT

This study examines the persistence in the international monthly tourist arrivals to Australia by using a variety of models based on fractional integration and seasonal autoregressions. The results based on disaggregated monthly data indicated that the series are on average mean reverting, though highly persistent, and present intense seasonal patterns. A forecasting performance of several competing models was also conducted where it was concluded that the models based on long range dependence outperform others more standard based on non-seasonal and seasonal unit roots. The model based on long memory at zero and the seasonal frequencies seems to be the most accurate in this context. More detailed analysis of the results are also derived.

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1. Introduction

This paper deals with the analysis of international tourist arrivals to Australia. It examines the degree of persistence and seasonality in several arrival series. The innovation of the paper resides in the adoption of a model that simultaneously analyses long run persistence and seasonality in tourism arrivals with fractional integration.

Two important features commonly observed in tourism data are the persistence across time and the seasonality. Modelling the degree of persistence is important in that it can reflect the nature and the effects of the shocks in tourism data. Thus, in the event of an exogenous shock, different policy measures should be adopted depending on their degree of persistence. If the shock is positive and the series is mean reverting, strong measures must be adopted to maintain the series at a higher level. On the other hand, if a shock is negative and the series contain, for instance, a unit root, the effect of that shock will be permanent, and again strong measures should be adopted to bring the series back to its original trend.

Seasonality is another important feature that is present in many quarterly and monthly tourism data and thus it should be modelled according to the specific characteristics of the data. However, there is little consensus on how seasonality should be treated in empirical applications on aggregate data. Since the statistical properties of different seasonal models are distinct, the imposition of one kind when another is present can result in serious bias or loss of information, and it is thus useful to establish what kind of seasonality is present in the data.

The motivation for the present research stems from the following considerations: First, we aim to analyse the persistent behaviour of Australian inbound tourism over time, using both fractional integration and autoregressions. Secondly, we aim to introduce fractional integration that identifies persistence in a continuous range between zero and one and not in the dichotomic range of zero and one as it is the case in the standard time series methods. Finally, we aim to test the forecasting accuracy of different competitive models, including those based on integer degrees of differentiation, in order to determine the one that best forecasts Australian tourism arrivals.

The main contribution of this paper is that it adopts simultaneously fractional integration and seasonal autoregressions to analyze the persistence in tourism arrivals to Australia, previously analysed by standard methods such as AR(I)MA models. The paper will proceed as follows: Section 2 presents the contextual setting. Section 3 presents the literature revision. Section 4 briefly describes the methodology employed in the paper. Section 5 is devoted to the empirical results. Section 6 deals with the forecasting accuracy of the selected models, while Section 7 contains discussions and concluding comments.

2. Contextual setting

The tourism industry is a major driver of the Australian economy. Figures from 2006-2007, for example, indicated that the industry contributed $67.8 billion to Gross Domestic Product (GDP) and generated employment for around 853,000 persons.

Domestic day trips[1] account for a major share of total tourism expenditure (close to 19%). International visitors are also a major segment accounting for about 18.0% of total visitor expenditure. A major boost in the international market occurred in 2007-08 where around 5.6 million international arrivals, up 27.8% from 4.17 million in 1997-98. In Figure 1 we present a summarised trend of the international tourism arrivals to Australia. Generally, the tourism industry has always achieved growth, especially between 1981 and 2001 (9.1 % per annum). However, the growth started to decrease gradually between 2000 and 2008 (1.6% per annum), due to many negative factors including the impacts of September 11th, Bali bombing and global financial crisis. Major visitor origin countries over the years included: New Zealand - 22.3% of visitors; North West Europe - (i.e. Germany and UK) - 21.5%; Southeast Asia (i.e. Indonesia, Singapore etc.) - 12.1%; Northeast Asia (i.e. Japan and China) - 27.1%; and the Americas (North and South) - 10.7%. Recently, strong growth has occurred from visitors from China, India, Korea, Hong Kong, Singapore, New Zealand and the UK.

[Insert Figure 1 about here]

The Australian tourism industry, similar to any other international industries is also subject to fluctuations in the domestic and international market. External environmental factors such as unfavourable exchange rates, high fuel prices and interest rates, as well airline schedule rationalisation due to fuel cost escalation, has undoubtedly influenced recent industry performance. Over the five years period to 2008-09, industry revenue is

[1] This is defined by Tourism Research Australia for survey purposes as domestic visitors aged 15 years and over who make a round trip distance of at least 50 kilometres, are away from home for at least four hours and who do not spend a night away from home as part of their trip.

forecast by IBISWorld to decrease at an average annual real rate of 1.4%, due to recent more subdued domestic and international economic growth, together with some rise in global unemployment.

Within this critical period, the present study thus takes an additional importance. As the study focuses on analysing the behaviour of tourism arrivals to Australia, the results can directly assist in future policy formulation towards improving tourist numbers. The study is also innovative in terms of adopting more accurate methodologies which aim to improve the reliability and robustness of the results reported. In the next section, we present a review of the literature before describing in more details the methodology used in the study.

3. Persistence in tourism demand

An important feature observed in tourism time series data is the persistence in its behaviour (see, for example, Maloney and Montes Rojas, 2005; Bhattacharya and Narayan, 2005; Narayan, 2005). Maloney and Montes Rojas (2005) documented high levels of persistence on tourist flows from eight origin countries to 29 Caribbean destinations from 1990–2002. On the other hand, Narayan (2005), Lim and McAleer (2000, 2001a, 2002), Goh and Law (2002), and Lim and Pan (2005) provided contradicting results regarding the presence of unit roots in different tourism data. Other papers documented the persistence in volatility models of tourism demand (see, for example, Hoti et al. , 2006a, b; and Kim and Wong, 2006 among others).

It is worth noting also that several studies have attempted to account for seasonality in modelling tourism demand. Alleyne (2006) has for example used the HEGY procedure to account for stochastic seasonality in tourism arrivals to Jamaica. His results indicated that forecasting can become more accurate if seasonal unit roots are pre-tested. Similar results were also reported by Alleyne (2006), Gustavsson and Nordstrom (2001), Diebold and Kilian (2000), Kulendran and Witt (2003), Tumer and Witt (2001), who indicated that the unit root pretesting routinely improves forecast accuracy.

Other studies on seasonality of tourism data include Lim and McAleer (2001b), Kulendran and Witt (2003), Rodrigues and Gouveia (2004), Kulendran and Wong (2005), Coshall (2006) and Lee et al. (2008). In general, most of these papers employed standard econometric techniques based on unit roots or seasonal unit root test statistics (Dickey and Fuller, ADF, 1979; Dickey et al., DHF, 1984; Phillips and Perron, PP, 1988; Kwiatkowski et al., KPSS, 1992; Hylleberg et al., HEGY, 1990; etc.). These methods, though highly efficient in some cases, have the drawback that they have extremely low power in the context of fractional alternatives. Thus, if the series is I(d) and d is different from 0 or 1, the use of these methods is not appropriate. This has been well documented by authors such as Diebold and Rudebusch (1991), Hassler and Wolters (1994), Lee and Schmidt (1996) and others**.**

The analysis of the persistence in time series has important policy implications since the effect of a given shock on a series is different depending on its univariate properties. When a series is stationary and mean reverting (i.e., $d < 0.5$), the effect of a given shock on it will have a transitory effect, disappearing its effect fairly rapid; if the series is non-stationary but mean reverting ($0.5 \leq d < 1$) the shock still will be transitory though it takes longer time to disappear completely, while it will be permanent if the series is non-stationary with $d \geq 1$. While the classical approach to study the stationarity of the series only allows for the I(1)/I(0) case, tourism series in this paper are allowed to be I(d), where d can be any real number. The estimation of the fractional differencing parameter d for each of the tourism series we analyze here will give us an idea of the stochastic nature of the series, which is clearly related to the level of persistence.

The fractional integration approach allows to identify the level of persistence of a series in a continuous way and therefore overcomes the restrictive view that traditional econometrics identify a series either persistent or non-persistent, but is unable to evaluate the middle term of the persistence level. (See, Gil-Alana and Hualde, 2009, for a recent review of fractional integration in time series). In this paper, we also extend the analysis of fractional integration to the seasonal part of the process. Thus, instead of restricting the model to be seasonal I(1) (as is the case in numerous empirical studies) we also allow for seasonal fractional integration, where the seasonal differencing parameter may be a fractional value, and, moreover, we consider a general process that includes fractional integration at both the zero and the seasonal frequencies in a single framework.

