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Research note

# Forecasting tourism demand: The Hamilton filter

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## Introduction

Studies on tourism demand forecasting techniques can be classified into two main groups: quantitative and qualitative methods (Song & Li, 2008). The use of quantitative methods in tourism demand forecasting is more popular than qualitative methods (Song & Li, 2008). The types of time series models include naïve, autoregressive, single exponential, moving average and historical averages (Song, Qiu, & Park, 2019). The decomposition of time series has been found to improve forecasting accuracy (Shabri, 2016; Zhang et al., 2017). The common techniques for time series decomposition in tourism forecasting are filters (Li, Wong, Song, & Witt, 2006); spectral analysis (Coshall, 2000); and empirical mode decompositions (Chen, Lai, & Yeh, 2012). Causal structural time series models perform less satisfactorily than univariate models (Turner & Witt, 2001). Li and Law (2019) examined the effectiveness of decomposed search engine data in forecasting tourism demand in Hong Kong. The proposed technique of using decomposed online search engine data was viable based on the out-of-sample forecast evaluation (Li & Law, 2019). When decomposing time series, it is important to account for seasonality as most tourism destinations are affected by seasonal patterns (Saayman & Botha, 2017; Vergori, 2012). Chen, Li, Wu, and Shen (2019) proposed a multiseries structural time series method as an alternative technique to seasonal tourism demand forecasting. The forecast evaluation support that the structural model is viable. Chu (2004) applied a cubic polynomial model to forecast tourist arrivals in Singapore. The cubic polynomial model was found to be less effective than the sine wave and ARIMA applications. The use of seasonal fractional models for modelling the seasonal component of Spanish tourism demand was pioneered by Gil-Alana, De Gracia, and Cuñado (2004). The authors found that the number of foreigners and foreign guest nights exhibit seasonal long memory behaviour.

An overview of the literature on forecasting tourism demand support that decomposition techniques such as filters, spectral, spectrum analysis and empirical mode decomposition have been applied in tourism demand forecasting. However, none of these studies have applied the linear projections decomposition approach proposed by Hamilton (2018) in tourism demand forecasting. The Hodrick-Prescott (HP) filter developed by Hodrick and Prescott (1997) proposed that a time series has a trend and cyclical component. While the technique has its failings, the decomposition technique has been popular in macroeconomics. In 2018, Hamilton (2018) detailed the shortcomings of the model and proposed a new approach which accounts for random walks based on linear projections. Based on the author's current knowledge, the Hamilton (2018) approach has not been applied in the current literature on tourism demand forecasting. Instead of discarding the HP filter altogether, this study includes it for comparison with the Hamilton filter. The strategy is to determine the viability of the HP filter in forecasting tourism demand. Secondly, this study applies the recent Hamilton (2018) approach to determine its feasibility in investigating trend analysis of tourism demand for the first time.

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## Methodology

The aim of this study is to use the HP filter and the Hamilton (2018) decomposition approach to evaluate the trends and cyclical components of tourism demand series. The data used in this study was obtained from the Australian Bureau of Statistics and spans the period 1991Q1–2019Q2 (114 observations). Australia is opted for this analysis because it is a popular tourist destination and has sufficient data (seasonally adjusted) to perform this task. The two series obtained were tourist arrivals data with seasonal adjustments and original data (unadjusted for seasonality). The data was not converted to logarithms or altered in any way to prevent tampering with volatility. The first step in our analysis is to use the HP filter to decompose tourist arrivals series. Tourist arrivals series not seasonally adjusted will be denoted by the variable *AR*. Consequently, *ARS* will denote tourist arrivals with seasonal adjustments. For the HP filter, the assumption is we have *T* observations on the variables *AR* and *ARS*. Following Hodrick and Prescott (1997), we can assign $S_t$ to be a smooth trend series that does not deviate too much from the series *AR* and *ARS*. Note that the smoothing parameter, $\lambda = 1600$. The series $S_t$ will be obtained as follows:

