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Tourism Forecasting Model for the Maldives

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By: Dhaha Shuaib[1]

Abstract

The tourism sector in the Maldives is the largest foreign currency earning sector of the country. With the inter-twined nature of our economy, the performance of various other sectors is also linked with that of the tourism sector. A reliable and accurate forecast of the tourism indicators for the Maldives is extremely important for policy making and planning. An accurate forecast of the tourist arrivals and bednights will enable the revenue authorities to estimate the revenue projections which further gets filtered into the forecasts of the country's Gross Domestic Product (GDP) and the Gross International Reserves (GIR). It is an important tool that will enable us to gauge the sector wise spillovers. Therefore, it is extremely important to develop a tourism forecast model that most reflects the trend in tourist arrivals and bednights in the Maldives. Hence, the purpose of the paper is to develop a suitable model that could be used for forecasting the tourism indicators; tourist arrivals and bednights. While different approaches are used in different countries, the paper focuses on using an ARIMA based approach for the error term dynamics.

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Introduction

Tourism is the largest economic sector in the Maldives, accounting for nearly a quarter of the country's GDP. While the industry attracts most of the foreign investments into the country, it also acts as one of the most important sources of foreign exchange, government revenue and employment in the tertiary sector.

For any country, tourism is not just limited to the activities in the accommodation and hospitality sector but rather tourism and its management is connected to all major functions, processes and procedures that are practiced in many other relevant areas. It involves various efforts at all levels offering a significant contribution to the economic growth of the region and to the labour market; creating employment opportunities directly and indirectly through the supply and demand chain.

As the sector remains the largest source of foreign currency revenue for the government, forecasting tourism demand is indispensable for tourism planning at all levels. Considering the rapid increase in tourist arrivals in the last few decades, accurate and reliable predictions of impending tourist arrivals and related indicators are essential for policy making and planning.

In the Maldives, the forecast for tourism is produced by the Maldives Monetary Authority (MMA) where these numbers are used for the projections of the GDP and revenue. These forecasts are made bi-annually; for the annual government budget and the fiscal strategy. The forecasts filters into the projections of the country's external reserves and the government budget. It is an important tool that will enable us to gauge the sector wise spillovers. Therefore, it is extremely important to develop a tourism forecast model that most reflects the trend in tourist arrivals and bednights in the Maldives.

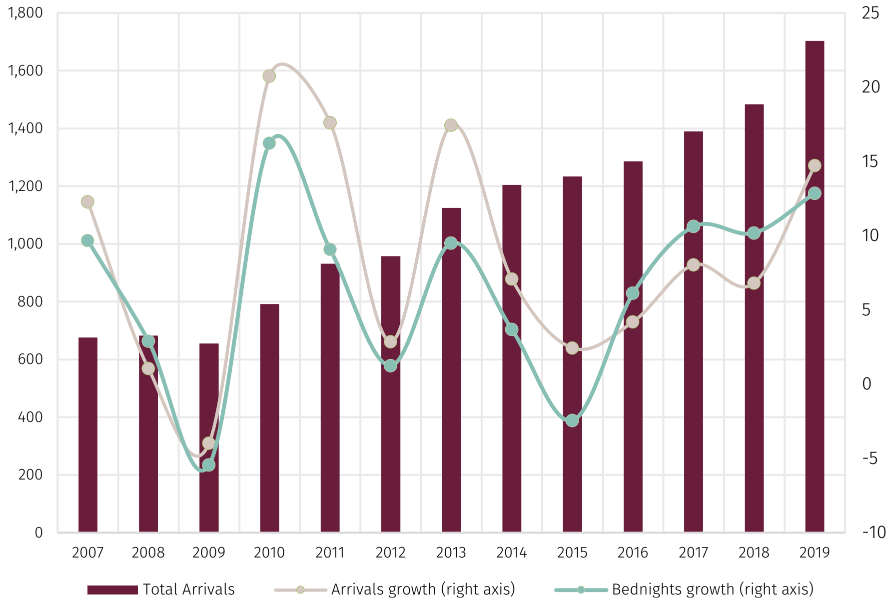
This paper presents a model that can potentially be used to forecast the essential indicators of the sector; tourist arrivals, bednights and average stay. The next section provides a brief overview of tourism developments in the Maldives. Section three introduces the reader to different econometric models and approaches used to forecast the tourism demand in other countries while section four represents the model specification and methodology. Finally, section five and six contains the results and conclusion, respectively.

Overview of the tourism sector in the Maldives

Since the opening of the first resort in Maldives in 1972, the industry has grown significantly. During the period 1987 to 2019, the tourism sector registered an average growth of 9.4%. A negative growth was only experienced in 2005 post the Indian Ocean Tsunami and in 2009 due to the Global Recession. Until recently, tourism was solely restricted to resorts on separate islands and was isolated from the local population. In 2010, local island guesthouses started emerging in inhabited islands allowing tourists to be able to reside among the local population rather than in a separate tourist islands. By the end of 2019, a total of 152 tourist resorts were in operation, while the number of operational guesthouses increased to 607 from only 25 guesthouses in 2010. With the booming of the guesthouse sector, the tourism sector is also able to provide both economic and social benefits to the local community.

The year 2013 was a landmark year for Maldivian tourism as the industry crossed the one million mark in tourist arrivals with a significant annual growth rate of 17% (Figure 1). The strong growth in arrivals during 2013 mainly driven by the robust growth in the Chinese market, largely reflected the recovery of the industry from the slowdown witnessed in 2012 which occurred because of the weak economic conditions of the main European markets and the political unrest during that year.