4. Methodology

In this section we describe the three basic specifications we employ to describe the two main characteristics of the data, which are the persistence and the seasonality.2 In **model 1** we assume that the series is I(d) so that the fractional differencing parameter d describes the long run persistence. On the other hand, seasonality is described throughout a simple seasonal AR(1) process. Therefore, model 1 is described as:

$$y_t = \alpha + \beta t + x_t; \qquad (1 - L)^d x_t = u_t; \qquad u_t = \rho_s u_{t-12} + \varepsilon_t. \quad (1)$$

where y_t is the time series we observe (in our case, the total number of monthly arrivals in Australia); α and β are the coefficients associated to the intercept and a linear time trend respectively, and x_t are the regression errors that are assumed to be I(d); finally the disturbances are modelled in terms of a seasonal AR(1) process where ρ_s describes the seasonal (short run) time dependence. In this context, if d > 0, x_t (and thus y_t) is said to be long memory, so-named because of the strong association between observations widely separated in time. This process is characterized because the spectral density function is unbounded at the zero frequency.[3] Applications using this type of model in tourism time series are among others the papers of Cuñado et al. (2004, 2008).

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[2] Seasonal dummy variables were discarded in this work because of the observed seasonal changing patterns in the data.

[3] The origin of these processes is in the 1960s, when Granger (1966) and Adelman (1965) pointed out that most aggregate economic time series have a typical shape where the spectral density increases dramatically as the frequency approaches zero. However, differencing the data frequently leads to overdifferencing at the zero frequency.

In **model 2** we change the nature of the process and impose a long memory process on the seasonal structure of the series, while the short term evolution is described through an AR(1) process. In other words, we consider now the model,

$$y_t = \alpha + \beta t + x_t; \qquad (1 - L^{12})^{d_s} x_t = u_t; \qquad u_t = \rho u_{t-1} + \varepsilon_t, \qquad \textbf{(2)}$$

where d_s can be again a fractional value. Here, if $d_s > 0$, x_t (and y_t) is defined as a 'seasonal long memory' process, so-named because of the strong association (in the seasonal structure) between observations apart in time. Few empirical applications have been carried out in relation to this model. Porter-Hudak (1990) applied a seasonally fractionally integrated model of form as in (2) to quarterly U.S. monetary aggregate with the conclusion that a fractional model could be more appropriate than standard (seasonal) ARIMAs. Advantages of seasonally fractionally integrated models for forecasting are illustrated in Ray (1993) and Sutcliffe (1994), and another empirical application can be found in Gil-Alana and Robinson (2001). In the context of tourism time series, Gil-Alana (2005) employed this approach using US international monthly arrivals.

Finally, we combine the two approaches described in (1) and (2) in a single framework, and consider a model with two fractional differencing parameters, one referring to the long run evolution (d) and the other affecting the seasonal structure (d_s). In other words, **model 3** is described by

$$y_t = \alpha + \beta t + x_t; \qquad (1 - L)^{d} (1 - L^{12})^{d_s} x_t = u_t, \quad (3)$$

and we assume here that u_t is white noise (model 3a), AR(1) (model 3b) and a seasonal AR(1) process (model 3c).

In all cases we will consider the three standard cases of no regressors in the undifferenced regressions (i.e., $\alpha = \beta = 0$ a priori), an intercept (α unknown and $\beta = 0$ a priori), and an intercept with a linear time trend ((i.e., α and β unknown). As mentioned earlier, deterministic seasonal dummies were not considered given the changing seasonal pattern observed in the data.

Remember once more that in model 1, d is the parameter describing the long run persistence, while ρ_s indicates the degree of seasonal (short run) persistence. In model 2, d_s determines the degree of seasonal long memory or seasonal persistence while the non-seasonal persistence is described throughout the parameter ρ. In model 3, we include both long run and seasonal long range persistence throughout the parameters d and d_s.

The three models described above include most of the standard cases examined in the literature. Thus, for example, in model 1, if $d = 0$ we obtain the classical "trend stationary" representation with seasonal AR(1) disturbances, while if $d = 1$ we obtain the "unit root" model advocated by many authors in the tourism literature. Similarly, in model 2, if $d_s = 1$, we have a "seasonal unit root" model (see, e.g., Beaulieu and Miron, 1993), and if $d = d_s = 1$ in model 3, the classical "airline model" of Box and Jenkins (1976).

The methodology employed in this paper is based on the Whittle function in the frequency domain (Dahlhaus, 1989) along with a testing procedure developed by Robinson (1994) that permits us to test all the above specifications in a unified treatment.

The latter is a Lagrange Multiplier (LM) procedure that is supposed to be the most efficient method in the context of fractional integration. It tests the null hypothesis H_o: d (or d_s) = d_o for any real value d_o, in either model (1), (2) or (3), and given its standard (normal) limit distribution we can easily build up confidence bands for the non-rejection values.[4] The functional form of this procedure is described in the Appendix.

5. Data and Results

The time series data considered are the numbers of monthly international tourist arrivals in Australia classified with intended length of stay. The variables considered are as follows: those with intended length of stay less than 1 month (Series 1), between 1 and 2 months (Series 2), between 2 and 3 months (Series

3), between 3 and 6 months (Series 4) and between 6 and 12 months (Series 5) are considered. The data are available from the Australian Bureau of Statistics publications (ABS Catalogue No. 3401.0). Each series consists of 220 monthly observations covering the period from 1991m1 to 2009m1. Table 1 describes each of the time series examined in the paper, and Figure 2 displays the time series plots.

[Insert Table 1, Figure 2 and Table 2 about here]

Summary statistics for the five time series are also reported in Table 2. We observe in this table that the highest mean corresponds to Series 1 and the lowest value to

[4] Empirical applications based on this procedure can be found in Gil-Alana and Robinson (1997) and Gil-Alana (2000) among many others.

Series 5. Even though normality is not satisfied as confirmed by the Jarque-Bera test, this is not a serious matter in our work since Robinson's (1994) method is robust against non-Gaussian disturbances.

[Insert Tables 3 and 4 and Figure 3 about here]

Table 3 displays for each series the estimates of d in model 1 for the three standard cases of no regressors, an intercept, and an intercept with a linear trend. The first issue we observe in this table is that the estimated values of d are in all cases positive and smaller than 1, providing thus evidence in favour of fractional integration, and clearly rejecting the two classical I(0) and I(1) representations. Moreover, the time trend coefficients are statistically significant in all cases and thus, we focus on this model in Table 4, reporting the estimates for each time series. We observe significant differences throughout the series, with values of d ranging from 0.118 (series 2) to 0.307 (series 3). In all cases, we reject the null hypotheses of d = 0 (a seasonal AR(1) process) and d = 1 (a unit root). Also, the seasonal AR coefficients are very large and close to 1 in all series implying a large degree of seasonal persistence. Adopting integer degrees of differentiation, we also estimated seasonal ARMA components, and the results, reported in Table 5, again show large AR coefficients in the five series. Figure 3 displays the first 60 impulse responses for each of the series according to the results of the fractional model in Table 4. We observe a strong seasonal pattern, with values decreasing very slowly. Due to this, we also examined the possibility of seasonal first differences in these data, and perform the tests of Dickey, Hasza and Fuller (DHF, 1984) and Beaulieau and

Miron (1993) to check for seasonal (monthly) unit roots. The results, though not reported, suggest in all cases that seasonal first differences might be appropriate. Figure 4 displays the differenced time series plots and seasonality seems to be removed in the series.[5]

[Insert Figure 4 and Tables 5 and 6 about here]

Table 6 displays for each time series the best specification assuming that seasonal first differenced are required in the data. We observe that for two of the series, an ARMA(1, 1) model seems to be the best specification in this context, while a simple AR(1) is sufficient to describe the short run dynamics in the remaining three series. However, imposing an integer degree of seasonal differentiation in the data is a very restrictive model to describe the nonstationary seasonality. Thus, we extend the seasonal unit root case and focus on <u>model 2</u> allowing for seasonal fractional integration and non-seasonal AR(1) disturbances. Table 7 reports the results again for the three cases of no regressors, an intercept, and an intercept with a linear trend, and all the values are again in the interval (0, 1), clearly rejecting the seasonal I(1) model. All except one series (series 4) present values which are above 0.5 implying now nonstationarity. Looking at the estimates in the context of a linear trend, the values are reported in Table 8 and their corresponding impulse responses are displayed in Figure 5.

[Insert Tables 7 and 8 and Figure 5 about here]

[5] Note however that seasonal (and non-seasonal) unit root tests may have very low power if the alternatives are of a fractional form. (See, e.g., Diebold and Rudebusch, 1991; Hassler and Wolters, 1994, etc. though these papers refer exclusively to the zero frequency unit root tests).