$$\min_{\{S_t\}_{t=-1}^{T}} \left\{ \sum_{t=1}^{T} (AR_t - S_t)^2 + \lambda \sum_{t=1}^{T} [(S_t - S_{t-1}) - (S_{t-1} - S_{t-2})]^2 \right\} \tag{1}$$

$$\min_{\{S_t\}_{t=-1}^{T}} \left\{ \sum_{t=1}^{T} (ARS_t - S_t)^2 + \lambda \sum_{t=1}^{T} [(S_t - S_{t-1}) - (S_{t-1} - S_{t-2})]^2 \right\} \tag{2}$$

Hamilton (2018) highlighted the technical flaws of the HP filter arguing that it results in spurious dynamics. Furthermore, the constant smoothing parameter may not be accurate for all series (Hamilton, 2018). Following the propositions by Hamilton (2018) if $\Delta^2 AR_t$ is $I(0)$, a regression of $AR_{t+h}$ on $(AR_t, AR_{t-1}, 1)'$, will yield predicted values which can be represented as $AR_t + h(AR_t - AR_{t-1}) + \mu_h$ for $\mu_h = E(w_t^{(h)})$. The resulting residuals generated should be stationary if *AR* is $I(2)$. The two approaches detailed above will be used to decompose original data and seasonally adjusted data for tourist arrivals in Australia.

## Results

Fig. 1 illustrates the trend fitted when using the two-sided and one-sided HP filter on the original series (*AR*). The results show that the one-sided HP filter outperforms the two-sided filter as its trend is closer to the pattern followed by the actual series *AR*. The $R^2$ value for the two-sided HP filter is 0.8803 while for the one-sided filter is 0.9032. The cyclical component of the series illustrated by Fig. 2 support that the one-sided filter is superior to the two-sided HP filter because the cyclical component is less volatile.

Fig. 3 shows the trend for tourist arrivals when using seasonally adjusted data (*ARS*). The two-sided HP filter produces a better trend as it is closer to the actual series ($R^2 = 0.9919$). The corresponding $R^2$ for the one-sided filter on seasonally adjusted data is 0.9914. The cyclical component for seasonally adjusted data when using the one-sided HP filter is more volatile which indicates that it is less preferable. For seasonally adjusted data, the two-sided HP filter outperforms the one-sided filter. In summary, for original series, the one-sided filter outperforms the two-sided filter. However, for seasonal data, the two-sided filter outperforms the one-sided filter. Figs. 1–4 present the results of the one-sided and two-sided HP filter.

Figs. 5–6 illustrate the trends and cyclical components when using the Hamilton (2018) method. One of the technical flaws of the HP filter is that it does not account for random walk of the original series as it produces a smooth trend. The resulting models for tourist arrivals following Hamilton (2018) are:

$$AR_t = 8861.0660 + 1.1692AR_{t-8} - 0.0643AR_{t-9} + 0.0725AR_{t-10} - 0.1035AR_{t-11} \tag{3}$$

$$ARS_t = 8239.8450 + 1.0997ARS_{t-8} + 0.2038ARS_{t-9} + 0.1575ARS_{t-10} - 0.3905ARS_{t-11} \tag{4}$$

When using original series, the Hamilton (2018) method captures the volatility in tourist arrivals better that the HP filter trends as illustrated by Fig. 5. The $R^2$ value for the original series when using the Hamilton (2018) method is 0.9356 which is greater than for

