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Anticipating Chinese tourists arrivals in Australia: A time series analysis

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ABSTRACT

Given the growing importance of the Chinese tourist market to Australia, an understanding of Chinese tourists' arrival patterns is essential to accurate forecasting of future arrivals. Drawing on 25 years of records (1991–2015), this study developed a time-series model of monthly arrivals of Chinese tourists in Australia. The model reflects the exponentially increasing trend and strong seasonality of arrivals. Excellent results from validation of the model's forecasts endorsed this time-series model's potential in the policy prescription and management practice of Australian tourism industries.

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1. Introduction

With its unique climate and beautiful environment, Australia is one of the world's most attractive tourism destinations. The tourism industry in Australia generates a total of US $31.5 billion revenue, which makes Australia the world's tenth largest tourism earner (UNWTO, 2013). Tourism has been a key driver of economic growth in Australia, and tourism's contribution to the nation's economy is estimated at $91 billion, equivalent to 6% of Australia's GDP (Tourism Research Australia, 2014). Particularly since the decline of the mining industry, the government has promoted tourism as a key source of future economic growth (McLennan, 2015).

In 2014, 859,500 Chinese visitors visited Australia, making China the second largest source market and the top expenditure market (Tourism Australia, 2015). Australia's interesting attractions, world-class beauty and nature, safe environment, good food and wine, and diversified cultures place it at the top of Chinese travelers' wish list (Tourism Australia, 2015). With China's strong economic growth and the lowered value of Australian dollars, the Australian government is confident this market will continue to boom (Tourism Australia, 2015).

Given the growing importance of Chinese tourist market, the ability to anticipate the growth pattern and arrival trends of Chinese tourists is essential in helping the Australian tourism industry prepare for opportunities and challenges that might accompany increased tourist numbers. Although over the past three decades many popular destinations in the Asia-Pacific regions have experienced a boom in Chinese travelers, only recently have researchers and destinations realized the importance of modeling tourist arrivals (e.g., Song & Li, 2008). While forecasting tourist arrivals has economic significance, it also carries a number of social and cultural implications. Without proper forecasting and strategic planning, a large in-flow of tourists could place a destination's hospitality and industry under strong pressure and disturb local residents (Doxey, 1975; Hsu, 2000). For example, in Hong Kong, residents' attitude toward Mainland Chinese travelers has changed from welcoming, to tolerance, to publicly expressed negativity toward the growing numbers of visitors from Mainland China. Since 2012, a number of "anti-locust"[1] protests have occurred in Hong Kong, which have badly hurt the tourism industry (Zuo, 2015).

Forecasting tourist arrivals is of critical importance, as forecasting not only benefits economic development and strategic planning but also takes into account the social and cultural impacts of tourism on the local destination and communities. This study has three major objectives: to identify the major characteristics of Chinese tourist arrivals in Australia for the past 25 years (1991–2015), to identify the patterns of Chinese tourist arrivals, and to develop and validate a model that can be used to forecast Chinese tourist arrivals in Australia.

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[1] "Locusts" is a pejorative term adopted by Hong Kong residents to describe mainland tourists after an account referred to crowds of passengers who left the subway in a messy state as a "locust invasion" (http://shanghaiist.com/2014/02/17/anti-locust-protestors-march-through-hk.php).

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2. Literature

2.1. Chinese outbound travel market

The Chinese have valued travel since ancient times—a Chinese saying is that "traveling one thousand miles equals reading ten thousand books." However, until recently, only a few pioneer voyagers traveled beyond Chinese cultural borders. During the twentieth century, political turmoil, wars, and the resulting isolation of China during the 1960s and 1970s impeded the development of both domestic and outbound tourism in China (China Outbound Tourism Research Institute, 2015). Before the economic reform and the beginning of the open-door policy in 1978, outbound travel was limited to government officials and diplomats (Wen & Tisdell, 2001). However, recognizing tourism as an important economic activity, the Chinese government started to support the development of tourism in the early 1980s, leading to the development of outbound tourism. Researchers in general agree that the growth of outbound tourism in China has occurred in three stages. Stage one, which began in 1983, comprised visiting relatives and friends in Hong Kong via package tours. The travel scope was small and overseas relatives or friends had to cover the Chinese travelers' expenses. Stage two encompassed package tours to Singapore, Malaysia, and Thailand during the 1990s. In Stage three, which began after 2000, outbound travel extended to visiting approved destinations beyond Asia (Chon, Pine, Lam, & Zhang, 2005). Chinese travelers' outbound destinations expanded quickly, and by 2013, the Chinese government had granted 146 countries approved destination status (ADS) (Ma, Zhang, & Qu, 2014).

Several factors contributed to the development of Chinese outbound tourism, the most important being China's strong economic growth and people's increased leisure time (Ryan, 2003). Since 2000, Chinese outbound travel has maintained a two-digit growth rate (Travel China Guide, 2015). A recent report by the World Tourism Organization noted that China has become the largest tourism source market in the world, with more than 22 billion outbound travelers (UNWTO, 2014a). China has also become the top source market for many tourism destinations. For example, China is Thailand's most important source market (Thailand Department of Tourism, 2014).

China is Australia's second largest inbound market in terms of visitor arrivals. In 2015, China became the leading source of inbound tourism to Australia, accounting for 18% of total international tourist spending (Terlato, 2015). Chinese tourists are regarded as the "world's biggest travelers" (Asia Raising, 2014). Nearly 100 million Chinese tourists visited foreign countries in 2013, earning them the distinction of being the "world's biggest-spending" travelers.