The values substantially differ across the series ranging from 0.484 (series 4) to 0.747 (series 2). Note that the largest (non-seasonal) AR coefficient takes now place in series 1, with $\rho = 0.422$. According to this table, series 1 and 2 are the most persistent ones. Figure 5 displays the first 60 impulse responses for this model and it can be seen that seasonality still account for an important component of the series.

[Insert Tables 8, 9 and 10 about here]

Finally, we employ model 3. The results are reported in Tables 9, 10 and 11, respectively for the cases of white noise, AR(1) and seasonal AR(1) disturbances. Once more, most of the estimates lie between 0 and 1. The only exceptions are some cases in Table 10 (with non-seasonal AR(1) u_t) with values of d being negative in some cases, and in Table 11 (seasonal AR(1) u_t) with negative values in d_s. These negative values (indicating anti-persistence) are clearly a consequence of the competition between the fractional and the AR polynomials in describing the time dependence.[6]

[Insert Tables 12, 13 and 14 about here]

Tables 12, 13 and 14 report the parameter estimates for each of the selected models assuming that the disturbances are respectively, white noise, AR(1) and seasonal AR(1).

[6] Note that d and ρ both describe the non-seasonal dependence while d_s and ρ_s describes the seasonal dependence. The difference between the long memory parameters (d and d_s) and the short memory ones (ρ and ρ_s) is that the former use a hyperbolic rate while the latter use a much faster exponential rate of decay in the autocorrelations.

We observe that for series 1, 2 and 5, the models include an intercept and a linear time trend, while for series 3 and 4 an intercept is sufficient to describe the deterministic part. We observe that practically all the fractional differencing parameters are in the interval (0, 1), the only exception being d_s in series 5 with seasonal AR disturbances (model 3c, in Table 14). We also notice that d_s is substantially higher than d in the majority of the cases, implying a stronger degree of dependence in the seasonal part than in the long run behaviour.

In what follows we focus on model 3a (white noise disturbances) with a linear time trend (Table 12). We choose this specification for the error term based on LR tests. Moreover, we conducted several tests for serial correlation in the d-differenced series in Table 12 (Box-Pierce-type statistics), and we do not find evidence of further need of autocorrelation. A remarkable finding observed in this table is that the five series are nonstationary with respect to the seasonal component ($d_s > 0.5$). Moreover, they are also non-stationary with respect to the long run behaviour. Note that although the d-coefficients are smaller than 0.5 (and would suggest stationarity at first sight), the contribution to the long run or zero frequency should also include the seasonal integration order. The reason for this is that the polynomial $(1- L^s)^{ds}$ can be decomposed into $(1-L)^{ds}S(L)^{ds}$, where $S(L) = (1 + L + L^2 + \ldots + L^{s-1})$ is formed exclusively by the seasonal frequencies, and thus $(1-L^s)^{ds}$ includes the zero frequency throughout $(1-L)^{ds}$.[7] Therefore, according to the results in this table, the contribution to the long run or zero frequency for series 1 is 0.98 (0.32 + 0.66). Similarly, for series 2 is 1.05; 0.87 for series 3, 0.81 for series 4, and 0.77 for series 5.

[7] Thus, for example, $(1 - L^4) = (1 - L)(1 + L + L^2 + L^3) = (1 - L)(1 + L)(1 + L^2)$.

So far we have presented for each of the five time series, three potential specifications based on long range dependence using fractional and autoregressive polynomials, along with other more standard specifications based on non-seasonal and seasonal ARIMA models. In the following section, we will try to determine which one is the preferred model for each of the five arrivals series examined.

6. Forecasting performance

In this section we compare the models presented in Section 5 in terms of their forecasting performance. Standard measures of forecast accuracy are the following: the Mean Absolute Percentage Error (MAPE), the Mean-Squared Error (MSE), the Root-Mean-Squared Error (RMSE), the Root-Mean-Percentage-Squared Error (RMPSE) and Mean Absolute Deviation (MAD) (Witt and Witt, 1992). On the other hand, there exist several statistical tests for comparing different forecasting models. One of these tests, widely employed in the time series literature, is the asymptotic test for a zero expected loss differential of Diebold and Mariano (1995).[8] The loss differential is defined as

$$d_t = g(e_{it|t-h}) - g(e_{jt|t-h}),$$

where $g(e_{it|t-h})$ is the loss function, and $e_{it|t-h}$ is the corresponding h-step ahead forecast error for the model i, $e_{it|t-h} = y_t - \hat{y}_{it|t-h}$. Given a covariance stationary sample realization $\{d_t\}_{t=T+h,\ldots,T+n}$, the Diebold-Mariano statistic for the null hypothesis of

[8] An alternative approach is the bootstrap-based test of Ashley (1998), though this method is computationally more intensive.

equal forecast accuracy (i.e., $E(d_t = 0)$) is given by: $\frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}}$, where $\bar{d}$ is the sample mean loss differential, $\bar{d} = \frac{1}{n-h+1}\sum_{t=T+h}^{t=T+n} d_t$, and where $\hat{V}(\bar{d})$ is a consistent estimate of the asymptotic variance of $\bar{d}$, which is computed as an unweighted sum of the sample autocovariances, that is, $\hat{V}(\bar{d}) = \frac{1}{n-h+1}\left(\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}_k\right)$, where $\hat{\gamma}_k = \frac{1}{n-h+1}\sum_{t=T+h+k}^{T+n}(d_t - \bar{d})(d_{t-k} - \bar{d})$. Harvey et al. (1997) note that the Diebold-Mariano test statistic could be seriously over-sized as the prediction horizon, h, increases, and therefore provide a modified Diebold-Mariano test statistic given by:

$$M - DM = DM\sqrt{\frac{n + 1 - 2h + h(h-1)/n}{n}},$$

where DM is the original Diebold-Mariano statistic. Harvey et al. (1997) and Clark and McCracken (2001) show that this modified test statistic performs better than the DM test statistic in finite samples, and also that the power of the test is improved when p-values are computed with a Student t-distribution.

[Insert Table 15 - 18 about here]

First, we make a pairwise comparison between the first differenced model (based on the results in Table 5) and the fractional I(d) model 1, and we report, in Table 15, the RMSE and the MAPE values for h = 1, 6, 12, 18 and 24 in a 24-period horizon. We observe that model 1 outperforms the ARIMA one in all cases. Based on these values, we computed, in Table 16, the M-DM statistic and, not surprisingly, model 1 results preferred in the five series.

Tables 17 and 18 are similar to Tables 15 and 16 but comparing now the SARIMA specification (presented in Table 6) with the seasonal fractional model 2. Again we observe here that the fractional model produces lower values than the non-fractional one in terms of both the RMSE and the MAPE, and the SFI model outperforms the seasonal ARIMAs in terms of the M-DM test in practically all cases.

In what follows, we focus on the three selected models in the previous section (i.e., models 1, 2 and 3a). The results are now displayed in Tables 19 and 20 respectively for h = 12 and 24. We observe that for the 12-period ahead predictions, model (3a) outperforms the others in four out of the five series examined (all except series 3 where the statistics cannot distinguish between one model and another). Less conclusive results are obtained at the 24-period ahead forecasts though still model (3a) seems to be the preferable one.

Finally, note that according to these results based on model 3a (in Table 9), series 1 and 2 seem to be the most persistent ones, while series 5 is the less persistent, implying that the degree of dependence decreases with the length of stay.

7. Discussions and Conclusions

In this paper we have presented three model specifications to describe the time series dependence and other implicit dynamics in the Australian tourism arrivals. Five univariate series are analysed. The models used are first, a long memory processes at the long run or zero frequency; second, a long memory one at the seasonal (monthly) frequencies; and third, a combination of the two structures using also long range dependence. We compared these models with other more conventional ones based on non-seasonal and seasonal unit roots. The results indicated first that the standard methods employed in the literature, based on stationary I(0) or non-stationary I(1) models are clearly rejected in favour of fractional degrees of integration. This applies to both non-seasonal and seasonal ARIMA models. If we focus on the models with long range dependence at the zero frequency, the orders of integration range between 0.118 and 0.307 depending on the series, and all of them present seasonal AR coefficients close to 1. Using a seasonal long memory model, the differencing parameters are in the range (0.484, 0.747) while the AR model coefficients range between 0.208 and 0.422. Finally, employing a model that uses long memory at both the zero and the seasonal frequencies, the results also indicate fractional degrees of integration, with higher values at the seasonal components. This implies that seasonality is a serious matter in these series displaying a large degree of dependence. Moreover, this latter model led to the most accurate results in terms of forecasting. Comparing standard ARIMA and SARIMA models with those based on non-seasonal and seasonal fractional integration, the results strongly support the latter specifications in all cases.