Figure 1: Tourism Indicators, 2007-2019
(thousands, annual percentage change)

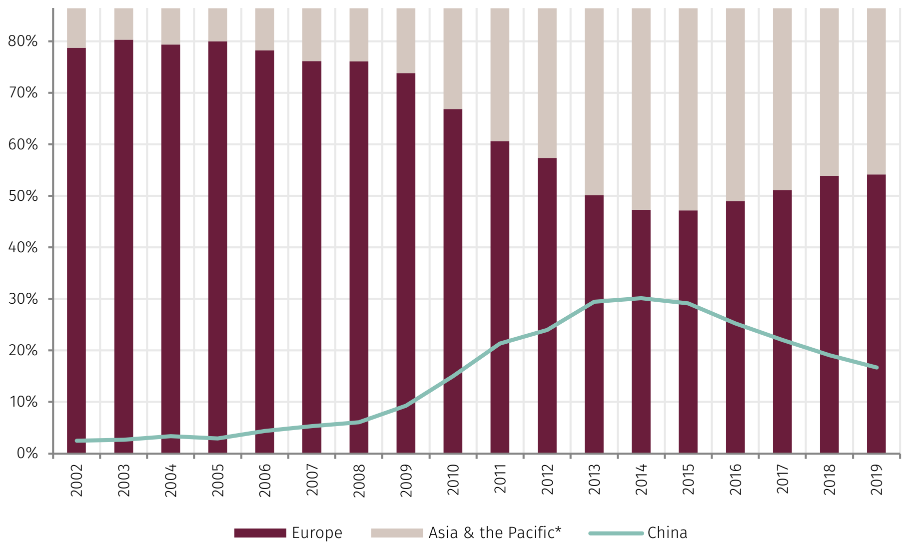


Source: Ministry of tourism

Market trends

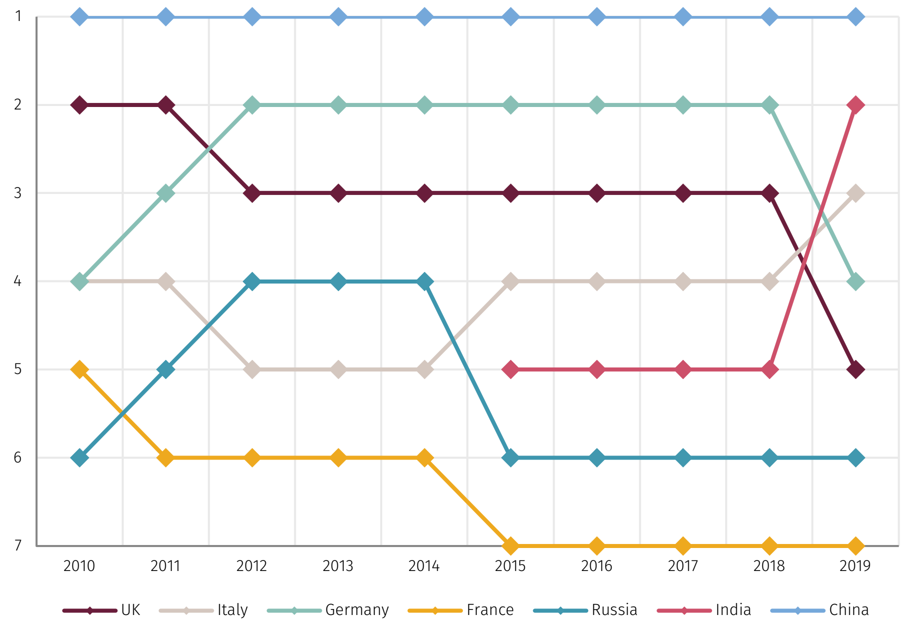
Prior to 2009, on average, 76% of the tourist arrivals were dominated by the European markets (Figure 2). Since then, the share of tourist arrivals from Europe has followed a decelerating trend, averaging to 47% during the past five years. This was largely associated with the increase in the share of tourists from the Asian market, more specifically from China. The Chinese market which was on average about 4% of the total arrivals prior to 2009, increased its share to more than 20% since then, causing a shift of dominance to the Asia Pacific arrivals to the Maldives. Of late, the Chinese market has been showing signs of a slowdown, thus reflecting the recent Chinese arrival statistics. In 2019, the Maldivian economy experienced a significant boom in tourist arrivals, attaining a double-digit growth of 15% growth per annum with a significant increase in arrivals from the Indian market.

Figure 2: Share of Tourist Arrivals by Specific region, 2002-2019



Source: Ministry of Tourism

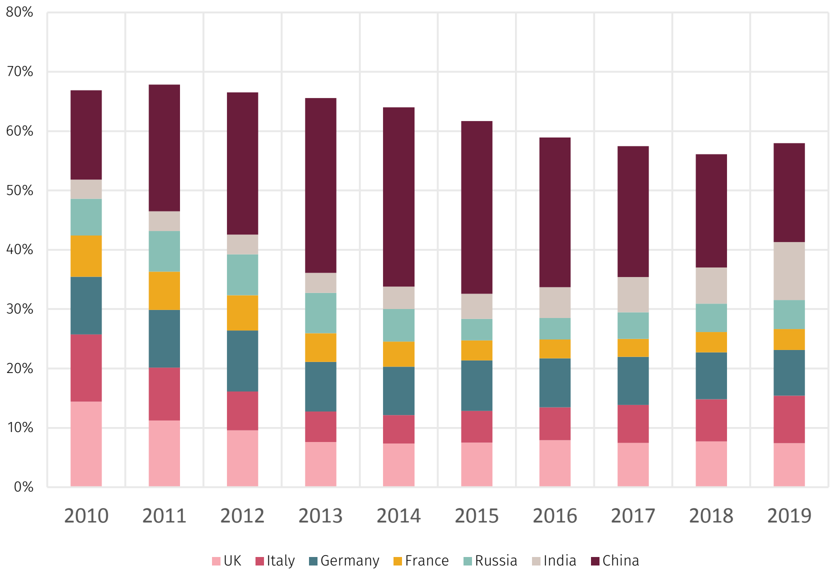
Figure 3: Tourist Arrivals - Ranking of Top Markets, 2009-2019



Source: Ministry of Toursim

Figure 4: Tourist Arrivals - Top Markets, 2010-2019

(as a percent of total arrivals)



Source: Ministry of Toursim

Figure 3 identifies the top markets; one being assigned to that country from which the greatest number of tourist arrivals are generated into the Maldives. Prior to 2010, China was at the fourth position in terms of arrivals. However, with the increase in tourists from China since 2010, the market attained the first rank. Since then, the market has remained as the single largest source market. More recently, India has joined the top five markets and has become the second largest market in 2019. Correspondingly, Figure 4 shows the changes in the arrival composition as a percent of the total arrivals for these markets.

