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COVID-19 Tourism Recovery in the ASEAN and East Asia Region: Asymmetric Patterns and Implications

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Abstract: *The aim of this paper is to produce forecasts for tourism flows and tourism revenue for ASEAN and East Asian countries after the end of the COVID-19 pandemic. By implementing two different machine-learning methodologies (the Long Short Term Memory neural network and the Generalised Additive Model) and using different training data sets, we aim to forecast the recovery patterns for these data series for the first 12 months after the end of crisis. We thus produce a baseline forecast, based on the averages of our different models, as well as a worst- and best-case scenario. We show that recovery is asymmetric across the group of countries in the ASEAN and East Asian region and that recovery in tourism revenue is generally slower than in tourist arrivals. We show significant losses of approximately 48%, persistent after 12 months, for some countries, while others display increases of approximately 40% when compared to pre-crisis levels. Our work aims to quantify the projected drop in tourist arrivals and tourism revenue for ASEAN and East Asian countries over the coming months. The results of the proposed research can be used by policymakers as they determine recovery plans, where tourism will undoubtedly play a very important role.*

Keywords: COVID-19; Tourism; Deep learning; ASEAN; East Asia

JEL classification: H12; P46; Z32

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1. Introduction

As the world is still experiencing the detrimental effects of the global coronavirus disease (COVID-19) pandemic, countries are preparing for recovery from this deep crisis. Pandemic crises often upend economies (Škare et al., 2021), and tourism is one of the sectors most affected by COVID-19 (Fotiadis et al., 2021), small businesses in particular (Sobaih et al., 2021). With this in mind, it is important for policymakers, academics, and industry professionals to forecast and address both the present and possible future pandemic crises. Consequently, it is crucial to obtain knowledge about the nature and true magnitude of the COVID-19 pandemic (Polyzos et al., 2020).

In this paper, we implement the approach proposed by Fotiadis et al. (2021), and build a 12-month forecast for tourism flows and revenue in ASEAN and East Asian countries. We choose to shift our focus from global tourism to region-specific flows, particularly in the ASEAN and East Asian region. This region represents an interesting candidate for study due to the strong integration ties amongst its members (Thanh et al., 2009; Harvie et al., 2015; Quang et al., 2020). In addition, we use data for tourist arrivals and tourism revenue, expanding our approach to more data series. As the current crisis is still evolving, we choose to present different scenarios, namely a baseline, a worst- and a best-case scenario for each of the two data series of the countries in the sample. In this manner, we can contribute to the strategy development of the recovery efforts in the region.

Our approach uses five different training samples, based on different crises of the last 20 years, and deploys two different models, namely the Generalized Additive Model (GAM) of Hastie and Tibshirani (1990) and the Long Short Term Memory (LSTM) neural network of Hochreiter and Schmidhuber (1997). The efficiency of these two approaches has been established in the literature (Athanasopoulos and de Silva, 2012; Law et al., 2019; Polyzos et al., 2020; Fotiadis et al., 2021). We use different training samples for each of the each of the two methodologies. The samples used are the Severe Acute Respiratory Syndrome (SARS) epidemic (2003–04), the H1N1 pandemic (2009–10) and the Great Financial Crisis (GFC). Finally, following Fotiadis et al. (2021), we implement a pessimistic training set that trains the model using the lowest available data from each year.

This paper makes three important contributions to the literature. First, we present recovery scenarios for the data series of international tourist arrivals and tourism revenue for ASEAN and East Asian economies. Second, by examining each country separately, we are able to demonstrate the differences amongst the countries in the group. Finally, we add to the discussion on the tourism-related economic costs of the COVID-19 pandemic in the ASEAN and East Asian economies.

The rest of this paper is structured as follows. Section 2 presents the literature review, Section 3 discusses the methodologies employed and the data, Section 4 presents the empirical results and Section 5 concludes with policy implications and suggestions.

2. Literature Review

2.1. Crises

As COVID-19 is the most influential issue currently around the world, there is a growing body of literature that addresses the effect of crises on tourism organisations, destinations, and stakeholders (Gössling et al., 2020; Niewiadomski, 2020; Quang et al., 2020; Seraphin, 2020). To this end, some studies have focused on the strategic responses by examining the problems faced by tourism systems at the national, subnational or supranational level by the decline in arrivals and overnight stays (Dumičić et al., 2015). Others have focused on proper business strategies in times of crisis (Ritchie, 2009; Korol and Spyridou, 2020). Terrorist attacks, natural disasters, and pandemics are the most common crises that affect tourism worldwide. For example, when there is a terrorist attack, we can expect a negative impact on tourism (Samitas et al., 2018, Polyzos et al., forthcoming). The same effect seems to exist when there is a natural disaster, as several studies have indicated (Becken and Hughey, 2013; Séraphin et al., 2019). The impact of pandemics on tourism can be found in earlier and recent studies (Abdullah et al., 2004; Hung et al., 2018).