2.2. Chinese Visitors to Australia

Australia, which gained Approved Destination Status in 1999, is one of the first countries outside Asia to hold that standing (Australia Embassy, China, 2015). Chinese visitors to Australia started to boom after 2000, and constituted about 2% of Australia's tourist arrivals (Australia Bureau of Statistics, 2015). By 2014, Chinese visitors represented about 12% of total tourist arrivals in Australia. Importantly, Chinese visitors to Australia are strong spenders. In 2014, Chinese visitors were responsible for $6.4 billion, or almost 20%, of the total spending by Australia's international visitors (Wilkinson, 2015), which is more than the combined spending by the UK (12%) and Japan (5%). The strong performance of the Chinese market in Australia can be attributed to the rising income of the Chinese middle class, improved living standards, strong currency, and open visa policies, all of which contributed to the growth in Chinese tourists to Australia (Terlato, 2015).

Over 50% of Chinese tourists visited Australia for holiday (Tourism Research Australia, 2014), followed by visiting family and friends, educational tourism, and business travel. About one-third of the tourists belong to the age group of 45–59, followed by the age groups of 15–29 and 30–44. Chinese visitors like the safety and security of Australia as a destination, the friendliness of local people, and attractions, as well as high quality food and wines, although satisfaction with shopping facilities and experiences was low. Severe pollution in China also motivated people to visit Australia as Australia is known for its good environment, clean air and water, and food safety.

3. Tourist arrival forecasting

Tourist arrival forecasting depends on two elements: "tourist arrivals" and "forecasting." In the context of tourism, an arrival is a statistical unit measuring the volume (number) of tourists or visitors (Statistics Finland, 2014). A tourist is defined as a visitor whose trip includes an overnight stay (UNWTO, 2014b). Thus, the term "tourist arrivals" refers to the number of overnight visitors who arrive at a tourism destination. Tourist arrivals are generally measured as annual or monthly arrivals or as the average daily census (Sheldon, 1993). Forecasting is a process of predicting a future performance (in tourist arrival) mainly relying on existing data (Hadavandi, Ghanbari, Shahanaghi, & Abbasian-Naghneh, 2011).

Tourism demand is usually measured by tourist arrivals from an origin place to a given destination, followed by tourist expenditure (Song & Li, 2008). Therefore, tourist arrival forecasting plays an important role in tourism planning and decision-making. A forecast of tourist arrivals is obtained by applying combined models or a single-equation forecasting model, with the purpose of accurately projecting the number of tourists to a destination at a future time so as to provide essential information to different sectors of the tourism industry and public sectors for planning, controlling, budgeting, and policy-making (Uysal & O'Leary, 1986; Athanasopoulos & de Silva, 2012). In the selection of a forecasting model, forecasting accuracy is a crucial criterion, and is measured by comparison of the forecasted volume with actual tourist volumes (Mahmoud, 1984; Chaitip, Chaiboonsri, & Mukhjang, 2008). The difference between the forecasted tourist arrivals and actual numbers is referred as a forecast error. Chu (2004) found that the most popular measures used to evaluate the accuracy of forecasting are the values of the mean absolute percentage error (MAPE) and the root mean square error (RMSE).

3.1. Forecasting Chinese tourists to Australia

Forecasting tourist arrivals, particularly Chinese tourist arrivals, is of paramount importance since China is Australia's most valuable and fast-growing inbound tourism market (Tourism Australia, 2011). In the past 20 years, Australia has experienced faster growth of tourist arrivals from China (with 19.4% CAGR between 1993 and 2013) than any other tourism market (Australia Trade Commission, 2013), and in 2013, China became Australia's second largest inbound market for visitor arrivals (Tourism Australia, 2015). The rapid growth of Chinese tourist arrivals has a significant impact on the Australian economy. In 2010, the Chinese inbound market contributed $3.26 billion to the Australian economy (Tourism Australia, 2011). In 2013, total spending from Chinese tourists reached $4.8 billion, which made China the largest tourism market for total expenditure and visitor nights in Australia (Tourism Australia, 2015). By 2020, this market has the potential to contribute $7.4 to $9 billion annually (Tourism Australia, 2011).

Both the private and public sectors in Australia have paid great attention to the Chinese market and aimed to further increase the number of Chinese tourist arrivals. As an example, Tourism Australia, in consultation with industry and government stakeholders, developed "Australia's China 2020 Strategic Plan" to ensure that Australian tourism would remain competitive in the fast-growing market for outbound travel from China and grow this market to as much as $9.5 billion in overnight expenditure and 860,000 visitors per year by 2020 (Tourism Australia, 2011). Hence, at a macro level, it is important to analyze and forecast Chinese tourist arrivals as a contributor to Australian GDP and source of revenue. For the public sector, most direct revenue from tourism is collected on a per head basis through departure taxes or disembarkation taxes (Dharmaratne, 1995), so an accurate forecast of the number of arrivals can provide reliable estimates of these revenues to government budgeting.

An additional factor of importance is that Chinese tourist arrivals constituted up to 10.9% of Australia's total short-term tourist arrivals (Australia Trade Commission , 2013), indicating that China has become a large source of demand for Australian tourism products. Therefore, from a micro point of view, accurate forecasts of Chinese tourist arrivals are essential to the planning by different sectors in Australian tourism and hospitality industries. Businesses such as hotels, airlines, or cruise ships need to forecast arrivals to ensure sufficient capacity to meet the existing and increasing demand (Tourism Australia, 2011). On the other hand, because unfilled hotel rooms, airline seats, and ship seats are perishable (Dharmaratne, 1995; Hadavandi et al., 2011), any oversupply may result in downward pricing pressure on suppliers and even cause big financial losses. Therefore, accurate forecasts are critical to avoiding shortages and surpluses of goods and services (Dharmaratne, 1995).