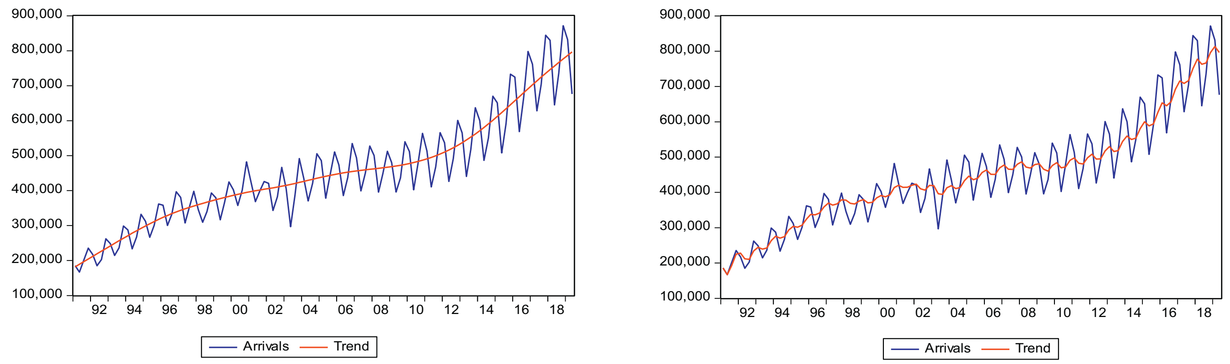


**Fig. 1.** The two-sided HP filter (left) and the one-sided HP filter (right) trend of tourist arrivals (not seasonally adjusted).

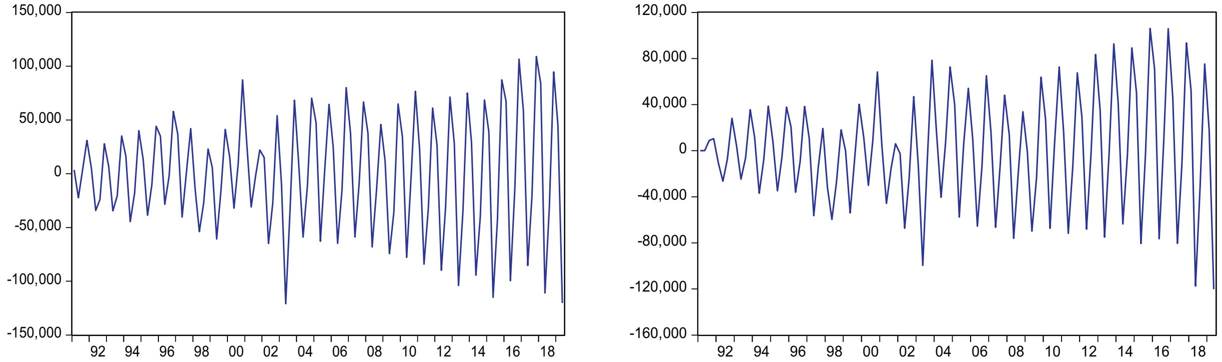


**Fig. 2.** The two-sided HP filter (left) and the one-sided HP filter (right) cyclical components (not seasonally adjusted).

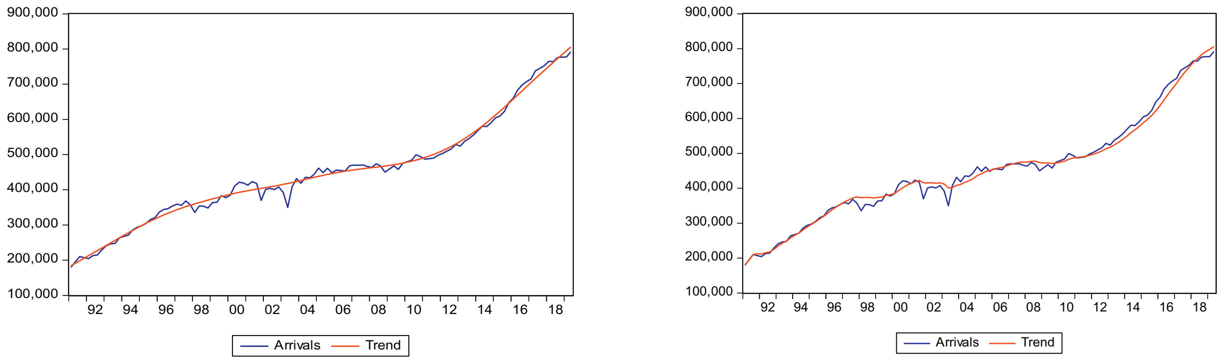


**Fig. 3.** The two-sided HP filter (left) and the one-sided HP filter (right) trend of tourist arrivals (seasonally adjusted).