These results mean that shocks affecting the seasonal structure of Australian tourism arrivals series (based on the estimates of d_s in model 2, Table 8), will have a transitory effect though taking a very long time to disappear in the long run. On the other hand, shocks related to the long run evolution of the Australian tourism arrivals series also have a transitory nature though disappear faster than in the seasonal case (based on estimates of d in model 1, Table 4). However, taking into account the two structures (simultaneously throughout a long memory model at zero and the seasonal frequencies, i.e., d and d_s in model 3, Table 12), the series are mean reverting though highly persistent, while the long term evolution is close to the unit root implying almost permanent effects of the shocks. Thus, it seems important for the authorities to distinguish the nature of the shock since the consequences are different (though highly persistent in the two cases): in case of a shock, related to the seasonal evolution of the series, short term and intensive policy measures (e.g. intensive marketing campaign, travel facilitation, etc..) must be adopted to recover the original level since in the event of a negative shock it will take long time to disappear. On the other hand, if the shock is related to the long term evolution of the series, long range intensive policies must be implemented since otherwise the series will tend to remain at a lower level. Some examples of long range policies that can be adopted include 1- the development of retention and career tourism employees, 2- the improvements of the industry's information base, 3- the reinforcement Australia's image as a safe and friendly destination 4- the development of efficient and competitive transportation networks.

What are the appropriate conclusions suggested by the findings of this study? Firstly, it was clear that taking first differences (or seasonal first differences) in the

Australian arrivals series, under the assumption of a unit root (or seasonal unit roots), would lead to series that are over-differenced, and subsequently such procedure might result in incorrect policy implications. Secondly, persistence behaviour is in general mean reverting though the adjustment process takes a very long time to disappear in the future. Therefore, an active tourism policy is needed to enforce the series to adjust more rapidly. Thirdly and finally, relative to forecasting performance of the different models, the one based on long range dependence at zero and the seasonal frequencies (i.e., model (3a) outperforms the others, and therefore it should be adopted as reference for policy purpose. In other words, this signifies that Australian tourism arrivals are influenced by long memory processes simultaneously affecting at zero and the seasonal (monthly) frequencies, and the two effects have to be taken into account when policy acting on the series.

How does this paper compare with alternative time series research in tourism? This paper adopts a fractional integration model (Chu, 2008; Gil-Alana, 2005), while the traditional unit root integrated models are common in tourism (Maloney and Montes Rojas, 2005; Bhattacharya and Narayan, 2005; Lim and McAleer, 2002). Gil-Alana (2005) employed a simple seasonal fractionally integrated model (i.e., model 2), while in this paper we have shown that a model incorporating fractional integration at both the zero and the seasonal frequencies outperforms those using fractional integration either at zero or the seasonal frequencies. Therefore, this paper is innovative in the present context. More research using other country applications is needed to confirm the present research.

Appendix: Robinson's (1994) parametric approach for fractional integration

Assuming that x_t are the errors in a regression model with a linear time trend,

$$y_t \;=\; \alpha \;+\; \beta t \;+\; x_t, \qquad t \;=\; 1, 2, ..., \qquad\qquad \text{(A1)}$$

we suppose that x_t adopt the form:

$$\rho(L; d)\, x_t \;=\; u_t, \qquad t \;=\; 1, 2, ..., \qquad\qquad \text{(A2)}$$

where ρ is a scalar function that depends on L and the fractional differencing parameter(s) d, and that will adopt different forms as shown below, and u_t is I(0). The function ρ is specified in such a way that all its roots should be on the unit circle in the complex plane, and therefore it includes polynomials of the form $(1\text{-}L)^d$ (as in model 1), $(1\text{-}L^s)^d$ (as in model 2), or even more generally, $(1\text{-}L)^d(1\text{-}L^s)^{ds}$ (as in model 3).

Robinson (1994) proposed a Lagrange Multiplier (LM) test of the null hypothesis:

$$H_o: \; d^* \;=\; d_o^*, . \qquad\qquad \text{(A3)}$$

in (A1) and (A2), where d^* is equal to d in <u>model 1</u>, d_s in <u>model 2</u>, and a (2x1) vector $(d, d_s)^T$ in <u>model 3</u>. Based on H_o given by (A3), the estimated $\hat{\gamma} = (\hat{\alpha}, \hat{\beta})^T$ and residuals are:

$$\hat{u}_t \;=\; \rho(L;\, d_o^*)\, y_t \;-\; \hat{\gamma}\,' w_t, \quad w_t \;=\; \rho(L;\, d_o^*)\, z_t; \quad \hat{\gamma} = \left(\sum_{t=1}^{T} w_t\, w_t\,' \right)^{-1} \sum_{t=1}^{T} w_t\, \rho(L;\, d_o^*)\, y_t .$$

with $z_t \;= (1, t)^T$. The functional form of the test statistic is then given by:

$$\hat{R} \;=\; \frac{T}{\hat{\sigma}^4} \hat{a}^T\, \hat{A}^{-1}\, \hat{a}, \qquad\qquad \text{(A4)}$$

where T is the sample size, and

$$\hat{A} \;=\; \frac{2}{T}\left(\sum_{j=1}^{*} \psi(\lambda_j)^2 \;-\; \sum_{j=1}^{*} \psi(\lambda_j)\hat{\varepsilon}(\lambda_j)' \times \left(\sum_{j=1}^{*} \hat{\varepsilon}(\lambda_j)\hat{\varepsilon}(\lambda_j)' \right)^{-1} \times \sum_{j=1}^{*} \hat{\varepsilon}(\lambda_j)\psi(\lambda_j) \right)$$

$$\hat{a} \;=\; \frac{-2\pi}{T}\sum_{j=1}^{*} \psi(\lambda_j)\, g(\lambda_j;\hat{\tau})^{-1}\, I(\lambda_j); \qquad \hat{\sigma}^2 \;=\; \sigma^2(\hat{\tau}) \;=\; \frac{2\pi}{T}\sum_{j=1}^{T-1} g(\lambda_j;\hat{\tau})^{-1}\, I(\lambda_j);$$

$$\hat{\varepsilon}(\lambda_j) = \frac{\partial}{\partial\tau}\log g(\lambda_j;\hat{\tau}); \qquad \lambda_j = \frac{2\pi\, j}{T}; \qquad \hat{\tau} \;=\; \arg\min_{\tau\in T^*} \sigma^2(\tau),$$

and the sums over * in the above expressions are over $\lambda \in M$ where $M = \{\lambda: -\pi < \lambda < \pi, \lambda \notin (\rho_l - \lambda_1, \rho_l + \lambda_1), l = 1, 2, \ldots, s\}$ such that ρ_l, $l = 1, 2, \ldots, s < \infty$ are the distinct poles of $\psi(\lambda)$ on $(-\pi, \pi]$. Also,

$$\psi(\lambda_j) = \mathrm{Re}\left[\log\left(\frac{\partial}{\partial d}\log\rho(e^{i\lambda_j};d) \right) \right], \qquad \text{(A5)}$$

and $I(\lambda_j)$ is the periodogram of u_t evaluated under the null. Note that in <u>model 1</u>,

$$\psi(\lambda_j) \;=\; \log\left| 2\sin\frac{\lambda_j}{2} \right|.$$

In <u>model 2</u>,

$$\psi(\lambda_j) \;=\log\left|2\,\sin\frac{\lambda_j}{2}\right| + \log\left(2\,\cos\frac{\lambda_j}{2}\right) + \log\left|2\,\cos\lambda_j\right| + \log\left|2\left(\cos\lambda_j - \cos\frac{\pi}{3}\right)\right| \;+$$

$$+\log\left|2\left(\cos\lambda \;-\cos\frac{2\pi}{3}\right)\right| \;+\; \log\left|2\left(\cos\lambda \;-\cos\frac{\pi}{6}\right)\right| \;+\; \log\left|2\left(\cos\lambda \;-\cos\frac{5\pi}{6}\right)\right|;$$

while in <u>model 3</u>, $\psi(\lambda_j) = [\psi_1(\lambda_j), \psi_2(\lambda_j)]^T$.

The function g above is a known function coming from the spectral density of u_t,

$$f(\lambda;\sigma^2;\tau) \;=\; \frac{\sigma^2}{2\pi}\, g(\lambda;\tau), \qquad -\pi \;<\; \lambda \;\le\; \pi.$$

Note that these tests are purely parametric, and, therefore, they require specific modelling assumptions about the short memory specification of u_t. Thus, if u_t is a white noise, then $g \equiv 1$, (and thus, $\hat{\varepsilon}(\lambda_j) = 0$), and if it is an AR process of the form $\phi(L)u_t = \varepsilon_t$, then, $g = |\phi(e^{i\lambda})|^{-2}$, with $\sigma^2 = V(\varepsilon_t)$, so that the AR coefficients are a function of τ.