4. Method

To describe the pattern and trend of Chinese tourists' arrival in Australia, we performed time-series analysis with autoregressive-integrated moving average (ARIMA) models, using monthly tourists' arrival data from the Australia Bureau of Statistics (Australia Bureau of Statistics, 2015). Time-series models explain a variable with regard to its own past and a random disturbance term (Song & Li, 2008). Time-series models are the most popular methods used in forecasting research (Song & Li, 2008). We also performed forecasting and verifications to test the validity of models.

4.1. Data

The current study analyzed the monthly counts of short-term visitor arrivals from mainland China to Australia from January 1991 to September 2015 (Australia Bureau of Statistics, 2015). Fig. 1 shows an exponential increase in the annual inbound market share of Chinese tourists over the last 25 years, starting from less than 1% in 1991 and growing to over 12% in 2014. In February 2015, 164,000 of all short-term foreign visitors to Australia (i.e., over 22%) came from mainland China, reaching a historical high record.

Fig. 2 plots the time series of monthly arrivals, presenting an exponential increase in the level with mounting variance proportional to the level. Further, this monthly time series starts to show increasingly clear seasonality since the beginning of the twenty-first century, although it might be difficult to see the pattern within each year in Fig. 2. The outlying low counts in April, May, and June of 2003 are possibly due to the massive outbreak of SARS in China. For convenience in further analysis, the counts of these three months are respectively replaced by the average of the same months in 2002 and 2004.

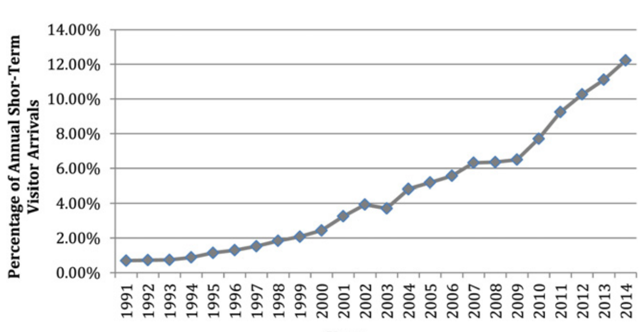

Fig. 1. Annual inbound market share of Chinese tourists over years 1991–2014.

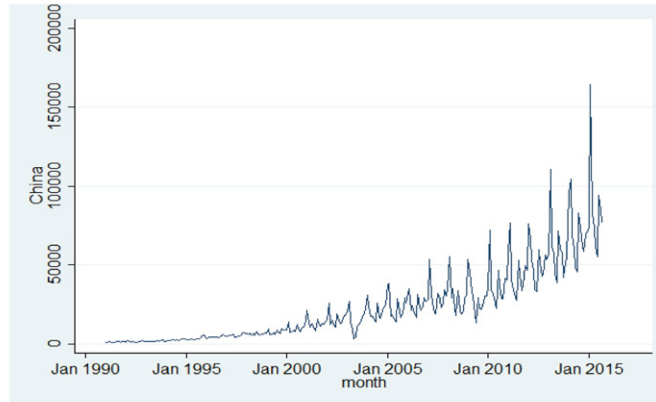

Fig. 2. Monthly short-term visitor arrivals from mainland China to Australia, January 1991–September 2015.

The box-and-whisker plots in Fig. 3 better illustrate the monthly pattern of the time series from January 1999 to September 2015. Monthly median arrival starts high in January and reaches its peak in February, then gradually drops to the bottom in June, followed by a jump in July and settling down until September before slowly climbing up for the next cycle. Fig. 3 also shows that the higher months experience larger variation. This monthly seasonality can be related to China's national holiday reform in late 1999 and tourism-supportive policies after the Asian Financial Crisis in 1998.

4.2. Analysis

Although timeline and box-and-whisker plots provide useful insights into the monthly patterns of short-term visitor arrivals from China, a time-series model is much more desirable to forecast the monthly arrivals. Despite limitations and competitors, univariate time-series models are still very popular in tourism forecasting (Song & Li, 2008). Among them, the most widely used is the Box-Jenkins seasonal ARIMA approach (Box, Jenkins, & Reinsel, 2008), as it is very useful in capturing the behavior of seasonal time series and generating accurate forecasts for such series (e.g., Coshall, 2006; Chu, 1998, 2008; Lim & McAleer, 2002, 2005; Kim & Moosa, 2005; Oh & Morzuch, 2005).

This study followed the Box-Jenkins seasonal ARIMA approach to develop univariate time-series models. We used data from January 1999 to September 2014 as the model estimation sample and left out the most recent twelve months (i.e., October 2014 to September 2015) for forecast validation. The general forms of additive and multiplicative

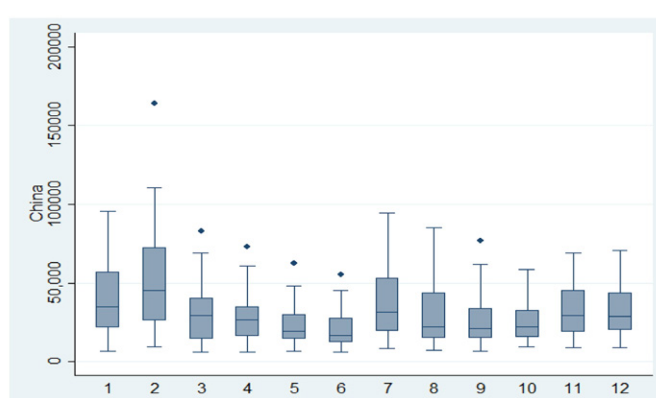

Fig. 3. Box-and-whisker plots of arrivals per month, January 1999–September 2015.