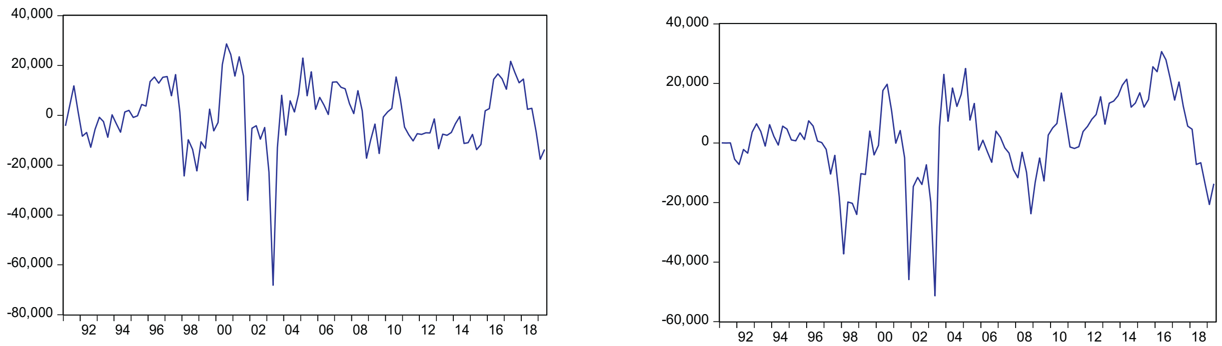


**Fig. 4.** The two-sided HP filter (left) and the one-sided HP filter (right) cyclical components (seasonally adjusted).

the two-sided and one-sided HP filter (0.9356 > 0.8803, 09032). For seasonally adjusted data, the Hamilton method is outperformed by both the one-sided and two-sided HP filter. The $R^2$ value for seasonal data using the Hamilton (2018) approach is 0.9299 which is lower than 0.9919 and 0.9914 for the two-sided and one-sided HP filters. In summary, when using the original series, the Hamilton approach provides a better trend than the HP filter. However, the one-sided and two-sided HP filters outperform the Hamilton (2018) method for seasonally adjusted series. Figs. 5–6 illustrates the results of the Hamilton approach.

The $R^2$ values of the decomposition techniques only reveal the goodness of fit of the models but provides limited evidence about the accuracy of the out-of-sample forecast. To achieve this objective, the rolling window estimation was used to estimate out-of-sample forecasts of the series. The procedure is for a window length, $K$ and $N$ sample length, the forecasting model was run $K - N$ times and a series of out-of-sample forecasts were used to determine the forecasting accuracy. The mean absolute percentage error (MAPE) and the root mean square error (RMSE) were used to evaluate the forecasts. MAPE is taken as the primary indicator for accuracy because it is ideal for comparing the forecasts by the three techniques than the RMSE (Turner & Witt, 2001; Vergori, 2012). The out-of-sample forecast evaluation shows that the Hamilton approach outperforms the HP filter approaches (Table 1). The Hamilton approach has the lowest MAPE for original and seasonally adjusted tourist arrivals. The Hamilton filter also outperformed the benchmark autoregressive integrated moving average (ARIMA) model (MAPE (AR) = 2.776; MAPE (ARS) = 1.999). In conclusion,