The global tourism industry is increasingly affected by different kinds of crises, particularly due to the influence of both social and traditional media. For Sausmarez (2007), crises can be categorised into potential crises and latent crises.

Using the crisis development speed, Ritchie (2004) categorised crises into immediate and emerging, with the former defining crises that come by surprise and the latter including those that develop more slowly and can be predicted. A small decrease in tourism is a legitimate concern for a travel destination or for tourism businesses, but it becomes a crisis only when the impact of an event or set of events is severe. Ritchie (2009) discussed in detail theoretical definitions of tourism crises and disasters and their various causes.

Generally, after the first report of a crisis, media outlets often cover it and may also invite 'experts' to examine its causes and the extent of its impact for the benefit of prospective and current tourists. When a destination gets into crisis, managers need to address tourists' scepticism and hesitancy to stay at a destination perceived as risky or unsafe (Boukas and Ziakas, 2014).

However, the COVID-19 pandemic is unusual in many ways. First, the crisis is a global phenomenon, with a concomitant decrease in overall demand for the tourism, travel and hospitality industries (UNWTO, 2020). Second, the predicted post-COVID-19 economic collapse is considered to be one of the worst the world has ever experienced (Welfens, 2020). Third, the ongoing crisis stemming from COVID-19 can cause important changes in numerous areas of tourism (Dolnicar and Zare, 2020). Lastly, there is an absolute uncertainty as to when the crisis will end (Collins-Kreiner and Ram, 2020), which is why we chose to not attach specific dates to our forecasting outcomes.

2.2. COVID-19

Pandemic crises and other health issues, natural disasters, terrorism, and wars are serious threats to the sustainability of the global tourism industry (Yeh, 2020). Though the Spanish flu 1918–20 is the most frequently discussed topic regarding a pandemic, the world has seen a chain of pandemics during the last 20–30 years, such as SARS, H1N1 and Ebola (Polyzos et al., 2020). At the time of this writing, 95,790,282 people have been infected by COVID-19, with 2,044,575 deaths following an unprecedented and large-scale economic collapse globally. COVID-

19 is possibly the greatest respiratory disease pandemic since the Spanish flu (Ferguson et al., 2020). The COVID-19 pandemic has been extremely deadly, and efforts to contain its spread have been coordinated. The treatment of those infected and the development of many candidate vaccines have shown promising results, but, at this moment, there is no sign of economic recovery. According to the World Tourism Organization (2020), international tourist arrivals decreased by 72% from January 2020 to October 2020, translating into a loss of US$935 billion in revenue from international tourism. A year after the outbreak of the pandemic, most countries are still struggling; therefore, it can be expected that a new era is coming for the tourism industry. Based on current forecasts, it may take some years to return to the pre-COVID-19 status (Lew et al., 2020), and only when the majority of the population in a country is vaccinated and interval travel is re-established (Fotiadis et al., 2021).

Within the debates amongst practitioners and academics regarding tourism and pandemic consequences, there has been a unanimous call to consider COVID-19 as a transformative prospect (Ioannides and Gyimóthy, 2020). As such, the tourism industry is being encouraged to reimagine itself and make sure it is ready for the next normal (Cave and Dredge, 2020). Also, researchers are encouraged not to use COVID-19 only as extra context to duplicate current knowledge for measuring and forecasting tourism impacts (Gössling et al., 2020; Sigala, 2020).

Several studies have tried to forecast the underlying social and economic consequences stemming from this pandemic outbreak in the 2 years onward. In this respect, Škare et al. (2021) show that the global tourism industry will need expanded recovery time, as the period is expected to last more than 10 months. Consequently, they suggest that is it crucial to coordinate the public and private sectors to sustain travel and tourism capacity during 2020–21. In a similar manner, Sobaih et al. (2021) investigated the resilience of small Egyptian hospitality businesses and the indirect impacts concerning their performance related to COVID-19. The results of their study show that enterprise resilience has a both indirect and direct consequences on sustainable tourism in the case of Egypt. The results also show that the performance of small businesses in the hospitality sector mediates the relationship between resilience and sustainable development and that restaurant owner-managers demonstrated more resilience than their hotel counterparts (Sobaih et al., 2021).