Box-Jenkins seasonal ARIMA models are respectively

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D\dot{Z}_t = \theta_q(B)+\theta_Q(B^s)a_t \tag{1 – a}$$

and

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D\dot{Z}_t = \theta_q(B)\theta_Q(B^s)a_t \tag{1 – b}$$

where

$$\dot{Z}_t = \begin{cases} Z_t-\mu, & \textit{if } d = D = 0, \\ Zt, & \textit{otherwise}. \end{cases}$$

Z_t is usually the natural logarithm of original time series to stabilize the variance and the white noise term a_t is normally distributed

$$a_t \sim N(0, \sigma^2)$$

and

$$\textit{Seasonal autoregressive term}: \Phi_P(B^s) = 1-\Phi_1 B^s-\Phi_2 B^{2s}-\cdots-\Phi_P B^{Ps.}$$

$$\textit{Non-seasonal autoregressive term}: \phi_p(B) = 1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p$$

$$\textit{Seasonal moving average term}: \theta_Q(B^s) = 1+\theta_1 B^s+\theta_2 B^{2s}+\cdots+\theta_Q B^{Qs}$$

$$\textit{Non-seasonal moving average term}: \theta_q(B) = 1+\theta_1 B+\theta_2 B^2+\cdots+\theta_q B^q.$$

In accordance with the Box–Jenkins approach, a preferred model specification was identified, estimated, and diagnosed for adequacy. In addition, several competing seasonal ARIMA models were estimated and compared with the preferred model in terms of in-sample model fit and out-of-sample forecast errors.

5. Results

5.1. Model identification

The sample time series was taken logarithm, first-order differenced, and seasonally differenced with a 12-month lag (see Fig. 4(a), (b), and (c)) to obtain a stationary time series (see Fig. 4(d)) for developing ARIMA models. The time series in Fig. 4 (d) seems to be stationary with levels randomly centering on zero. Further, the Dicky-Fuller test for unit root confirmed that the resulting series did not have a unit root (i.e., was covariance stationary) ($Z = -18.785$, $Z_{1\%\ crit} = -3.483$, $p < 0.0001$).

The standard autocorrelation function (ACF) analysis is still the most useful method in identifying seasonal ARIMA models (Wei, 2006). The ACF pattern of the stationary time series (Fig. 5) indicates a typical multiplicative seasonal ARIMA model with a first-order non-seasonal moving average term and a 12-lag seasonal moving average term—that is, ARIMA $(0,1,1) \times (0,1,1)_{12}$, the well-known "airline model."

The airline model was first introduced by Box and Jenkins to represent international air travel data (Box et al., 2008). The model is specified as (i.e., $P = p = 0$, $D = d = 1$, $Q = q = 1$, and $S = 12$ in the general form of multiplicative seasonal ARIMA model)

$$(1-B)\left(1-B^{12}\right)Z_t = (1+\theta\mathrm{B})\left(1+\theta B^{12}\right)a_t. \tag{2}$$

The left-hand side of the equation indicates that the dependent variable in this model is the first-order non-seasonal difference and the lag-12 seasonal difference to Z_t. This model has been found very useful to

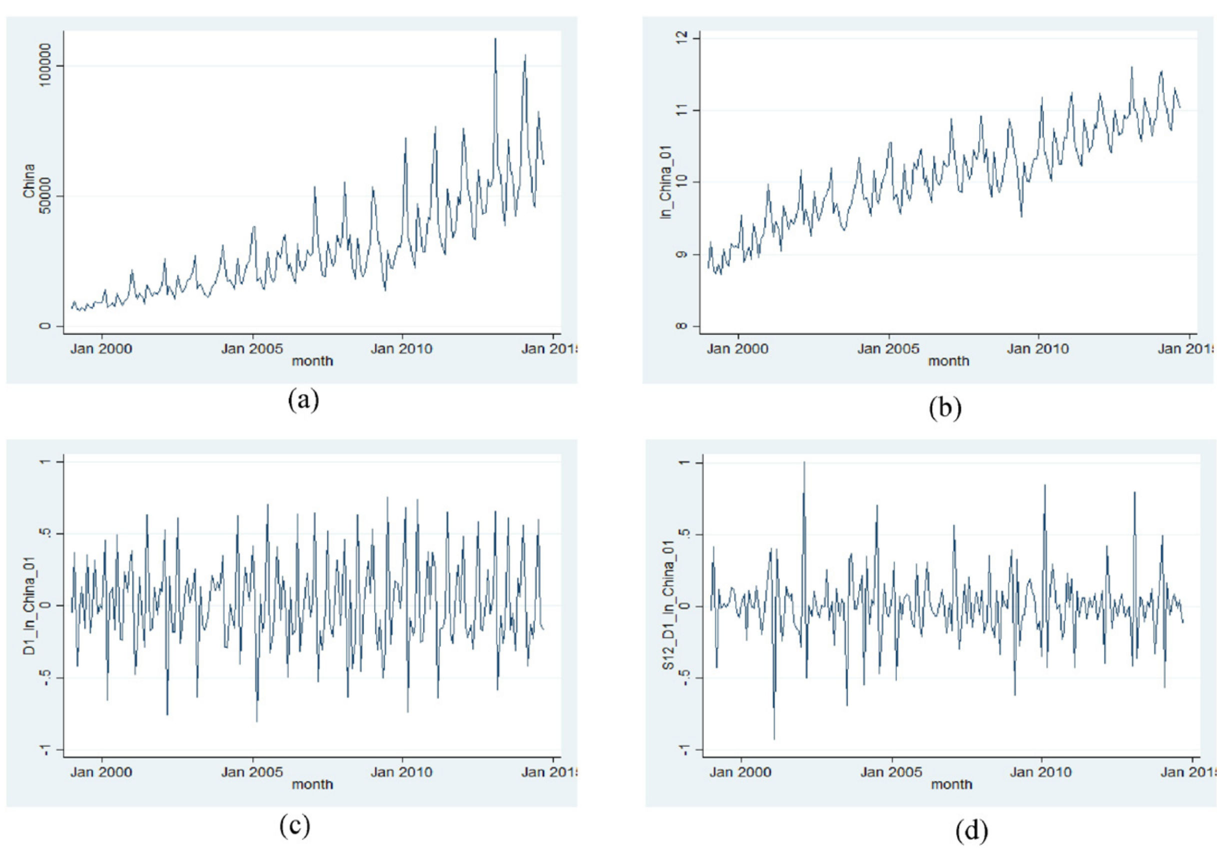

Fig. 4. Operations to obtain stationary time series: (a) original time series from 1991 m1 to 2014 m9; (b) natural logarithms of series in (a); (c) first-order differenced series in (b); (d) 12-lag seasonally differenced series in (c).