Literature review

Tourism demand, in many cases depends on various variables such as the income in the tourist-source country and the relative inflation and exchange rates between the origin and destination country (Croes & Vanegas Sr, 2005). Despite the increasing sophistication of forecasting methods, the majority are traditional single-equations models and the advantages are three-fold; it provides useful information through the estimation of elasticities, the elasticity value can be calculated over time providing information about the adjustment time required for any countervailing policy to have effects, and lastly the elasticity can be estimated for different products of customers (Sinclair & Stabler, 1997). However, single-equation specifications ha ve also been criticized to being ad-hoc and lacking explicit theoretical base. Croes & Vanegas Sr (2005) attempted to study tourist arrivals in Aruba and its implications using dynamic econometric models for modelling short-term and long-term dynamics. Their study defines tourism demand as the amount of tourist goods that a customer is willing and able to buy at a certain time under certain conditions[2]. According to their literature review, the observed significance of the lagged dependent variable in such models indicates that a dynamic structure is likely to be a necessary part of the model specifications. The Box and Cox procedure applied in the study chose from either double log-linear or linear functional forms. Results revealed that in the short-run,

[2] Tourism demand, in other studies/cases may also be defined as the number of persons who wish to travel and use tourist facilities and services at places away from their work or residence.

changes in tourism demand for Aruba was determined by the changes in income and relative inflation rates between the destination and the origin country. Exchange rate was also an important determinant while the national inflation rates carried a lesser weight with regard to its importance.

In modelling the demand for tourism, most studies have either used tourist arrivals or tourism earnings as a dependent variable (Narayan, 2002). For the purpose of extending the study and assessing the tourism demand for Fiji, Katafano & Gounder (2004) used cointegration and error correction models (ECM) to estimate the tourism demand model while treating the tourist arrivals as the dependent variable. They also accounted for income and relative prices using GDP and real effective exchange rate (REER), respectively while the study failed to take into consideration the transportation costs. Results revealed that the income of the major trading partners of Fiji was positively related to the demand for tourism, both in the long-run and short-run. In contrast to expectations, increase in long-term prices does not deter tourists. As such, in the case of Fiji, coups are a major deterrent to demand while major cyclones were insignificant (Katafano & Gounder, 2004).

Jackman & Greenidge (2010) in their study utilised structural time series modelling (STSM) to explain and forecast tourist arrivals to Barbados from its major generating markets. The techniques employed in this analysis to model quarterly long stay tourist arrivals from the largest source markets were a naïve model adjusting for trend and seasonality, Winter's three-parameter model and seasonal autoregressive intergrated moving average (SARIMA) models. In this study and also in most cases, the naïve model is used as a baseline model. For each model, four-step, eight-step and twelve-step ahead forecasts were generated and evaluated representing the short-term, medium-term and the long-term, respectively. Even though to some extent, the performance of the models depended on the forecasting horizon, the outcomes revealed that in general the naïve model was the best model while Winter's ranked second (Jackman & Greenidge, 2010).

Empirical evidence suggests that seasonal patterns of tourism demand and the effects of other influencing factors on this demand tend to change over time. Another study by Song, Li, Witt, & Athanasopoulos (2011) develops the STSM further by introducing time-varying-parameter (TVP) which was used to forecast tourist arrivals of Hong Kong from four source markets. The STSM without the inclusion of explanatory variable reflects the seasonal variation in tourism demand better than the traditional constant seasonal time series models, but fail to take into account for the effects of economic determinants on the variable of interest. An improvement to the STSM known as casual structural model (CSM) includes the variable in the model specification. However, it still produced less accurate forecasts than the STSM, possibly due to the treatment of the explanatory variables. TVP, introduced in 1990 was mainly to overcome such limitations. This approach relaxes the restriction of the constancy of the coefficients of the explanatory variables and allows for stochastic parameters, paving way for evolution of demand elasticities over time. Song, Li, Witt, & Athanasopoulos (2011) attempted to incorporate TVP into the STSM model for the first time. The general to specific approach was adopted for the TVP-STSM estimation where the initial equation includes trend, cycle, seasonal and irregular components, three explanatory variables and some dummy variables, all treated as time varying. In general, the model had fewer significant explanatory variables than other models, because the unobserved components in a well specified TVP-STSM are able to capture most of the variation in the demand (Song, Li, Witt, & Athanasopoulos, 2011). Evidence shows that the TVP-STSM model consistently outperforms the time series models.

The approach used in this paper combines some of these approaches and techniques and such creates an augmented autoregressive integrated moving average (ARIMA) model.

Methodology and model specification[3]

The augmented ARIMA model presented in this paper can be used to forecast the tourism indicators; total arrivals and total bednights. The average stay is calculated implicitly using the two variables.

The model eliminates seasonality by running a regression with seasonal dummies. This technique also allows the forecaster to capture the seasonality in the model. The data used in the estimation covers the period January 2006 to December 2018 at monthly frequency and thus with 156 observations.

Variables

The dependent variables considered for the model include:

- lnTA – the natural logarithm of total tourist arrivals and
- lnBN – the natural logarithm of tourist bednights.