Months after the COVID-19 outbreak, governments have provided substantial support in the form of tax relief, stimulus checks, grants, and payment deferrals to guarantee the feasibility and continuity of businesses across different sectors, including tourism (Hao et al., 2020). Governments have also interfered in movement restrictions and company closures. For this reason, COVID-19 has led to greater government intervention in the tourism industry (Del Chiappa et al., 2021). This is truly rare and only visible in the COVID-19 crisis, as prior crises that sparked new research and interest from different institutions nonetheless had no limited policy impact, especially in the tourism and hospitality sector (Hall et al., 2020).

2.3. COVID-19 and ASEAN Countries

Following SARS in 2003, international tourism declined by 12 million visitors, with Southeast Asia, which experienced an almost 14% drop, being hit the hardest, (Wenzel and Edmond, 2003). In particular, the number of international visitors was split into two consecutive months (April and May), as noted in Quang et al. (2020). International tourism arrivals to the Asia-Pacific region, which were constantly growing, dropped 9.0% and arrivals to Southeast Asia decreased by 13.9% (UNWTO, 2005).

Viet Nam is an example of an ASEAN country that has done an excellent job reducing the impact of COVID-19. The Vietnamese government swiftly and consistently applied decisive measures as a strategy adapted to the collectivist culture of Vietnamese society (Dinh and Ho, 2020). On the other hand, COVID-19 has shown how unsustainable the country’s dependence on international tourism is, as Chinese arrivals, which represents a third of the total, declined by more than 90%. Therefore, to improve resilience, the Vietnamese tourism industry needs to diversify by supporting domestic tourism, preserving its traditional market and expanding into other international markets (Quang et al., 2020).

Indonesia, with 23,000 active cases, and the Philippines, with 19,000, face the biggest outbreaks. Yet, in per capita terms, the data suggest that Indonesia has lower rates of infection than nearby countries in East Asia, which is puzzling for many informed observers. Singapore has registered the highest confirmed cases in Southeast Asia (partly due to higher testing rates) but has also registered the highest recovered cases (Olivia et al., 2020). At the time this paper is written, Indonesia has already registered 927,380 coronavirus cases, 26,590 deaths and 753,948 recovered cases, while the Philippines has registered 504,084 coronavirus cases, 9,978 deaths and 466,249 recovered.

3. Methodology

This paper combines two machine-learning methodologies for data forecasting. In addition, each methodology uses different training samples and implements a rolling-window approach to train and calibrate the model. Following Fotiadis et al. (2021), we suggest different sets of forecasts based on GAM (Hastie and Tibshirani, 1987; Taylor and Letham, 2017) and on the LSTM neural network (Hochreiter and Schmidhuber, 1997). Both these methodologies have exhibited good performance in demand forecasts and are used extensively in the literature (Athanasopoulos and de Silva, 2012; Law et al., 2019; Polyzos et al., 2020). GAM is an extension of the decomposable time series model of Harvey and Peters (1990) and breaks down the data into three components, namely the trend, the seasonality and the 'irregular' component, with the last mirroring the outcome of the training and calibration process. We implement the rolling-window backtesting process described in Polyzos et al. (2020) to cross-validate the forecasting models and utilise the Mean Absolute Percentage Error (MAPE), the Mean Absolute Error (MAE), and the Rooted Mean Square Error (RMSE) as the performance metric for the accuracy of the predictions.

Both methodologies exhibit some clear advantages in forecasting, especially for multiple data sets, and this has been established in the literature. Taylor and Letham (2017) showed that GAM provides fast performance and thus allows researchers to calculate many different models with alternative parameters. The LSTM network is part of the deep learning algorithm group and is based on neural networks. Their main use is to model time series with high degrees of autocorrelation by adapting to long-term dependencies (Bengio et al., 1994; Gers et al., 2000).

Following Fotiadis et al. (2021), we use five different training sets, but our handling of the forecast outcomes is different. In addition, we select different points of interest in the tourist demand bibliography, by replacing the Middle East Respiratory Syndrome outbreak (which is not significant enough for ASEAN and East Asian economies) with the H1N1 outbreak period. Hence, our baseline training samples are the SARS epidemic (Overby and al., 2004), the H1N1 outbreak (Lee et al., 2012) and the Great Financial Crisis (GFC) of 2007–09 (Sheldon and Dwyer, 2010). We complement these training sets with a worst-case scenario approach, as in Fotiadis et al. (2021) and a training data set that spans the entire sample, which has variables for each country. We build 12-month forecasts based on these outcomes and produce as output two scenarios for each of the coming 12 months, namely the worst- and best-case scenario.