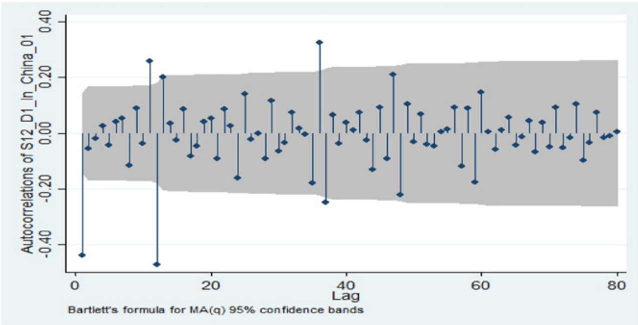

Fig. 5. Autoregressive correlation function (ACF) of the stationary time series.

represent a variety of seasonal time series, such as airline data and trade series (Wei, 2006).

If Z_t is described by the airline model, the theoretical ACF of $W_t = (1-\mathrm{B})(1-\mathrm{B}^{12})Z_t$ are

$$\begin{aligned}
&\rho_1 = \frac{\theta}{1+\theta^2} \\
&\rho_{11} = \rho_{13} = \frac{\theta\mathrm{\theta}}{\left(1+\theta^2\right)\left(1+\mathrm{\theta}^2\right)} \\
&\rho_{12} = \frac{\mathrm{\theta}}{1+\mathrm{\theta}^2} \\
&\rho_j = 0, \textit{otherwise}.
\end{aligned} \tag{3}$$

That is, the ACF is significantly different from zero only at the 1st, 11th, 12th, and 13th lags, with signs related to the signs of θ and θ. The sample ACF in Fig. 5 suggests both parameters are negative for the time series in the current study.

5.2. Parameter estimation

This study used STATA13 (Stata Press, 2013) to estimate model parameters. The standard errors were estimated using robust estimation to control for possible heteroskedasticity. Table 1 presents the parameter estimates of the ARIMA (0,1,1) × $(0,1,1)_{12}$ model fit to the sample series. The overall model is significant ($LL = 76.72$, $\chi^2_{(2)} = 373.28$, $p < 0.001$). The estimates of θ and θ are significant and negative, as expected on the basis of the ACF analysis.

After taking in the parameter estimates and rearranging Eq. (2), the natural logarithm of the arrivals of short-term visitors from mainland China to Australia in month t is:

$$Z_t = Z_{t-1} + Z_{t-12} - Z_{t-13} - 0.8147a_{t-1} - 0.7009a_{t-12} + 0.5710a_{t-13} + a_t. \tag{4}$$

The coefficient on a_{t-13} is the product of the coefficients on the $a_{t\text{-}1}$ and $a_{t\text{-}12}$ terms, i.e., $0.5710 = (-0.8147) \times (-0.7009)$.

Table 1
Parameter estimates of the ARIMA (0,1,1) × $(0,1,1)_{12}$ model.

Parameter	Coefficient	Std. error	Z ratio	P	95% confidence interval	
					Lower limit	Upper limit
θ	−0.8147	0.0615	−13.25	***	−0.9352	−0.6942
θ	−0.7009	0.0558	−12.55	***	−0.8103	−0.5915
σ	0.1573	0.0116	13.52	***	0.1345	0.1801

Notes:
*** $p < 0.001$.

5.3. Diagnostic checking

To examine the adequacy of the ARIMA (0,1,1) × $(0,1,1)_{12}$ model, we first checked the assumptions of the white noise term a_t. The diagnosis plots of residuals in Fig. 6 support the assumption of a normally distributed homoskedastic random noise term. Second, the ACF of residual series indicated no serial correlations either. Further, the Ljung–Box Q test also confirmed that the residual series was white noise ($Q_{40} = 36.06$, $p = 0.65$). Last, the closeness between the predicted values and sample data leads to the conclusion that the ARIMA (0,1,1) × $(0,1,1)_{12}$ model adequately fit the sample series (see the statistics of model fit and prediction errors in next section).

5.4. Model selection

The time line of the data (Fig. 2) suggests that the seasonal effect is proportional to the mean of the series. Thus, the seasonal effect is probably multiplicative and a multiplicative seasonal ARIMA model may be appropriate. Indeed, Box et al. (2008) suggest starting with a multiplicative seasonal ARIMA model with any data that exhibit seasonal patterns and then exploring non-multiplicative SARIMA models if the multiplicative models do not fit the data well. On the other hand, Chatfield (2004) suggests that taking the logarithm of the series will make the seasonal effect additive, in which case an additive seasonal ARIMA model, as fit in the previous example, would be appropriate. In short, the analyst should probably try both additive and multiplicative seasonal ARIMA models to see which provides better fits and forecasts (Stata Press, 2013). Therefore, we tested seven alternative seasonal ARIMA models, which were different combinations of multiplicative, addition, autoregressive, and moving average specifications, as shown in Table 2.