The natural logarithm has been used here for general ease of interpretation. Additional dummy variables that has been used are as follows:

I. **The global financial crisis:** The global financial crisis that occurred in the period 2008-2009, is commonly regarded as the worst financial crisis since the Great Depression. What began with a crisis in the subprime mortgage market in the US escalated resulting into a full-blown international banking crisis. As many countries faced a slowdown in their economy during this period, a dummy variable taking the value one for the year 2008 has been incorporated to test for the influence of this event towards the movement of tourists.

II. **Chinese New Year:** A dummy variable of one is associated corresponding to the month of Chinese New Year each year, otherwise zero.

III. **Exchange rate:** The MVR exchange rate per US dollars since 1986 has been considered in the analysis. In 2011, the exchange rate was devalued and then changed into a pegged exchange rate regime, where the rate for the US Dollar is determined by the MMA. The mid-point of exchange rate is MVR12.85 and the rate is permitted to fluctuate within the ± 20% band, i.e. between MVR10.28 and MVR15.42. This has currently stabilized at the upper band of MVR15.42. Hence, a dummy variable of one has been associated from devaluation date and thereafter considering it to be a structural-break event.

IV. **Flight movements:** Based on the forecast of the flight movements received from the Maldives Airports Company Plc. (MACL), a dummy variable is created which takes the values between one and zero. Historical data reveal that the largest flight movement growth was experienced in 2010 since 2005. Therefore, the dummy associates 2010 to be the base-year and respectively the forecasts are converted to ratios based on this base-year.

V. **Monthly seasonality:** For each month; i=1 to 12, a dummy variable at time t is defined to take the value 1 if the month at time t is i, else 0. The dummy variable captures any monthly seasonality effect present in the variable at time t.

[3] The model was developed before the COVID-19 pandemic. Hence the current model in use will be a slight alteration to the one presented in the paper. The adjustments are to include the COVID-19 impacts. Overall, the main model remains the same.

Estimation of the model

For any regression, ensuring stationarity of the variables is highly advised. This being so because stationarity allows preserving model stability; meaning the parameters and structure of the model is stable in time. The Augmented Dickey Fuller (ADF) unit root test is used to check the stationarity.

Both arrivals and bednights were I (1) variables at 5% significance (Table 1). Hence, the regression models were expressed as the first difference of natural logarithm of the variables to make the variable stationary. A stationary time series is one whose statistical properties such as mean, variance and autocorrelation are all constant over time.

Table 1: Unit root tests[4] results

LnTA – Levels	0.3617	(ADF)
LnTA – 1st difference	0.0274**	(ADF)
LnBN – Levels	0.4599	(ADF)
LnBN – 1st difference	0.0247**	(ADF)

Test Statistics are reported

Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1

Determining the ARIMA structure

The model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. The AR part involves regressing the variable on its own lagged (i.e., past) values. The MA part involves modelling the error term as a linear combination of error terms occurring contemporaneously and at various times in the past. ARIMA models are a more generalized version of the autoregressive moving average (ARMA) models and they are in theory, the most general class of models for forecasting a time series which can be made to be "stationary" by differencing. It is expressed as ARIMA (p, d, q) p refers to the number of autoregressive terms, d refers to the order of differencing the variable in order to make it stationary and q refers to the moving average terms.

Several variations on the ARIMA model are commonly employed. If multiple time series are used, then it can be thought of as vectors and a VARIMA (vector ARIMA) model may be appropriate. Sometimes a seasonal effect is suspected in the model; in that case, it is generally better to use a SARIMA (seasonal ARIMA) model than to increase the order of the AR or MA parts of the model.

Model

In the case of tourist arrivals, the functional form is of a log-linear model. For forecasting the bednights, an autoregressive distributive lag model (ARDL) in log-linear form has been used. The models are depicted as,

[4] MacKinnon (1996) critical values have been used. The null hypothesis (H0) in the case of the ADF tests is that the given series is non-stationary.

$$y_t = \beta_0 + \sum_{i=2}^{12} \alpha_i D_{it} + \beta_1 recession_t + \beta_2 flight\ movement_t + \beta_3 exchange\ rate_t + \beta_4 Chinese\ new\ year_t + \sum_{p=1}^{4} \phi_p y_{t-p} + \epsilon_t + \sum_{q=1}^{4} \theta_q \epsilon_{t-q}$$

$$x_t = \delta_0 + \sum_{i=2}^{12} \alpha_i D_{it} + \delta_1 \Delta\ total\ arrivals_t + \sum_{p=1}^{4} \phi_p y_{t-p} + \epsilon_t + \sum_{q=1}^{4} \theta_q \epsilon_{t-q}$$

where $y_t = \Delta LnTa_t$, $x_t = \Delta LnBn_t$, $\sum_{p=1}^{4} \phi_p y_{t-p}$ *is the AR component*, $\sum_{q=1}^{4} \theta_q \epsilon_{t-q}$ *is the MA component*

and $\sum_{i=2}^{12} \alpha_i D_{it}$t refers to monthly seasonality, *i* ranging from 2 to 12 months in both equations[5].

The equations include an ARIMA (4, 1, 4) and ARIMA (3, 1, 3) for tourist arrivals and bednights respectively. While the arrivals equation consists of a set of dummies, in the case of bednights, the difference of arrivals forecast has been used as an exogenous variable.

[5] Month one is left out of the regression as the reference period, and all seasonal dummy coefficients will be relative to this reference category.

Results

Model selection is a fundamental part of economic modelling. Once the set of candidate models were chosen, the statistical analysis allowed us to select the best of these models. What is meant by best is controversial. A good model selection technique would balance goodness of fit with simplicity.