3.1. Generalised Additive Model

GAM is linear and auto-regressive, though it applies potentially non-linear smoothers to the system regressors. It is based on the Prophet model presented by Taylor and Letham (2017) and includes separate components for trend, seasonality and special events. It is an extension of the decomposable time series model of Harvey and Peters (1990). The model specifications are discussed in Hastie and Tibshirani (1987) and Taylor and Letham (2017), while its implementation for time series forecasting is presented in Fotiadis et al. (2021). We will thus only briefly explain the steps.

The general form of the model is as follows:

$$y(t) = g(t) + s(t) + k(t) + \varepsilon(t) \tag{1}$$

where g is the general trend of the time series, s is the seasonal component and k represents the effect of the training set and is implemented to capture possible irregular effects on the time series. Thus, systematic variations are modelled through the seasonality and trend components respectively, while any unsystematic outcomes are modelled by the 'irregular' component. The error term ε captures the residual changes. The errors are assumed to be normally distributed, which we confirm using the Jarque-Bera and the Shapiro Wilk (Shapiro and Wilk, 1965) tests for normality.

The trend component is modelled using the non-linear, saturating growth approach, due to the non-linear patterns in the data series (Hassani et al., 2017; Fotiadis et al., 2021), and is described by the following equation:

$$g(t) = \frac{P(t)}{1 + e^{-h(t-m)}} \tag{2}$$

where P represents the global population at each period, h is the growth rate (non-constant, with structural breaks) and m is an offset parameter. After adjusting for structural breaks, we get the following growth model:

$$g(t) = \frac{P(t)}{1 + e^{-(h+\boldsymbol{a}(t)\top\boldsymbol{\delta})(t-(m-\boldsymbol{a}(t)\top\boldsymbol{\vartheta}))}} \tag{3}$$

where $\boldsymbol{\delta}$ is a vector of growth rate adjustments ($\boldsymbol{\delta} \in \mathbb{R}^B$), θ is the growth rate adjustment and $\boldsymbol{\alpha}$(t) is the adjustment vector.

Finally, the seasonality component uses the periodic effects of Harvey and Shephard (1993) as follows:

$$s(t) = \sum_{n=1}^{N} \left[\varphi_n \cos\frac{2\pi nt}{12} + \omega_n \sin\frac{2\pi nt}{12}\right] \tag{4}$$

A strong advantage of this model is its performance in both predictive accuracy and in fitting speed, which is necessary given the number of models that need to be developed. Thus, GAM is an excellent candidate for tourism demand forecasting, both for the arrivals and for the revenue data series.

3.2. Long Short Term Memory neural network

Following Fotiadis et al. (2021), we also develop models based on the LSTM neural network. This is a deep learning algorithm, first introduced by Hochreiter and Schmidhuber (1997), which is an appropriate choice modelling time series with high degrees of autocorrelation. LSTM networks are known to overcome the errors of similar algorithms in the back-propagation of information contained in recent input events (Bengio et al., 1994) and can thus adapt to long-term dependencies (Gers et al., 2000).

The general setup of LSTM is that of Recurrent Neural Networks, which include an input and an output layer, with many hidden layers in between. Our approach includes a network with a recurrent learning unit and several decision gates. In addition, the process also implements an ‘attention’ mechanism that can assign different weights to the inputs of the model, thus permitting it to learn the importance of new input during data processing; this memory of the new, more recent data is preserved for a long period of time. Our implementation is that of a stateful LSTM methodology, which means that cell states are preserved after each iteration and updated with the new information. We calibrate the logic gates of the model using rolling- window backtesting (Christoffersen, 2010).

The model is as follows:

$$\{\widehat{y_t}\}_{t=T+1}^{T+n} = \vartheta(\{y_t\}_{t=1}^{T}) \tag{5}$$

where ϑ is a forecasting network for *n* future (predicted) values based on a vector of *T* previous values of the data series.

The decision functions at each gate (forget gate *f*, include gate *i* and output gate *o*) and the hidden layer (*h*) are as follows:

$$f_t = \sigma\left(W_f \cdot (h_{t-1}, y_t) + b_f\right) \tag{6}$$

$$i_t = \sigma\,(W_i \cdot (h_{t-1}, y_t) + b_i) \tag{7}$$

$$o_t = \sigma\,(W_o \cdot (h_{t-1}, y_t) + b_o) \tag{8}$$

$$h_t = o_t \times tanh(C_t) \tag{9}$$

where σ represents a sigmoid function, $W_{f,\,i,o}$ represents the weight vector of inputs, h_{t-1} is the hidden layer from previous periods, y_t is the new input vector and $b_{f,i,o}$ is the bias of each gate. The *tanh* function is used in the hidden layer of equation (9) to overcome the vanishing gradient problem, which is a common choice in LSTM networks.