Based on H_o (A3), Robinson (1994) showed that under certain very mild regularity conditions:

$$\hat{R} \rightarrow_d \chi_p^2, \quad as \quad T \rightarrow \infty.$$

where p is the dimension of d^*.

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Table 1. Description of the time series

Series 1	Number of movements: 2 weeks and under 1 month
Series 2	Number of movements: 1 weeks and under 2 month
Series 3	Number of movements: 2 weeks and under 3 month
Series 4	Number of movements: 3 weeks and under 6 month
Series 5	Number of movements: 6 weeks and under 12 month

All series are monthly running from January 1991 to January 2009.

Table 2. Summary statistics

	M	SD	Skew	Kurtosis	Jarque-Bera
Series 1	80434	35447	1.386	2.102	78.53
Series 2	48942	25998	1.878	4.605	154.32
Series 3	17090	6830	0.521	-0.345	113.54
Series 4	15418	5155	0.688	0.228	88.59
Series 5	13144	3562	0.761	0.871	63.54

Table 3. Estimates of d in model (1)

Series	No regressors	An intercept	A linear trend
Series 1	0.261 (0.233, 0.303)	0.387 (0.354, 0.426)	0.127 (0.076, 0.195)
Series 2	0.182 (0.152, 0.225)	0.336 (0.286, 0.397)	0.118 (0.038, 0.226)
Series 3	0.227 (0.136, 0.479)	0.383 (0.304, 0.485)	0.307 (0.191, 0.455)
Series 4	0.504 (0.165, 0.657)	0.339 (0.260, 0.449)	0.283 (0.158, 0.449)
Series 5	0.631 (0.525, 0.752)	0.258 (0.196, 0.343)	0.195 (0.104, 0.310)

The values in parenthesis refer to the 95% confidence band.

Table 4. Estimates of the parameters in model (1) with a linear time trend

Series	Intercept	Time trend	d	Seas. AR(1)
Series 1	**33124.109 (6.820)**	**436.457 (11.845)**	0.127 (0.076, 0.195)	0.939
Series 2	**26115.375 (5.302)**	**207.584 (5.545)**	0.118 (0.038, 0.226)	0.974
Series 3	**12376.602 (4.592)**	**40.176 (1.943)**	0.307 (0.191, 0.455)	0.941
Series 4	**11149.335 (6.632)**	**36.803 (2.877)**	0.283 (0.158, 0.449)	0.903
Series 5	**10435.898 (11.872)**	**24.662 (3.725)**	0.195 (0.104, 0.310)	0.929

In parenthesis in columns 2 and 3, t-values. In bold the significant coefficients.

Table 5: Estimates of SARMA components in the undifferenced and differenced data

Series	d = 0 (undifferenced data)		d = 1 (differenced data)	
	Model	Parameters	Model	Parameters
Series 1	SARMA (1, 0)	AR1 = 0.973	SARMA (1, 0)	AR1 = 0.962
Series 2	SARMA (1, 1)	AR1 = 0.975	SARMA (1, 1)	AR1 = 0.978
Series 3	SARMA (1, 0)	AR1 = 0.942	SARMA (1, 0)	AR1 = 0.916
Series 4	SARMA (1, 1)	AR1 = 0.925	SARMA (1, 0)	AR1 = 0.858
Series 5	SARMA (1, 0)	AR1 = 0.943	SARMA (1, 0)	AR1 = 0.914

Table 6: Estimates in the seasonal differenced data

Series	Model	Parameter estimates
Series 1	ARMA (1, 0)	AR1 = 0.456
Series 2	ARMA (1, 0)	AR1 = 0.462;
Series 3	ARMA (1, 0)	AR1 = 0.224; MA1 = 0.117
Series 4	ARMA (1, 1)	AR1 = 0.210; MA1 = 0.119
Series 5	ARMA (1, 1)	AR1 = 0.163; MA1 = 0.121

Table 7. Estimates of d in model (2)

Series	No regressors	An intercept	A linear trend
Series 1	0.736 (0.690, 0.787)	0.693 (0.638, 0.754)	0.723 (0.676, 0.775)
Series 2	0.753 (0.719, 0.790)	0.767 (0.731, 0.805)	0.747 (0.712, 0.786)
Series 3	0.602 (0.565, 0.645)	0.602 (0.563, 0.645)	0.597 (0.560, 0.638)
Series 4	0.492 (0.456, 0.534)	0.485 (0.446, 0.529)	0.484 (0.448, 0.523)
Series 5	0.511 (0.475, 0.553)	0.607 (0.566, 0.653)	0.563 (0.526, 0.604)

The values in parenthesis refer to the 95% confidence band.

Table 8. Estimates of the parameters in model (2) with a linear time trend

Series	Intercept	Time trend	d_s	AR(1) coeff.
Series 1	**10720.077** **(10.291)**	**537.973** **(15.109)**	0.723 (0.676, 0.775)	0.422
Series 2	**22698.439** **(3.528)**	**236.236** **(9.027)**	0.747 (0.712, 0.786)	0.367
Series 3	**13505.138** **(9.470)**	**39.566** **(5.323)**	0.597 (0.560, 0.638)	0.310
Series 4	**11552.676** **(13.035)**	**36.867** **(7.161)**	0.484 (0.448, 0.523)	0.350
Series 5	**10059.126** **(15.208)**	**24.320** **(6.799)**	0.563 (0.526, 0.604)	0.208

In parenthesis in columns 2 and 3, t-values. In bold the significant coefficients.

Table 9. Estimates of d and d_s in model (3a) (with white noise disturbances)

	No regressors		An intercept		A linear time trend	
	d	d_s	d	d_s	d	d_s
Series 1	0.34	0.65	0.32	0.66	0.32	0.66
Series 2	0.37	0.75	0.30	0.74	0.30	0.75
Series 3	0.26	0.60	0.29	0.60	0.29	0.60
Series 4	0.30	0.51	0.31	0.50	0.29	0.50
Series 5	0.24	0.55	0.21	0.58	0.21	0.56

Though not reported, the I(0) and the I(1) hypotheses were rejected in all cases at the 95% level.

Table 10. Estimates of d and d_s in model (3b) (with non-seasonal AR(1) disturbances)

	No regressors		An intercept		A linear time trend	
	d	d_s	d	d_s	d	d_s
Series 1	---	---	0.41	0.64	0.41	0.64
Series 2	---	---	0.34	0.74	0.34	0.74
Series 3	---	---	0.29	0.60	0.29	0.60
Series 4	---	---	0.25	0.49	0.11*	0.48
Series 5	---	---	0.25	0.57	0.31	0.55

--- means that the estimates do not converge. * means that the I(0) hypothesis was not rejected at 5% level.

Table 11. Estimates of d and d_s in model (3c) (with seasonal AR(1) disturbances)

	No regressors		An intercept		A linear time trend	
	d	d_s	d	d_s	d	d_s
Series 1	0.50	0.92**	0.29	-0.38	0.35	0.86
Series 2	0.65	1.00**	0.18	-0.24	0.34	0.86
Series 3	0.26	0.69	0.28	0.65	0.28	0.64
Series 4	0.29	0.60	0.30	0.59	0.28	0.59
Series 5	0.22	0.67	0.23	-0.41	0.13	-0.41

**: The I(1) hypothesis (d_s = 1) cannot be rejected at the 5% level.

Table 12. Estimates of the parameters in model (3a)

Series	Intercept	Time trend	d	d_s
Series 1	**73721.210 (2.603)**	**455.211 (3.524)**	0.32	0.66
Series 2	**71100.140 (4.237)**	**262.129 (2.469)**	0.30	0.75
Series 3	**44731.316 (5.241)**	---	0.28	0.59
Series 4	**20431.910 (3.455)**	---	0.31	0.50
Series 5	**6266.955 (1.839)**	**31.904 (2.577)**	0.21	0.56

In parenthesis in columns 2 and 3, t-values. In bold the significant coefficients.

Table 13. Estimates of the parameters in model (3b)

Series	Intercept	Time trend	d	d_s	AR coeff.
Series 1	**75856.828 (3.204)**	**497.880 (2.513)**	0.41	0.64	-0.217
Series 2	**70607.843 (4.558)**	**284.359 (2.196)**	0.34	0.74	-0.075
Series 3	**44731.316 (5.241)**	---	0.29	0.60	0.0009
Series 4	**11844.199 (5.556)**	**35.961 (3.821)**	0.11	0.48	0.236
Series 5	**-1927.364 (-0.388)**	**40.786 (2.523)**	0.31	0.55	-0.133

In parenthesis in columns 2 and 3, t-values. In bold the significant coefficients.