Table 2: Results for arrivals model

Dependent Variable: ΔLnTa

	Coefficient	Prob.
C	-0.0234	0.2502
$Recession_t$	-0.0267	0.0002***
Chinese New $Year_t$	0.1054	0.0004***
Flight $movement_t$	0.0089	0.1645
Exchange $rate_t$	-0.0045	0.2394
@MONTH=2	0.0034	0.9032
@MONTH=3	-0.0099	0.7252
@MONTH=4	-0.0369	0.1843
@MONTH=5	-0.1696	0.0000 ***
@MONTH=6	-0.1131	0.0000***
@MONTH=7	0.2636	0.0000***
@MONTH=8	0.1061	0.0018***
@MONTH=9	-0.0602	0.0521*
@MONTH=10	0.1936	0.0000***
@MONTH=11	-0.0376	0.1527
@MONTH=12	0.1394	0.0000***
AR(1)	0.4123	0.0078***
AR(2)	0.2115	0.0435**
AR(3)	0.8467	0.0000***
AR(4)	-0.6198	0.0000***
MA(1)	-0.862	0.992
MA(2)	-0.2747	0.9945
MA(3)	-0.862	0.9959
MA(4)	1	0.9973
Adj. R^2	0.847	
Number of observations	155	

Test Statistics are reported

Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1

Note: The Adj R^2 without ARIMA specification was 0.775

Table 3: Results for bednights model

Dependent Variable: ΔLnBn

	Coefficient	Prob.
C	0.1023	0.0000***
ΔTa	0	0.0000***
@MONTH=2	-0.1352	0.0000***
@MONTH=3	-0.0656	0.0001***
@MONTH=4	-0.1533	0.0000***
@MONTH=5	-0.2042	0.0000***
@MONTH=6	-0.2921	0.0000***
@MONTH=7	0.0568	0.0061***
@MONTH=8	0.0039	0.7648
@MONTH=9	-0.2126	0.0000***
@MONTH=10	0.0156	0.4221
@MONTH=11	-0.1083	0.0000***
@MONTH=12	-0.1051	0.0000***
AR(1)	0.1902	0.02477**
AR(2)	-0.809	0.0000***
AR(3)	0.2908	0.0754*
MA(1)	-0.4406	0.989
MA(2)	0.7392	0.9957
MA(3)	-0.7764	0.9467
Adj. R^2	0.969	
Number of observations	155	

Test Statistics are reported

Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1

For both models, regressions were run with and without the ARIMA structure. Results showed that including the ARIMA specification improved the model fit. For example, in the case of arrivals, the adjusted R-square was 85% while it was 78% without the ARIMA specification. Hence, giving the selected model more explanatory power[6].

Results also showed that most variables were highly significant at 1% significance levels. However, it was seen that the exchange rate and the flight movement variable were insignificant. However, given the high correlation between the flight movements and the tourist arrivals, the variable has been retained in the equation, the main objective of the study being, the development of a forecasting model. Results of both models depict the desired sign and direction in the variables that is economically perceived.

In order to further verify the robustness of the model, residual diagnostics were conducted. While the Durbin-Watson[7] statistic supports the fact that there exists no serial correlation in the model, the Breusch-Pagan-Godfrey test and the Jarque-Bera test indicate that both the models are homoscedastic at 10% significance and follow a normal distribution. For both models F-statistic is highly significant supporting the fact that the combined effect of all the regression coefficients were significant.

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[6] Although all the MA terms in both the models were insignificant, including the ARIMA specification still improved the model in explaining the data as seen from the better Adjusted R-square value.

[7] The Durbin-Watson d-Statistic is a test for serial correlation. As a rule of thumb, if the d is expected to be around two, one may assume that there is no first order autocorrelation.

Table 4: Results of robustness checks of the models

Models	Breusch-Godfrey (Heteroskedasticity)	Probability (F-statistic)	Jaque-Bera (Normality)	Durbin-Watson (Autocorrelation)
LnTa	0.0840*	0.0000***	0.6803	2.000
LnBn	0.1103	0.0000***	0.9711	2.0653

Significance levels: *** p < 0.01 ** p < 0.05 * p < 0.1

Breusch-Pagan-Godfrey test H_0: No Heteroskedasticity

Jarque-Bera test H_0: Normal distribution

Performance evaluation

The total arrivals and total bednights were forecasted using these models. The out-of-sample forecast covers the period January 2019 to December 2019. The average stay is calculated implicitly using the forecast for both the indicators as follows.

Average stay = Bednights/Total arrivals

Results for the out-of-sample forecast for 2019 gave the following results:

Table 5: Forecasts

	Model forecast 2019	Adjusted actual 2019	Actual 2019
Tourist Arrivals	7%	8%	15%
Bednights	7%	NA	13%

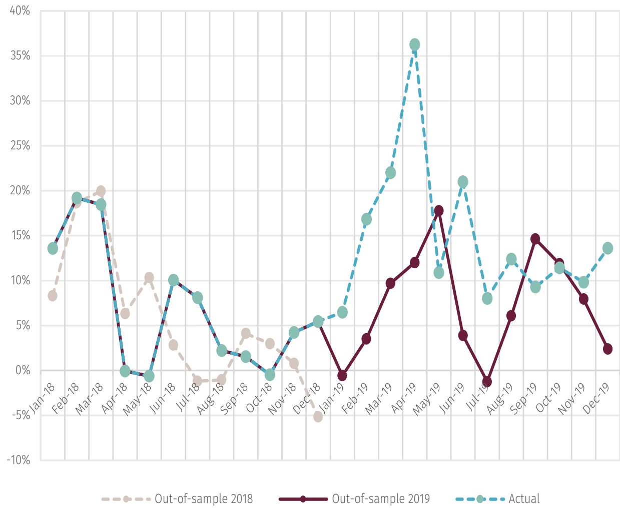
The high deviation of the model forecast when compared to the actuals of 2019 points towards the extremely well performance of the tourism sector in the year. The main reason being the robust growth of the Indian market along with the growth of the top five markets. The top five markets in 2019 registered an average growth of 14% when compared to a baseline expected growth of 2019. This expected growth is based on the average growth of these markets from 2015-2018 which was 8%. Hence, a total increase of 102,841 tourists were observed when the baseline growth was considered for 2019. It can be seen from table 5, that if the increased and unexpected performance in 2019 is adjusted[8], the model quite closely predicts the arrival growth rate in the out-of-sample forecast.