When new information is added to the model, the new cell state, C_t, is as follows:

$$\begin{aligned} C_t = \sigma\left(W_f \cdot (h_{t-1}, x_t) + b_f\right) \times C_{t-1} \\ + \sigma\,(W_i \cdot (h_{t-1}, x_t) + b_i) \\ \times tanh(W_C \cdot (h_{t-1}, x_t) + b_C)_t \end{aligned} \tag{10}$$

We prevent overfitting by implementing early stopping, which is considered a robust algorithm for this purpose (Li et al., 2020). The model is optimised using the Adam algorithm. Since this approach is a stochastic gradient-descent method, it is computationally efficient and yields robust results with low memory requirements (Kingma and Ba, 2014), which is an appropriate choice given the number of variations in our methodology. Consequently, this approach ensures efficiency in explaining autoregressive data series (Athanasopoulos and de Silva, 2012; Law et al., 2019) and permits us to execute the process numerous times.

3.3. Data and Training Periods

Our data set is constructed from two distinct series, namely International Tourist Arrivals and Tourism Revenue, for 16 different countries belonging to the ASEAN and East Asian region. The countries and the data sources are shown in Appendix I. The data span different periods and different availabilities; we thus had to perform separate analyses for each of the countries in our sample. We require monthly data for our work and such data were not available in all cases.

Wherever the sourced data were with annual frequency, we mined the monthly figures by performing fractal interpolations (Barnsley and Harrington, 1989; Bouboulis et al., 2006) to accurately reconstruct the monthly approximations of the data series. To train the fractal interpolation algorithm, we utilised the sample selection from the arrivals data series of the same country where available, or from an average of the monthly data series in the group. Contrary to Fotiadis et al. (2021), the data series are deseasonalised to extract the trend component, since our forecasts do not necessarily correspond to specific months of the year, as the starting period for recovery is still unknown.

4. Empirical Results

As mentioned, our analysis includes two data series for each of the 16 countries. For each of the 32 data series, we implemented our two methodologies based on the five different training data sets, thus resulting in 320 12-month forecasts. We discuss the accuracy results based on different metrics and then summarise the findings as follows. For the two data series of each country, we present a baseline and a best- and a worst-case outcome based on the two methodologies and the five training samples for the time period 6 months and 12 months after the end of the pandemic. In this way, we can produce policy suggestions for the region and for each country for the short and medium time horizon. At the same time, presenting only three scenarios (baseline, best and worst) based on the results of 10 different forecasts will help the logistics of our presentation and enable us to discuss all the countries in the sample.

For our subperiod training samples, we have designated three specific periods that existing literature has examined as having a strong effect on the tourism industry. The periods are shown in Source: Authors.. The first period that can help train our models is the SARS epidemic, which affected tourism flows to a great extent (Overby et al., 2004). A similar pandemic crisis was the H1N1 pandemic (Lee et al., 2012) which, despite having originated in Mexico, had negative effects in many regions of the world, including the ASEAN and East Asian region. Finally, the GFC has been characterised as one of the deepest crises for tourism (Sheldon and Dwyer, 2010). These three training periods are complemented by a worst-case scenario, which takes the minimum value for each training data, and by a training period that spans the entire data sample for the each of the series available.