Model selection was based on the comparison of parameter estimates' significance, Akaike's information criteria (AIC), Schwarz's Bayesian information criteria (BIC), and error statistics of in-sample predictions—the mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). As shown in Table 3, the ARIMA (0,1,1) × $(0,1,1)_{12}$ model (Model 1) is the best-fitting model as it has the smallest AIC, BIC, and lowest prediction errors.

5.5. Validation and forecast

Using the ARIMA (0,1,1) × $(0,1,1)_{12}$ model for forecasting, for a forecast origin (e.g., $t = 285$, September 2014, the last time point in the estimation sample), the l-step-ahead forecast can be calculated as:

$$\begin{aligned}
\hat{Z}_{285}(l) = {} & \hat{Z}_{285}(l-1) + \hat{Z}_{285}(l-12) - \hat{Z}_{285}(l-13) + E(a_{285+l}|Z_{285}, Z_{284}, \cdots) \\
& -0.8147E(a_{285+l-1}|Z_{285}, Z_{284}, \cdots) - 0.7009E(a_{285+l-12}|Z_{285}, Z_{284}, \cdots) \\
& +0.5710E(a_{285+l-13}|Z_{285}, Z_{284}, \cdots)
\end{aligned} \tag{5}$$

where

$$\hat{Z}_{285}(j) = Z_{285+j}, \qquad j \le 0,$$

and

$$E(a_{285+j}|Z_{285}, Z_{284}, \cdots) = \begin{cases} \hat{a}_{285+j}, & j \le 0, \\ 0, & j > 0. \end{cases}$$

We compared the forecast errors between the eight competing ARIMA models, where their forecasts of October 2014 through September 2015 were validated against the ABS records. As shown in Table 4, all the models performed well in forecasting, although the ARIMA (0,1,1) × $(0,1,1)_{12}$ model (Model 1) was not the best. However, short forecast horizons are often associated with weak power to distinguish one from the other. Considering the results in model identification,

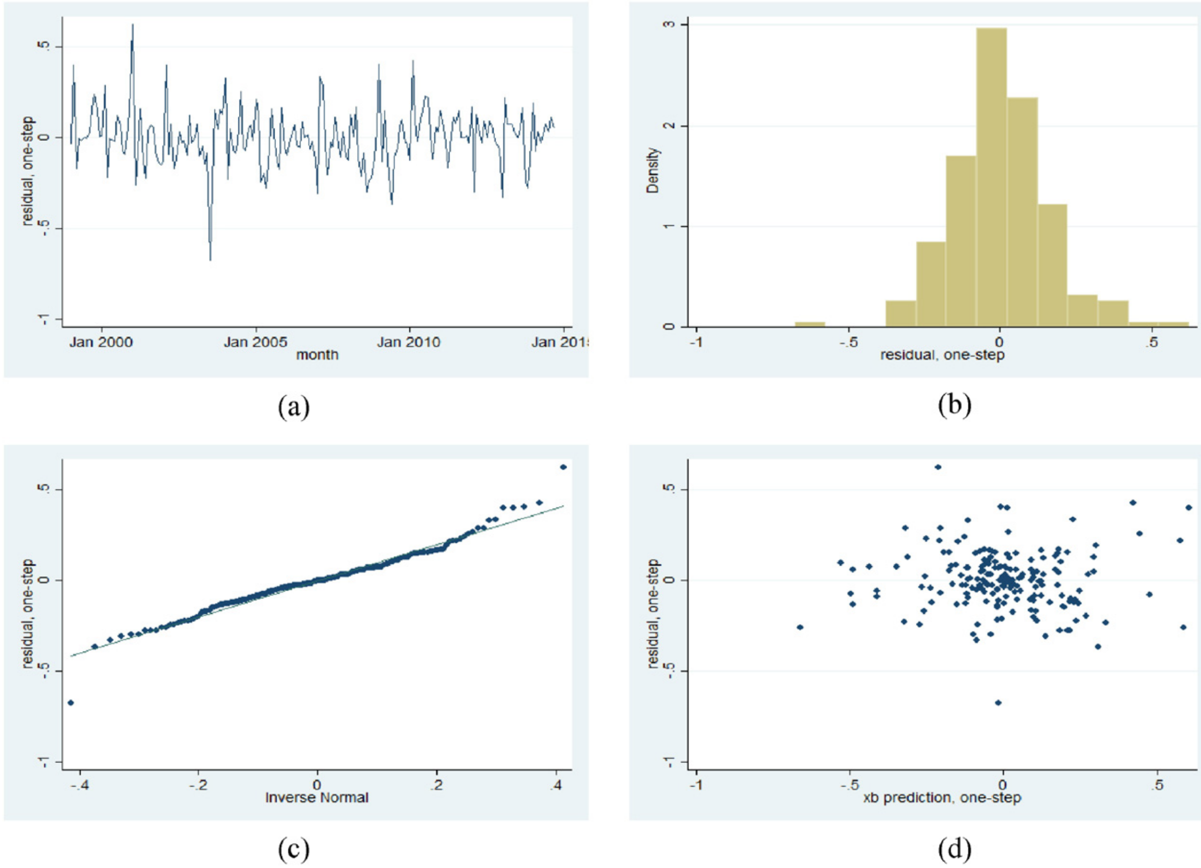

Fig. 6. Diagnostic plots of residuals: (a) time line of residuals; (b) histogram of residuals; (c) Q-Q plot of residuals; (d) scatter plot of residuals vs. predicted values.

diagnosis, and selection, we still prefer the ARIMA $(0,1,1) \times (0,1,1)_{12}$ model.