Furthermore, by restricting the out-of-sample forecast to 2018, the results were much closer. While the model predicted an average growth of tourist arrivals of 5% for 2018, the actual tourist arrivals in the year stood at 7%. Similarly, the model forecasted an average bednight growth of 7% in 2018 while bednights recorded a growth of 10% in the same year. As seen from Figure 5 and 6 below, the out-of-sample forecasts for 2019 had

[8] The increase in tourist arrivals compared to other years (102,841 arrivals in 2019) was deducted from the actual 2019 arrivals to get the adjusted actual

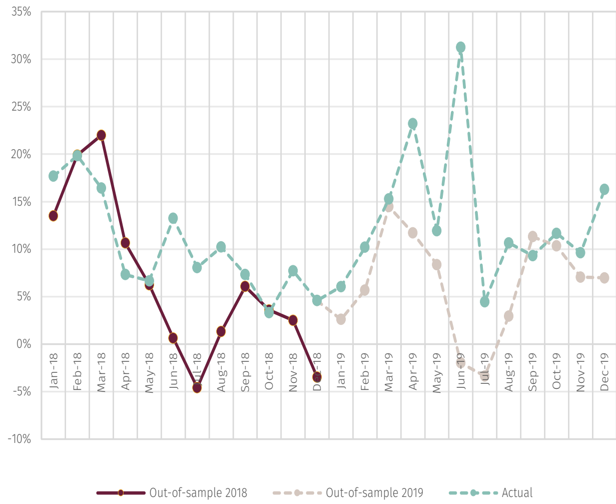
quite a few deviations from the actual 2019, mostly due to the better than expected arrivals from the major markets, especially India. Regarding the out-of-sample forecasts for 2018, the major deviation arose from the forecast July 2018 where the month-on-month growth in actual arrivals and bednights were more than 30%, with more than 50% of the arrivals increasing from European markets.

Figure 5: Tourist arrivals vs. forecasts



Source: Maldives Monetary Authority, Ministry of tourism

Figure 6: Bednights vs. forecasts



Source: Maldives Monetary Authority, Ministry of tourism

In this paper, root mean squared error (RMSE) and mean absolute percentage error (MAPE) have been chosen to evaluate the performance of the forecasting capability of the model. The criterion chosen determines the absolute fit of the model to the data. It helps in deciding how close the actual data points are in comparison to the models predicted values. Thus, a lower RMSE and MAPE indicate a better fit.

Table 6: Forecast evaluation using RMSE and MAPE

	2019 model forecast vs. actual	2019 model forecast vs. 2019 adjusted actual	2018 model forecast vs. actual
RMSE	116,546	13,705	20,539
MAPE	7%	0.90%	1%

Table six shows that both RMSE and MAPE were lower if the adjusted actuals are considered, further supporting the fact that the deviation was mostly due to the high performance in 2019. The error percentage reduces drastically from 7% to 0.9% in this case. Although the out-of-sample forecasts for 2019 showed higher deviations for both arrivals and bednights, the selected model which included the ARIMA specification is still accepted as superior. This is evident from the fact that errors were significantly reduced in the out-of-sample forecasts for 2019 when the unexpected performance was adjusted accordingly.

BOX 1: Impact of COVID-19 on tourism modelling[9]

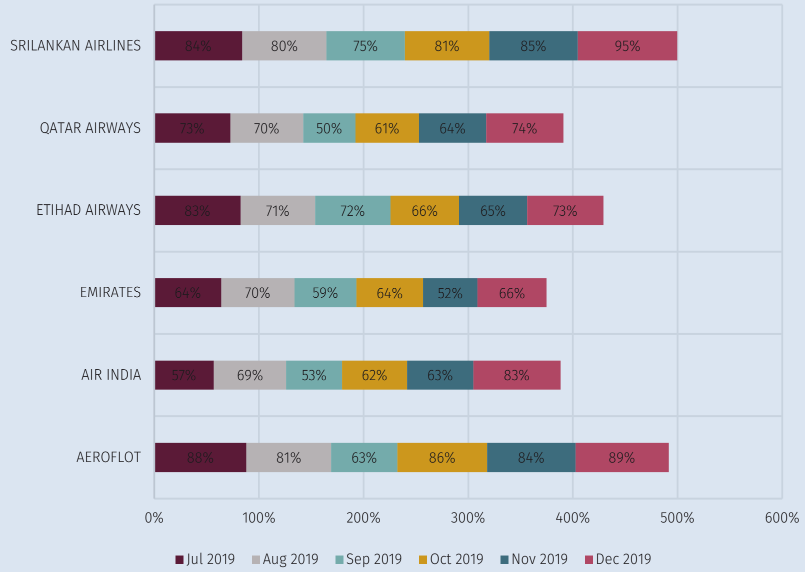
The COVID-19 pandemic has made countries vividly aware of the major global imbalances and challenges that can occur at any time. The pandemic has been by far the worst crisis faced by the Maldives in the recorded history. While the Maldives had looked forward to a very prosperous year 2020, economic events took a radical turn during the first quarter of the year. With the unprecedented hit to the tourism sector, the Maldives faced the worst the economic downturn, with GDP contracting by 33.6% in 2020, worsening the already prevalent macroeconomic imbalances in the economy.