Table 14. Estimates of the parameters in model (3c)

Series	Intercept	Time trend	d	d_s	AR coeff.
Series 1	**61277.996 (4.042)**	**544.601 (2.135)**	0.35	0.86	-0.137
Series 2	**53840.609 (4.904)**	**325.351 (1.886)**	0.34	0.86	-0.127
Series 3	**43297.722 (5.022)**	---	0.28	0.65	-0.107
Series 4	**17873.589 (2.483)**	---	0.30	0.59	-0.091
Series 5	**108055483 (20.731)**	**22.6651 (4.985)**	0.13	-0.44	0.992

In parenthesis in columns 2 and 3, t-values. In bold the significant coefficients.

Table 15: Forecasting accuracy in terms of RMSE and MAPE

Series 1	RMSE		MAPE	
	ARIMA	Model 1	ARIMA	Model 1
1	1.1543	0.9609	0.4455	0.2880
6	2.2209	1.7386	0.8909	0.3227
12	2.6785	2.3755	0.9012	0.3956
18	3.9092	3.2589	1.1101	0.4555
24	7.8123	5.1813	1.5677	0.5670
Series 2	RMSE		MAPE	
	ARIMA	Model 1	ARIMA	Model 1
1	0.4095	0.2735	0.4321	0.1896
6	1.3345	1.1761	0.6776	0.3367
12	3.4541	2.0670	0.7089	0.3982
18	2.9081	1.8140	0.7091	0.3867
24	3.1159	2.0610	0.7345	0.4632
Series 3	RMSE		MAPE	
	ARIMA	Model 1	ARIMA	Model 1
1	0.5567	0.2627	0.6787	0.3409
6	1.1903	0.6594	0.8732	0.5280
12	2.1184	1.0856	0.9044	0.5849
18	1.9043	1.0446	0.8876	0.5787
24	1.9944	1.1144	0.9182	0.6426
Series 4	RMSE		MAPE	
	ARIMA	Model 1	ARIMA	Model 1
1	1.1143	0.9469	0.7765	0.5590
6	0.6654	0.4952	0..7098	0..4411
12	0.7833	0.5386	0.7765	0.4774
18	0.6765	0.4744	0.6592	0.4223
24	0.9083	0.6824	0.7812	0.5450
Series 5	RMSE		MAPE	
	ARIMA	Model 1	ARIMA	Model 1
1	0.3456	0.0312	0.4432	0.1325
6	0.5430	0.3387	0.7893	0.4627
12	0.6756	0.4491	0.8092	0.5322
18	0.5987	0.5120	0.8443	0.5870
24	0.6430	0.5790	0.6574	0.1217

Table 16. Pairwise comparisons between ARIMA and FI models using M-DM statistic

Series	h = 12	h = 24
Series 1	**3.411 (FI)**	**2.889 (FI)**
Series 2	**3.567 (FI)**	**3.421 (FI)**
Series 3	**3.112 (FI)**	**2.557 (FI)**
Series 4	**3.409 (FI)**	**2.905 (FI)**
Series 5	**3.356 (FI)**	**2.009 (FI)**

In parenthesis the selected model

Table 17: Forecasting accuracy in terms of RMSE and MAPE

Series 1	RMSE		MAPE	
	SARIMA	Model 2	SARIMA	Model 2
1	0.5517	0.4617	0.2987	0.1996
6	0.8893	0.7930	0.3455	0.2211
12	0.8973	0.7341	0.4094	0.2069
18	0.9567	0.9112	0.4241	0.2247
24	2.0098	1.0999	0.5376	0.2373
Series 2	RMSE		MAPE	
	SARIMA	Model 2	SARIMA	Model 2
1	0.5504	0.3607	0.3421	0.2177
6	0.8334	0.5647	0.4355	0.2295
12	0.9075	0.7326	0.3611	0.2605
18	1.0943	0.7206	0.5876	0.2616
24	1.1183	0.7854	0.6788	0.2711
Series 3	RMSE		MAPE	
	SARIMA	Model 2	SARIMA	Model 2
1	0.5477	0.3388	0.4456	0.3871
6	0.3654	0.1635	0.3091	0.2253
12	0.1613	0.1694	0.2017	0.2290
18	0.1509	0.1755	0.2115	0.2376
24	0.2033	0.2076	0.2334	0.2477
Series 4	RMSE		MAPE	
	SARIMA	Model 2	SARIMA	Model 2
1	0.3341	0.1418	0.4366	0.2164
6	0.2290	0.1381	0.7572	0.2502
12	0.4432	0.1407	0.5364	0.2348
18	0.5327	0.1381	0.6788	0.2415
24	0.6675	0.1453	0.7566	0.2563
Series 5	RMSE		MAPE	
	SARIMA	Model 2	SARIMA	Model 2
1	0.1132	0.0532	0.3765	0.1729
6	0.2432	0.0920	0.4378	0.2447
12	0.3315	0.0931	0.5366	0.2326
18	0.4453	0.1177	0.6789	0.2698
24	0.3654	0.1404	0.7623	0.2912

Table 18. Pairwise comparisons between SARIMA and SFI models using M-DM statistic

Series	h = 12	h = 24
Series 1	**2.314 (SFI)**	**1.914 (SFI)**
Series 2	**2.817 (SFI)**	**2.011 (SFI)**
Series 3	**2.019 (SFI)**	1.657
Series 4	**2.303 (SFI)**	**1.808 (SFI)**
Series 5	**2.343 (SFI)**	**1.819 (SFI)**

In parenthesis the selected model

Table 19. Pairwise comparison using the modified DM statistic (h =12)

Series 1					Series 2			
	Mod.1	Mod.2	Mod.3a			Mod.1	Mod.2	Mod.3a
Mod.1	XXXX	XXXX	XXXX		Mod.1	XXXX	XXXX	XXXX
Mod.2	3.456	XXXX	XXXX		Mod.2	3.117	XXXX	XXXX
Mod.3a	4.567	3.567	XXXX		Mod.3a	4.002	3.055	XXXX
Series 3					**Series 4**			
	Mod.1	Mod.2	Mod.3a			Mod.1	Mod.2	Mod.3a
Mod.1	XXXX	XXXX	XXXX		Mod.1	XXXX	XXXX	XXXX
Mod.2	2.143(2)	XXXX	XXXX		Mod.2	2.345	XXXX	XXXX
Mod.3a	1.654	1.456	XXXX		Mod.3a	2.113	1.998	XXXX
Series 5								
	Mod.1	Mod.2	Mod.3a					
Mod.1	XXXX	XXXX	XXXX					
Mod.2	2.134	XXXX	XXXX					
Mod.3a	2.007	1.903	XXXX					

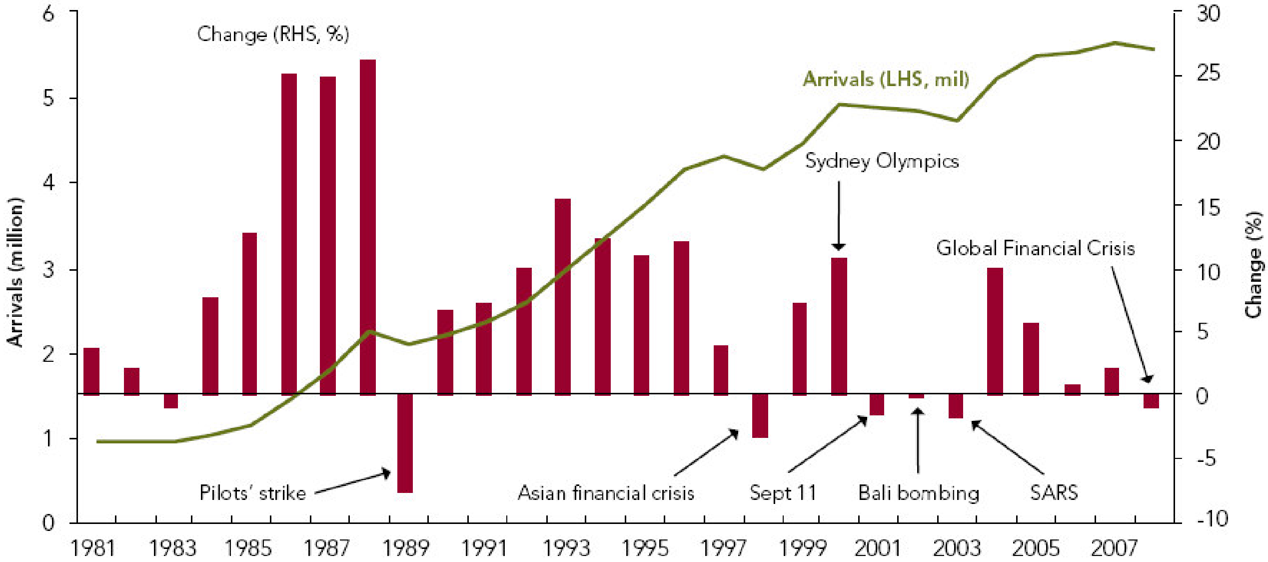
The critical value at the 5% level is1,796