Table 1. Periods for Training Subsamples

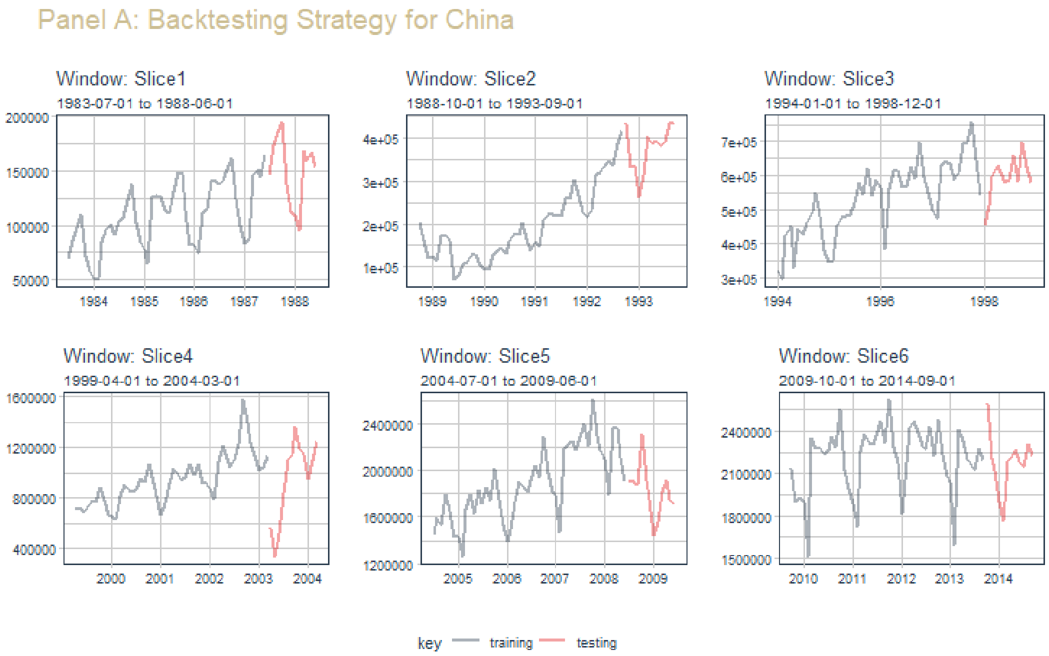
Training Subsample	Period	
	Start	**End**
SARS Epidemic	November 2002	May 2004
Great Financial Crisis	April 2007	January 2009
H1N1/09 Pandemic	January 2009	August 2010

SARS = Severe Acute Respiratory Syndrome.
Source: Authors.

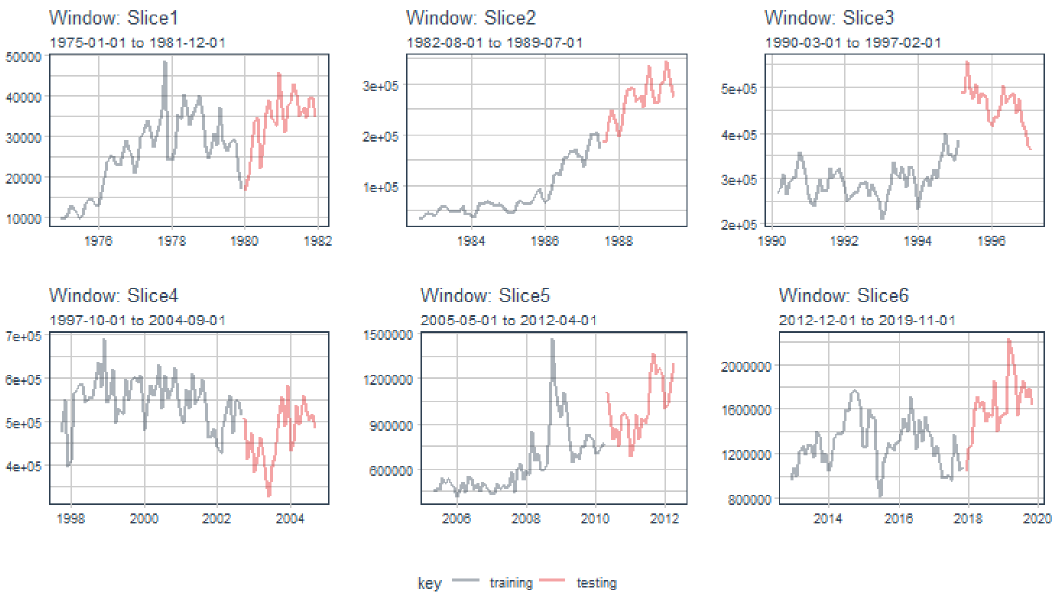
It must be noted that the sourced data for some countries do not cover all the subsamples (the SARS epidemic period, in particular); in these cases, the specific subsample was ignored. The last observation in our data series is at most December 2019. We have deseasonalised the data and normalised the series, setting the last observation to the value of 1. This will facilitate calculations on the expected losses in tourist arrivals and tourism revenue following the COVID-19 crisis and will enable us to make recovery suggestions.