Hence, we used the ARIMA $(0,1,1) \times (0,1,1)_{12}$ model to calculate 36-month-ahead forecasts as of October 2014 with 95% confidence intervals. The details appear in the Appendix A. As illustrated in Fig. 7, of the ten months' records as the validation sample, none is out of the 95% confidence interval of the model's forecasts, although the uncertainty increases with the forecasting horizon (i.e., the fanning out pattern in forecast confidence intervals). According to this forecasting, the seasonal pattern of monthly arrivals of tourists from mainland China to Australia would persist in the next two years, the monthly arrival number would peak in February for each year, and the forecast for February 2017 is approximately 180,000, with a 95% chance of lying anywhere between 110,000 and 300,000.

Table 2
Parameter estimates of eight competing seasonal ARIMA models.

Seasonal component	Model specification	Parameter estimates		
		Non-seasonal term	Seasonal term	Sigma
Multiplicative	$1{:}(0,1,1) \times (0,1,1)_{12}$	$-.8147^{***}$	$-.7009^{***}$	$.1573^{***}$
	$2{:}(0,1,1) \times (1,1,0)_{12}$	$-.8287^{***}$	$-.4406^{***}$	$.1745^{***}$
	$3{:}(1,1,0) \times (0,1,1)_{12}$	$-.3815^{***}$	$-.7452^{***}$	$.1743^{***}$
	$4{:}(1,1,0) \times (1,1,0)_{12}$	$-.4114^{***}$	$-.4662^{***}$	$.1978^{***}$
Additive	$5{:}(0,1,1) + (0,1,1)_{12}$	$-.3010$	$-.6333^{**}$	$.1832^{***}$
	$6{:}(1,1,0) + (1,1,0)_{12}$	$-.3309^{***}$	$-.4035^{***}$	$.2018^{***}$
	$7{:}(0,1,1) + (1,1,0)_{12}$	$-.8287^{***}$	$-.4406^{***}$	$.1745^{***}$
	$8{:}(1,1,0) + (0,1,1)_{12}$	$-.3815^{***}$	$-.7452^{***}$	$.1743^{***}$

Notes:
** $p < 0.01$.
*** $p < 0.001$.

6. Conclusions and future research

The forecasts have implications for the policy agenda and management practice of Australian tourism industries. With the demand side looking good, is Australian tourism industry China ready?

Reports from Australia Bureau of Statistics (2015) suggest that the average occupancy rate of Australian accommodations is about 65%, with hotels having higher occupancy rate (about 72%) than service apartment (67.5%) and motels (55.9%). Although just looking form numbers, there seems still room to accommodate growing needs from international visitors, a recent report suggested that Australia major cities are short of hotel rooms to cope with increased visitors from China (Freed, 2015). There are not many hotels in Australia with 400 rooms or more and many of them have their regular customers, such as captain crew and business travelers from large companies. Mr. Louis Lu, boss of China Southern Airline also commented that Australia needs to provide more restaurants and hotel rooms and less public holidays, so that services are accessible for Chinese visitors (Freed, 2015).

Table 3
Model fit comparison of eight competitive seasonal ARIMA models.

Model	AIC	BIC	MAE	RMSE	MAPE
1	−147.43	−137.71	3483	5557	11.9%
2	−113.79	−104.06	3725	6438	12.5%
3	−108.13	−98.41	3848	6511	13.0%
4	−67.12	−57.39	4284	7772	14.3%
5	−91.01	−81.28	4039	7123	13.4%
6	−60.01	−50.28	4455	8118	14.6%
7	−113.79	−104.06	3725	6438	12.5%
8	−108.13	−98.41	3848	6511	13.0%

Table 4
Forecast error comparison of eight competitive seasonal ARIMA models.

Model	MAE	RMSE	MAPE
1	7813	13,155	8.7%
2	6674	11,312	7.4%
3	8293	13,184	9.7%
4	5810	10,254	6.3%
5	9372	15,236	11.7%
6	6153	9609	7.1%
7	6674	11,312	7.4%
8	8293	13,184	9.7%

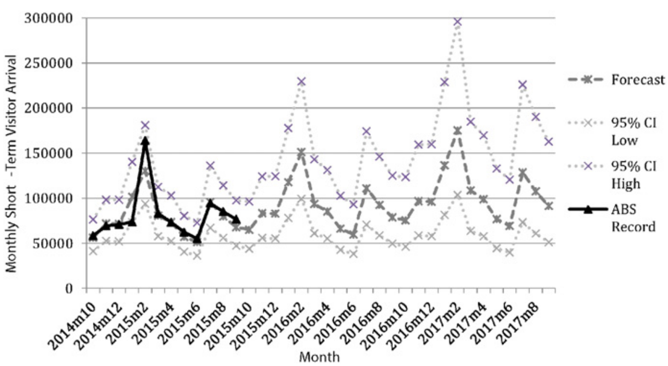

Fig. 7. Forecast of arrivals and 95% confidence interval with ten months validation (October 2014–September 2015).

On the other hand, seeing the robust growth of inbound tourism in Australia, many local and foreign investors entered the tourism market. For example, China's billionaire Jianlin Wang, stepped into the Gold Coast Hotel sector and decided to invest 1.7 billion Australian dollars and build a beachfront hotel (Cranston, 2014). This has caused a Domino effect of Chinese billionaires investing in Gold Coast for about 60 billion Australian dollars over the next 5–6 years (Skene, 2015). Forecasting tourists arrivals and carefully monitoring accommodation supply and investment are essential for good strategic planning of Australian tourism industry development.

In addition, there are certain characteristics with the Chinese visitor market. Chinese visitors to Australia find that the luxury level of Australia hotels could not compare with what they used to experience in China and other destinations in Asia (Leong, Ma, & Beesley, 2014). Australia hotels need to improve their service standards and facilities to better accommodate Chinese visitors' needs. Attention to particular Chinese culture aspects is also desired (Huang, 2012). The tourism industry in Australia may need to take special considerations to accommodate the large number of Chinese tourists in the near future.