Table 20. Pairwise comparison using the modified DM statistic (h =24)

Series 1					Series 2			
	Mod.1	Mod.2	Mod.3a			Mod.1	Mod.2	Mod.3a
Mod.1	XXXX	XXXX	XXXX		Mod.1	XXXX	XXXX	XXXX
Mod.2	1.443	XXXX	XXXX		Mod.2	2.019	XXXX	XXXX
Mod.3a	1.456	2.009	XXXX		Mod.3a	2.399	2.133	XXXX
Series 3					**Series 4**			
	Mod.1	Mod.2	Mod.3a			Mod.1	Mod.2	Mod.3a
Mod.1	XXXX	XXXX	XXXX		Mod.1	XXXX	XXXX	XXXX
Mod.2	1.654	XXXX	XXXX		Mod.2	1.992	XXXX	XXXX
Mod.3a	1.034	0.997	XXXX		Mod.3a	1.811	1.556	XXXX
Series 5								
	Mod.1	Mod.2	Mod.3a					
Mod.1	XXXX	XXXX	XXXX					
Mod.2	1.895	XXXX	XXXX					
Mod.3a	1.546	1.238	XXXX					

The critical value at the 5% level is1,711.

Figure 1. International tourist arrivals to Australia.



Source: Adopted from the Jackson Report (http://www.ret.gov.au), based on data from the Australian Bureau of Statistics (ABS Cat. No. 3401.0).

Figure 2. Time series plots

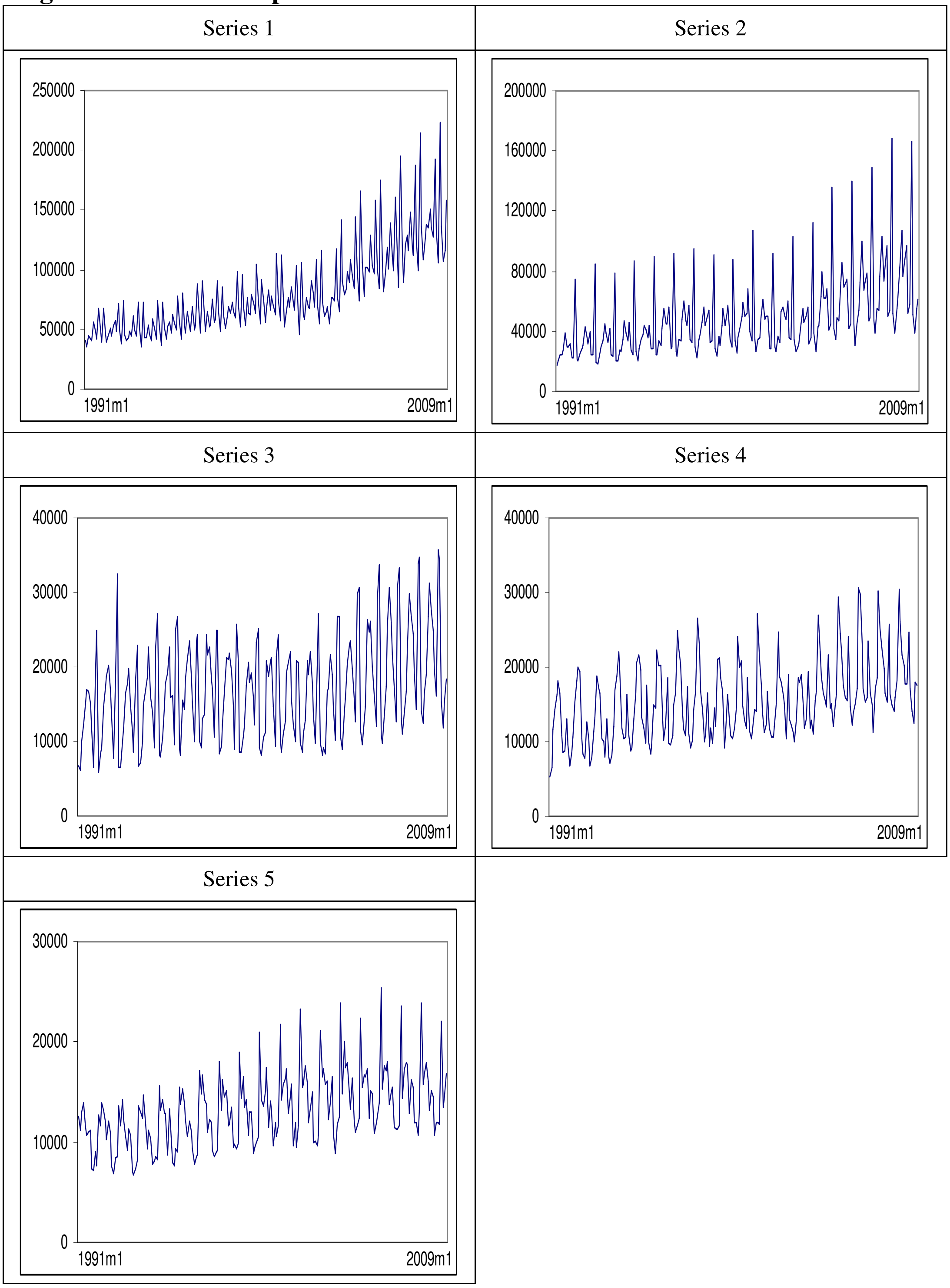


Figure 3. First seasonal differenced time series plots

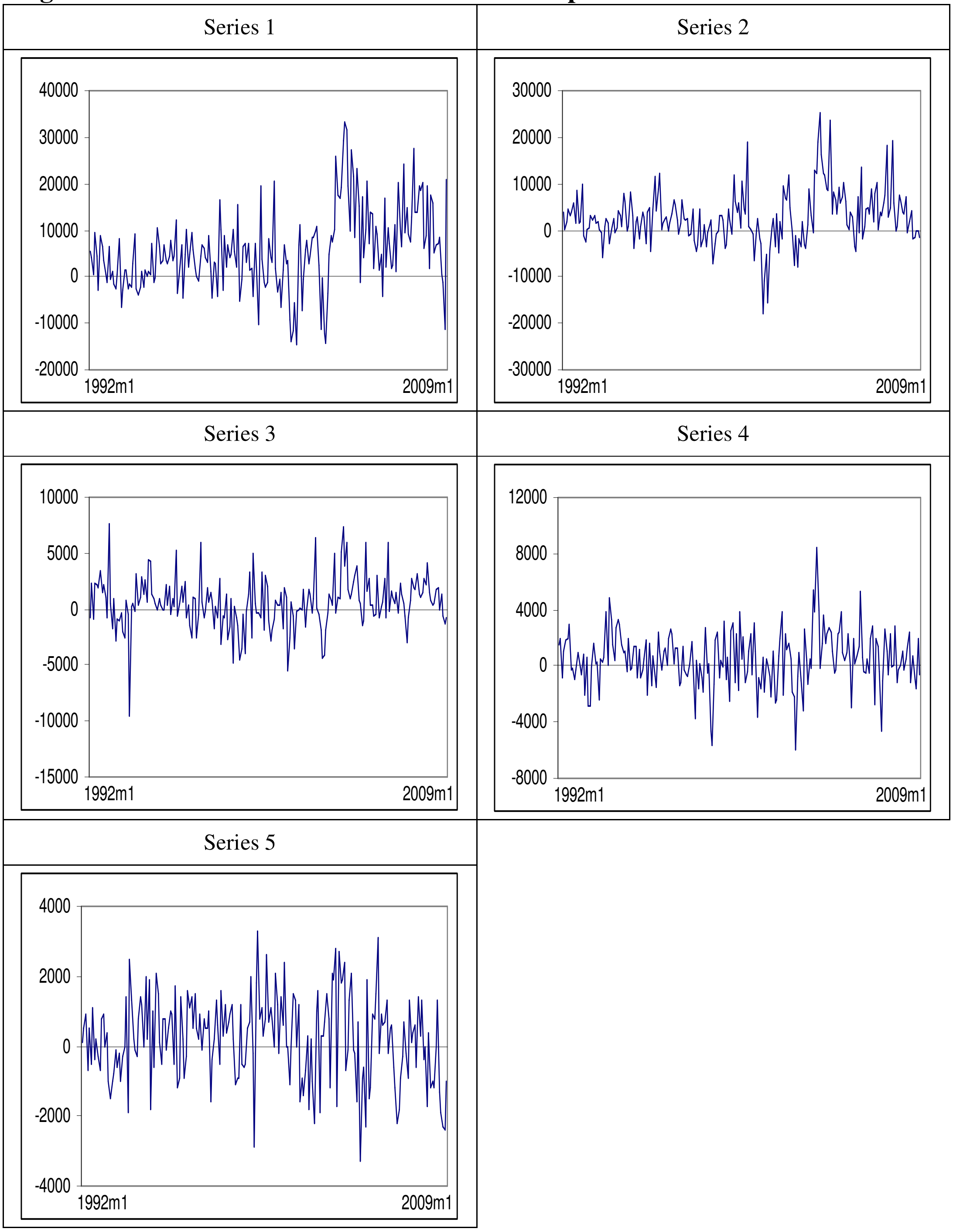
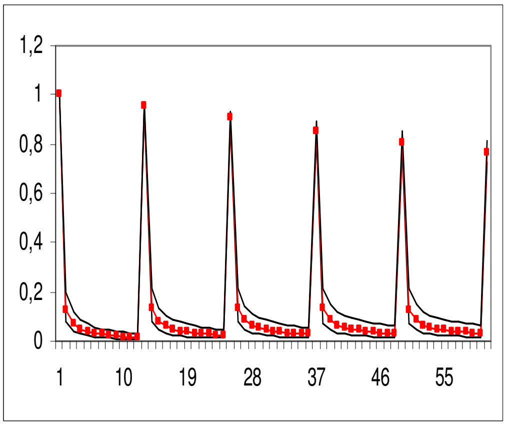
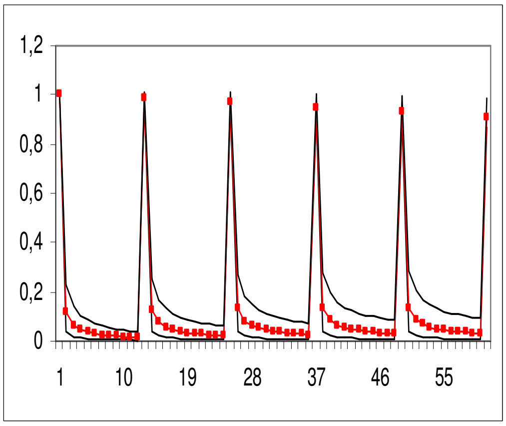