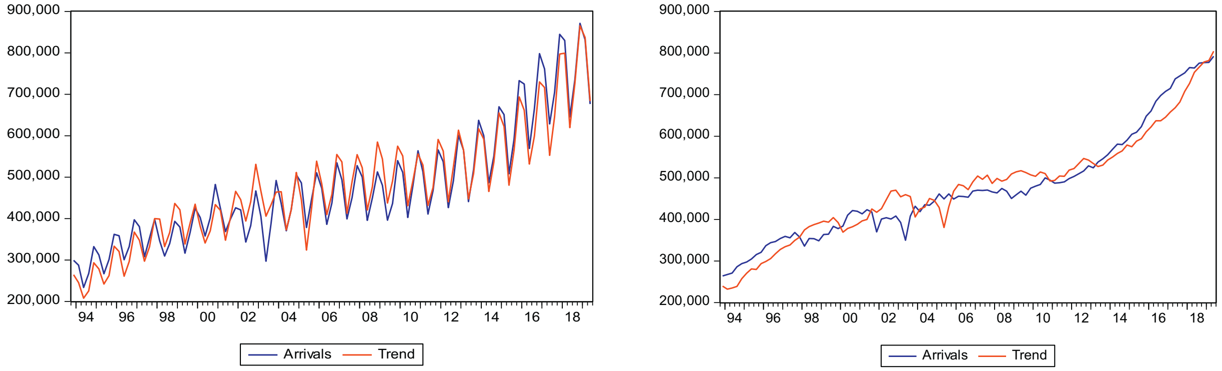


**Fig. 5.** Hamilton (2018) method trend. Original tourist arrivals (left) and seasonally adjusted arrivals (right).

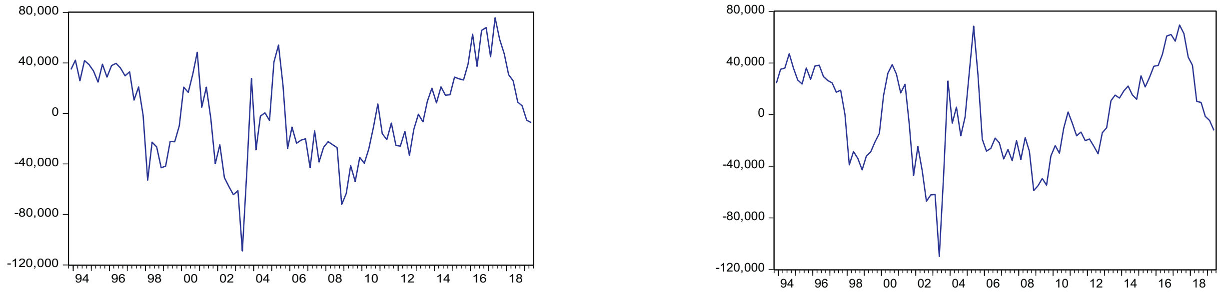


**Fig. 6.** Hamilton (2018) method cyclical components. Original tourist arrivals (left) and seasonally adjusted arrivals (right).

**Table 1**
Results of the out-of-sample forecasts.

| Method | MSE | RMSE | MAPE |
|---|---|---|---|
| Out-of-sample forecasts (AR) | | | |
| One-sided HP filter | 18.800 | 4.336 | 1.194 |
| Two-sided HP filter | 30.810 | 5.551 | 1.054 |
| Hamilton filter | 18.570 | 4.309 | 0.998 |
| Out-of-sample forecasts (ARS) | | | |
| One-sided HP filter | 17.310 | 4.161 | 4.077 |
| Two-sided HP filter | 21.760 | 4.665 | 4.117 |
| Hamilton filter | 28.140 | 5.305 | 1.298 |

the Hamilton approach provides better forecasts than the two HP filter approaches.

## Conclusion

This study applied the Hamilton filter and the HP filter to evaluate the trends of tourist arrivals in Australia. The results show that the two-sided HP filter outperforms other techniques when decomposing seasonally adjusted series. However, when using time series not adjusted to seasonal effects, the Hamilton approach outperforms the one-sided and two-sided HP filter. Moreover, the out-of-sample forecast evaluation support that the Hamilton approach is the ideal technique for forecasting tourism demand.

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