For each country and each data series, we construct five models for each methodology (GAM and LSTM) based on each of the samples. After constructing the models, we perform the rolling-window sampling plan to compute accuracy metrics and confirm that our modelling approaches are appropriate for the given data series. We implement the setup of Polyzos et al. (2020), but the training and testing subsamples are not fixed as each data series differs in observations and time span. Our goal is to create at least six subsamples that allow us to test the prediction models employed. The rolling-window strategy ensures that the testing window is shifted with each subsample to create more subsamples and thus enable us to compute accuracy metrics on each of the model's predictions. **Error! Reference source not found.** demonstrates the results of our GAM backtesting strategy on the tourism revenue data series of China and Republic of Korea.

Figure 1. Backtesting Strategy



Panel B: Backtesting Strategy for Republic of Korea



Note: This figure demonstrates the rolling-window backtesting strategy. Training data are shown in blue and validation data are shown in red.
Source: Authors.

After completing our backtesting strategy, we calculate the accuracy metrics for each of the 320 prediction models. These are the MAPE, the MAE, and the RMSE, which are defined as follows:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|y_t - \widehat{y}_t|}{y_t} \tag{11}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|y_t - \widehat{y}_t| \tag{12}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \widehat{y}_t)^2} \tag{13}$$

where y_t and $\widehat{y}_t$ are the observed and fitted values of the variable at time t, respectively.

Table 2. Expected Change in Tourism Revenue

		Tourism Revenue					
		6 months			12 months		
		Worst	Average	Best	Worst	Average	Best
ASEAN	**Brunei Darussalam**	–51.2%	-49.7%	-48.2%	–31.0%	–30.4%	–29.5%
	Cambodia	**–61.9%**	–58.4%	–57.8%	**–45.2%**	–42.6%	–41.3%
	Indonesia	–56.8%	–53.6%	–51.5%	–29.1%	–27.7%	–27.2%
	Lao PDR	**–66.7%**	–64.8%	–62.8%	**–57.2%**	–55.0%	–52.8%
	Malaysia	–29.0%	–27.7%	–27.1%	–5.3%	–5.2%	–5.1%
	Myanmar	**–63.6%**	–62.4%	–59.9%	**–48.4%**	–46.1%	–44.2%
	Philippines	–34.7%	–34.1%	–32.7%	–15.8%	–15.2%	–15.1%
	Singapore	–26.4%	–25.4%	–24.7%	+25.6%	+24.6%	**+24.1%**
	Thailand	–32.2%	–30.3%	–29.7%	–4.0%	–3.8%	–3.7%
	Viet Nam	–51.7%	–50.2%	–48.7%	–10.7%	–10.3%	–9.8%
Australia		–51.5%	–49.0%	–47.5%	–38.8%	–37.7%	–36.5%
China		–44.0%	–42.8%	–41.5%	+19.2%	+18.1%	+17.4%
India		–35.7%	–34.6%	–33.6%	–21.6%	–20.9%	–20.1%
Japan		–19.6%	–19.2%	–18.4%	+20.2%	+19.2%	+18.7%
New Zealand		–11.0%	–10.3%	–10.2%	+31.4%	+29.9%	**+29.0%**
Republic of Korea		–20.4%	–20.0%	–19.8%	+25.3%	+24.1%	**+23.1%**

ASEAN = Association of Southeast Asian Nations, Lao PDR = Lao People's Democratic Republic.
Note: This table shows the expected change in the Tourism Revenue data series for each country after 6 and 12 months. The Average column depicts the average prediction across 10 different forecasting models. In the Worst column, which shows the worst-case scenario, the minimum three values are shown in bold. In the Best column, which shows the best-case scenario, the maximum three values are shown in bold.
Source: Authors.

Table 3. Expected Change in International Tourist Arrivals

International Tourist Arrivals							
		6 months			12 months		
		Worst	Average	Best	Worst	Average	Best
ASEAN	Brunei Darussalam	–41.5%	–39.5%	–38.7%	–14.3%	–13.8%	–13.3%
	Cambodia	**–55.9%**	–52.7%	–51.7%	–33.4%	–32.1%	–31.4%
	Indonesia	–43.5%	–42.7%	–41.4%	–13.2%	–12.4%	–12.0%
	Lao PDR	**–68.1%**	–66.8%	–64.1%	**–45.9%**	–45.0%	–43.7%
	Malaysia	–18.0%	–17.4%	**–17.1%**	+7.4%	+7.2%	+7.1%
	Myanmar	**–60.0%**	–56.6%	–54.3%	**–38.5%**	–37.7%	–36.2%
	Philippines	–26.9%	–25.9%	–25.4%	+10.3%	+9.8%	+9.7%
	Singapore	–16.0%	–15.5%	**–14.9%**	+42.4%	+41.2%	**+40.4%**
	Thailand	–29.9%	–28.3%	–27.7%	–5.1%	–4.9%	–4.8%
	Viet Nam	–37.4%	–36.7%	–35.2%	–10.1%	–9.5%	–9.3%
Australia		–44.6%	–43.8%	–42.5%	**–39.3%**	–37.8%	–37.4%
China		–46.3%	–44.5%	–43.2%	+14.8%	+14.5%	+14.1%
India		–42.9%	–41.6%	–40.0%	–16.4%	–15.7%	–15.4%
Japan		–29.5%	–28.7%	–28.1%	+11.2%	+10.7%	+10.6%
New Zealand		–14.6%	–14.2%	**–13.9%**	+17.5%	+17.1%	**+17.0%**
Republic of Korea		–22.7%	–21.8%	–21.1%	+23.4%	+22.5%	**+21.6%**