Figure 4. Impulse response functions based on the results in model (1)

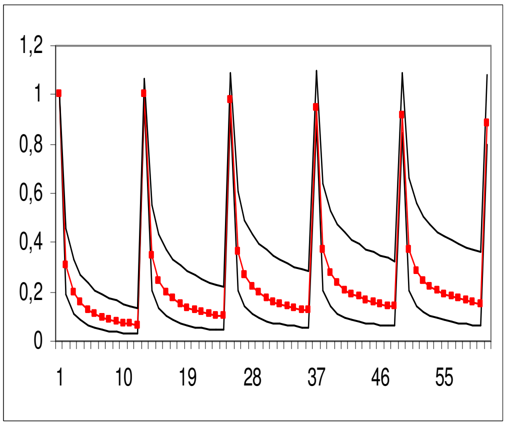
Series 1



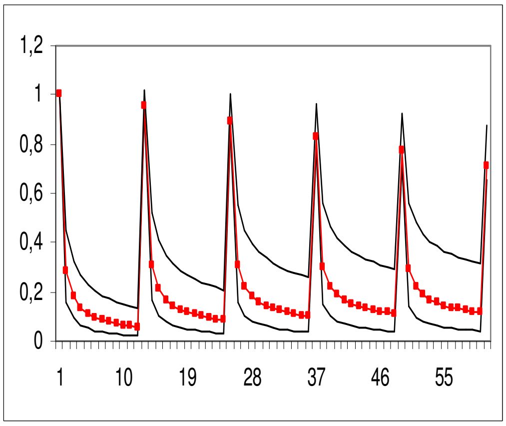
Series 2



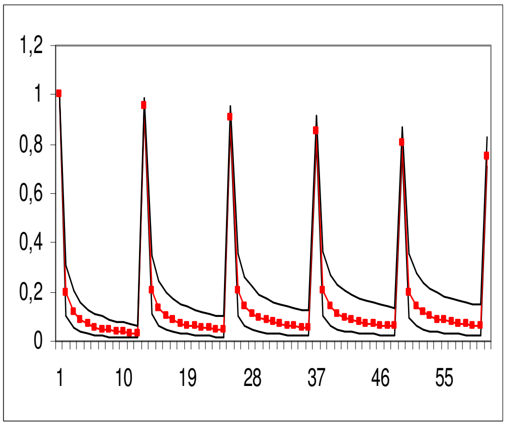
Series 3



Series 4

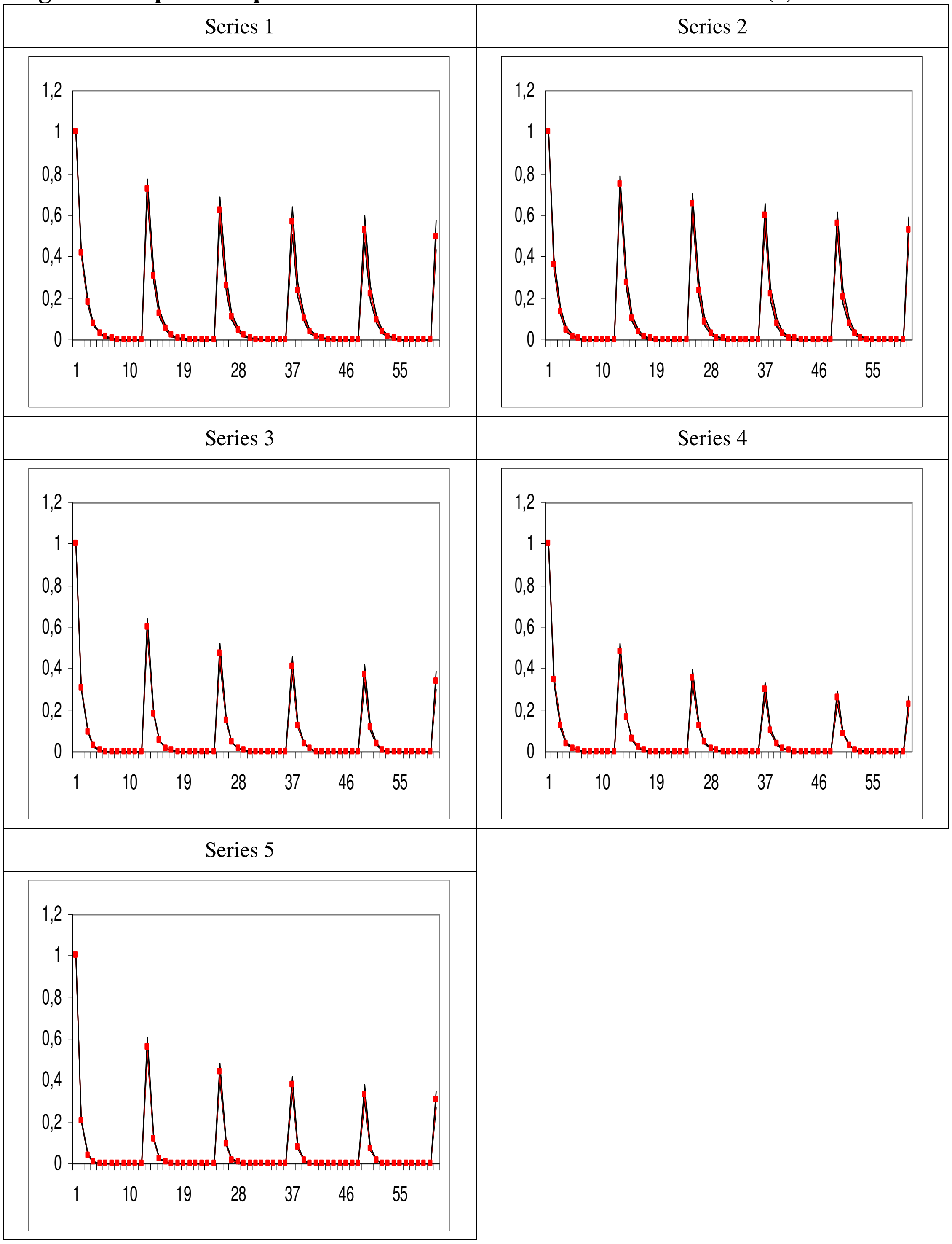


Series 5



The thin lines refer to the 95% confidence bands.

Figure 5. Impulse response functions based on the results in model (2)



The thin lines refer to the 95% confidence bands.