In order to curb the spread of the infection, the Maldives closed off its international borders on 27 March, resulting in a halt of tourist arrivals at the end of the first quarter. The ban had a major impact on the overall tourism industry with February 2020 registering a decline of 11%; the biggest decline recorded since the financial crisis. As a result of the border closure, tourist arrivals for the month of March 2020, registered at 59,630 arrivals, indicating a marked decline of 63% for the month of March 2020. Post the re-opening of the border on 15th July 2020, the pace of recovery was relatively slower and the number of tourists that visited Maldives registered significantly lower than 2019.

Historically, main flights operating to the Maldives experience a load factor (percent of seats filled) in excess of 50%, while carriers such as the Sri Lankan Airlines and Qatar Airways register load factors more than 60% (Figure 1). However, the contraction in the demand that arose with the COVID-19 is evident from the significantly low seats filled in these carriers. For instance, Sri Lankan Airlines registered a load factor of around 10% since border opening (Figure 2).

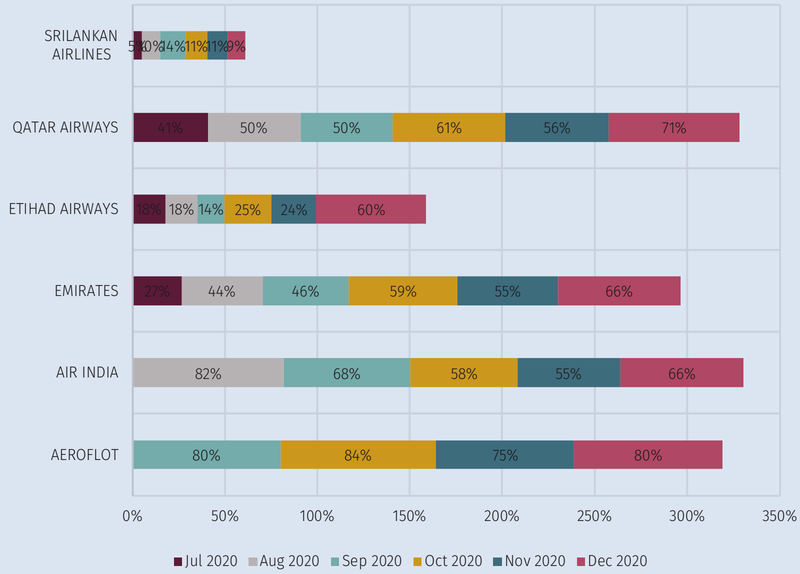
[9] The forecasts and methodology presented in this box article represents the forecasts for the budget 2021 which was produced in September 2020. The assumptions in the latest revisions made in 2021 will slightly differ.

Figure 1: Load factor, 2019



Source: Maldives Airports Company Ltd

Figure 2: Load factor, 2020



Source: Maldives Airports Company Ltd

With the new developments and uncertainty around the containment of the coronavirus disease, growth projections across the globe were revised to account for the economic impact of the COVID-19 crisis. Accordingly, the initial projections were revised down during mid-year.

The model presented in the paper does not account for the drastic impact that the economy faced in 2020 due to COVID-19. Since there were no similar pandemics within the sample period that could have been used as a guiding point to model the developments in 2020, the model could not be used as it is to forecast the tourism indicators for 2020.

To account for this downward adjustment, the new projections since the outbreak used the Maldives Airports Company Private Limited (MACL) international passenger movement forecasts to derive an estimate for the monthly tourist arrivals. Given that a fraction of international passenger movements would be tourist arrivals, three scenarios were computed by defining the percent of international passengers who are going to be tourists:

- Optimistic case: 82% of international passengers are tourists – this number is the historical fraction of tourists among international passenger arrivals.
- Moderate case: 73% of international passengers are tourists – this is the halfway point between 82% and 64%.
- Worst case: 64% of international passengers are tourists – this number is the fraction of tourists among international passenger arrivals in July and August 2020.

Accordingly, three scenarios were computed to forecast the arrivals where in the number of tourist arrivals for 2021 was estimated and the projections were produced from 2022 onwards. This method was used for data up to August 2021. Moreover, the total bednights for each month in 2020 was derived by obtaining the product of tourist arrivals and an average stay of 9.5 days (average stay registered around 9.5 in March, April and July 2020 and data from the immigration health declaration database IMUGA also reported a higher average stay than the historical numbers).

Similar to the methodology used to forecast the tourism indicators in the main paper, annual models were utilized to project the tourism indicators; arrivals and bednights for the medium term. The main difference compared to the previous technique was in the estimation for 2021. Since MACL had provided international passenger movement forecasts until August 2021, monthly tourist arrivals were derived for each scenario like the methodology mentioned above in this section. Hence it would be more reflective of both the demand and supply-side constraints facing the industry as MACL estimates were compiled from information provided by airlines. The next assumption was regarding the number of tourist arrivals to register in December 2021:

- For optimistic case: Assume 80% of tourist arrivals in December 2019 will register in December 2021.

- For moderate case: Assume 70% of tourist arrivals in December 2019 will register in December 2021.

- For worst case: Assume 60% of tourist arrivals in December 2019 will register in December 2021.

For the remaining months which needed to be forecasted (September to November 2021), by assuming the seasonally adjusted arrivals would increase steadily (increase in a straight line), the seasonally adjusted series was interpolated and then re-seasonalised to obtain tourist arrivals projections for 2021.

Once the figures for 2021 was obtained, this data was incorporated into the annual model stated below. The annual model used data from 1984 onwards and accounts for the different crises that the Maldivian economy has experienced; global financial crisis 2008/2009 and Tsunami 2004. Furthermore, the recovery trajectory was replicated using a dummy variable

Table 1: COVID recovery dummy variable – Expected recovery trajectory

	Optimistic Case	Moderate Case	Worst Case
2020	1	1	1
2021	-0.1	-0.1	-0.1
2022	-0.35	-0.45	-0.55
2023	-0.1	-0.1	-0.1
Except for the aforementioned years, the dummy variable will be equal to zero.			

called COVID recovery, for which numbers were trialed till 90% or more of the level of tourist arrivals in 2019 was registered in 2023 (Table 1). The bednights model followed the monthly model closely; main dependent variable being arrivals.