Methodologically, limitation of the current study is that we developed only univariate time series models, which are weak in explaining tourists' behavior. Future research will need to consider establishing a multivariate database and then conduct multivariate analysis to obtain more in-depth understanding of Chinese tourists' arrivals in Australia.

Appendix A

Table A
36-month-ahead forecast as of October 2014.

Month	Forecast	95% LB	95% UB
Oct-14	56,118	41,230	76,384
Nov-14	71,838	52,502	98,295
Dec-14	71,458	51,956	98,281
Jan-15	101,448	73,387	140,238
Feb-15	130,189	93,708	180,871

Table A (*continued*)

Month	Forecast	95% LB	95% UB
Mar-15	80,636	57,756	112,581
Apr-15	73,479	52,374	103,087
May-15	57,086	40,496	80,474
Jun-15	51,465	36,336	72,893
Jul-15	95,676	67,237	136,143
Aug-15	79,876	55,876	114,184
Sep-15	67,867	47,260	97,458
Oct-15	65,101	44,012	96,295
Nov-15	83,336	55,948	124,131
Dec-15	82,896	55,273	124,324
Jan-16	117,684	77,941	177,692
Feb-16	151,026	99,363	229,553
Mar-16	93,542	61,143	143,111
Apr-16	85,239	55,359	131,249
May-16	66,223	42,737	102,617
Jun-16	59,703	38,289	93,092
Jul-16	110,988	70,743	174,129
Aug-16	92,661	58,704	146,260
Sep-16	78,729	49,579	125,017
Oct-16	75,521	46,198	123,455
Nov-16	96,674	58,643	159,370
Dec-16	96,164	57,853	159,846
Jan-17	136,520	81,466	228,781
Feb-17	175,199	103,712	295,961
Mar-17	108,514	63,732	184,762
Apr-17	98,882	57,625	169,677
May-17	76,823	44,428	132,839
Jun-17	69,258	39,752	120,667
Jul-17	128,753	73,350	226,003
Aug-17	107,491	60,788	190,075
Sep-17	91,330	51,275	162,676

The forecast origin is the last observation of a time series Z_n (i.e., observations at $t \le n$). The forecast origin and forecasts can be *updated* once a new observation Z_{n+1} is available (i.e., forecast origin n is updated to be $n+1$) (Wei, 2006).

$$\hat{Z}_{n+1}(l) = \hat{Z}_n(l+1) + \psi_l\left[Z_{n+1} - \hat{Z}_n(1)\right]$$

where the ψ weights are

$$\psi_0 = 1$$
$$\psi_j = \sum_{i=0}^{j-1} \pi_{j-i}\psi_i, \quad j = 1, 2, \cdots, l-1$$

where the π weights are

$$\pi(B)Z_t = a_t$$

for the estimated ARIMA $(0,1,1) \times (0,1,1)_{12}$ model,

$$\pi(B) = 1 - \pi_1 B - \pi_2 B^2 - \cdots = \frac{(1-B)\left(1-B^{12}\right)}{(1-0.8147B)\left(1-0.7009B^{12}\right)}.$$

Equating the coefficients of B^j,

$$\pi_j = 0.8147^{j-1} \times 0.1853, 1 \le j \le 11,$$
$$\pi_{12} = 0.8147^{11} \times 0.1853 - 0.7009 + 1,$$
$$\pi_{13} = 0.8147\pi_{12} + 0.7009\pi_1 + 0.571 - 1,$$
$$\pi_j = 0.8147\pi_{j-1} + 0.7009\pi_{j-12} - 0.571\pi_{j-13}, j \ge 14.$$

The variance of the error of l-step-ahead forecast from forecast origin t is

$$\mathrm{Var}[e_t(l)] = \hat{\sigma}^2 \sum_{j=0}^{l-1} \psi_j^2.$$

Thus, the 95% forecast limits are

$$\hat{Z}_t(l) \pm 1.96\sqrt{Var[e_t(l)]}.$$

The forecast of the natural logarithm of arrivals Z_t can be converted back into arrivals Y_t. We modeled the natural logarithms of the original series, namely, $Z_t = \ln(Y_t)$. The naive forecast Exp $[\hat{Z_t}(l)]$ is not the minimum mean square error forecast of Y_{t+l} because logarithm is a nonlinear transformation. The minimum mean square error forecast in the original series is given by

$$\hat{Y_t}(l) = Exp\left\{\hat{Z_t}(l) + 0.5\mathrm{Var}[e_t(l)]\right\}.$$

The importance of this correction factor depends on the value of $\mathrm{Var}[e_t(l)]$. If it is very small, the correction factor will hardly change the forecasts and so could be neglected without major concern, especially as errors from other sources are likely to be significantly greater (Cowpertwait & Metcalfe, 2009).

If Z_t has a normal distribution, then $Y_t = \mathrm{Exp}\ (Z_t)$ has a log-normal distribution. Since the log-normal distribution is asymmetric and has a long right tail, a criterion based on the mean absolute error may be more appropriate. For this criterion, the naive forecast Exp $[\hat{Z_t}(l)]$ is the optimal forecast for Y_{t+l} in the sense that it minimizes the mean absolute forecast error (Cryer & Chan, 2008). We calculated $\hat{Y_t}(l)$ for the 36-month-ahead forecasts using both approaches and the average correction ratio is as small as 1.0257 (SD = 0.01).

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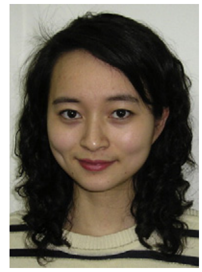

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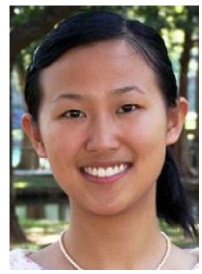

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