Annual model used for arrivals:

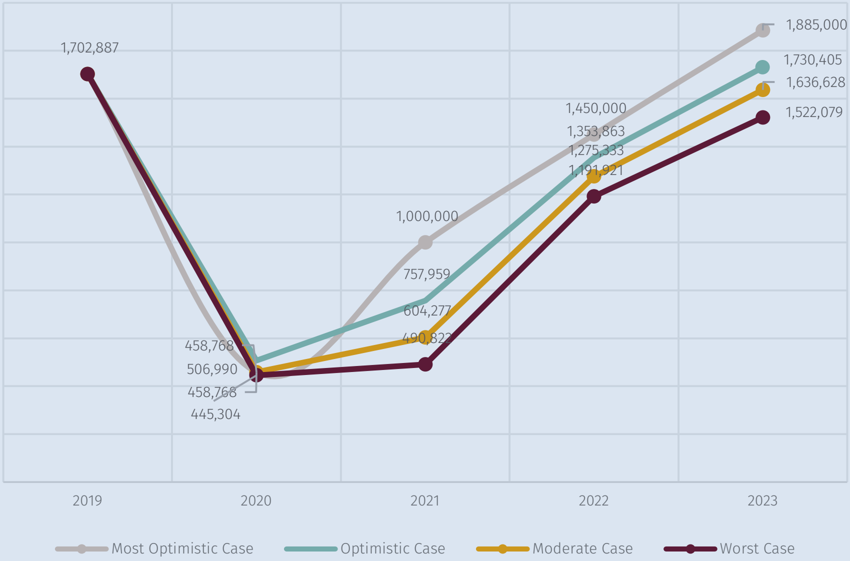
$$ln\Delta Ta = recession2008 + tsunami_t + covid\ recovery_t + constant$$

Annual model used for bednights:

$$ln\Delta Bn = arrivals_t + constant$$

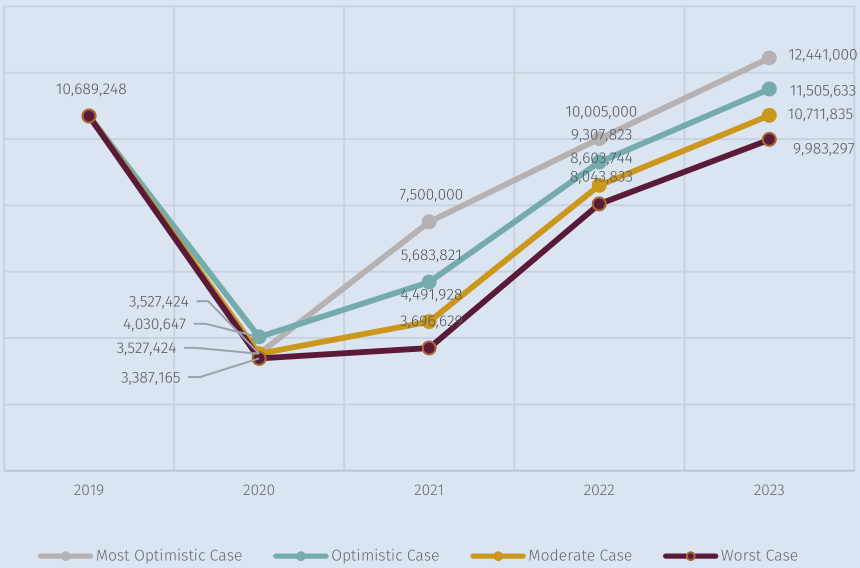
[10] These forecasts were made during September 2020.

Figure 3: Tourist arrivals, 2019-2023



Source: Ministry of Tourism

Figure 4: Tourist bednights, 2019-2023



Source: Ministry of Tourism

The annual forecasts utilized the monthly aggregate forecasts obtained for 2020 and 2021 as a data point. Following were the medium-term forecasts for each of the tourism indicators.

While tourist arrivals averaged at 3,111 as at 31st August 2021, actual arrivals as at 2020 registered a total of 555,494 arrivals, 10% more than the optimistic case forecast (Figure 3). With the increased frequency of flights and the commencement of new flights, it is likely that the sector may perform better in 2021. While a total of 755,957 arrivals were registered as at 31st August 2021, the top two markets for the year include Russia and India. However, more recently, with the new variant and uncertainty around COVID-19 especially in India, the recovery of the tourism sector is subject to risks and challenges in the near term.

Conclusion

The performance of the tourism sector in the Maldives is also largely dependent on the supply side factors. According to the structure of the model presented in the paper, it only captures the demand side with a minimal supply impact through the flight movements. However, the model is not able to capture the other factors that may affect the forecast for tourist arrivals and bednights such as the tourism marketing expenditure by the government and the development of the runway and the new terminal of the Velana International Airport. These factors could significantly improve the movement of tourists in and out of the country.

Further, as the bednights statistics for guesthouses, resorts, hotels and safaris are currently not available on a nationality basis, region-wise analyses are not possible in this category. Availability of such data could further improve the predictive power of the forecast. With the upcoming new developments, the model should be subject to improvements. A much-needed effort could be put in the area of improving the data availability and the collection of new data that may be relevant and those which are not currently compiled. The model can be further improved by capturing the impact of peak seasons on tourism and the inclusion of REER to account for the general affordability of the Maldives as a destination. In this regard, a more enhanced research in this regard is extremely important for the model to most efficiently capture the tourism indicators in a more efficient and effective manner.

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