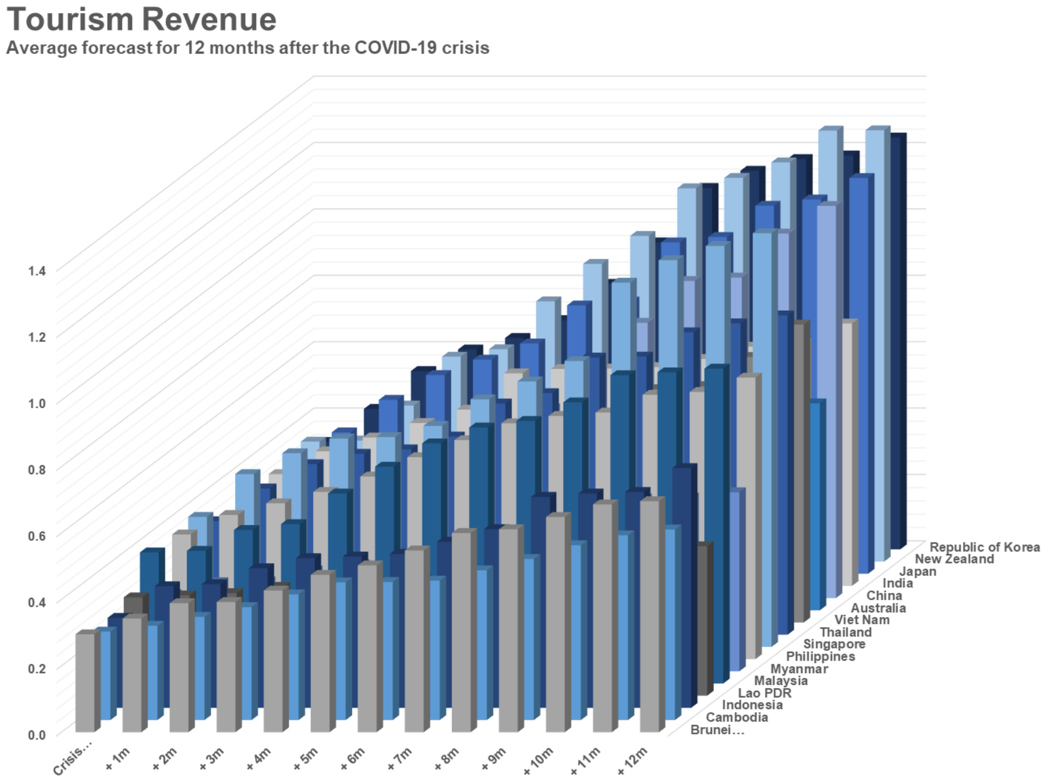
ASEAN = Association of Southeast Asian Nations, Lao PDR = Lao People's Democratic Republic.
Note: This table shows the expected change in the Tourism Revenue data series for each country after 6 and 12 months. The Average column depicts the average prediction across 10 different forecasting models. In the Worst column, which shows the worst-case scenario, the minimum three values are shown in bold. In the Best column, which shows the best-case scenario, the maximum three values are shown in bold.
Source: Authors.

Since the superior performance of LSTM and GAM with respect to other alternatives (e.g. ARIMA[3]) has been established in the literature (Athanasopoulos and de Silva, 2012; Law et al., 2019; Fotiadis et al., 2021), we do not supply comparison data in this instance. Our findings agree in part with Fotiadis et al. (2021), who found that LSTM yields better accuracy, when compared to GAM. However, this was not the case in all scenarios, as, in certain cases (particularly for

[3] ARIMA: Auto-Regressive Integrated Moving Average

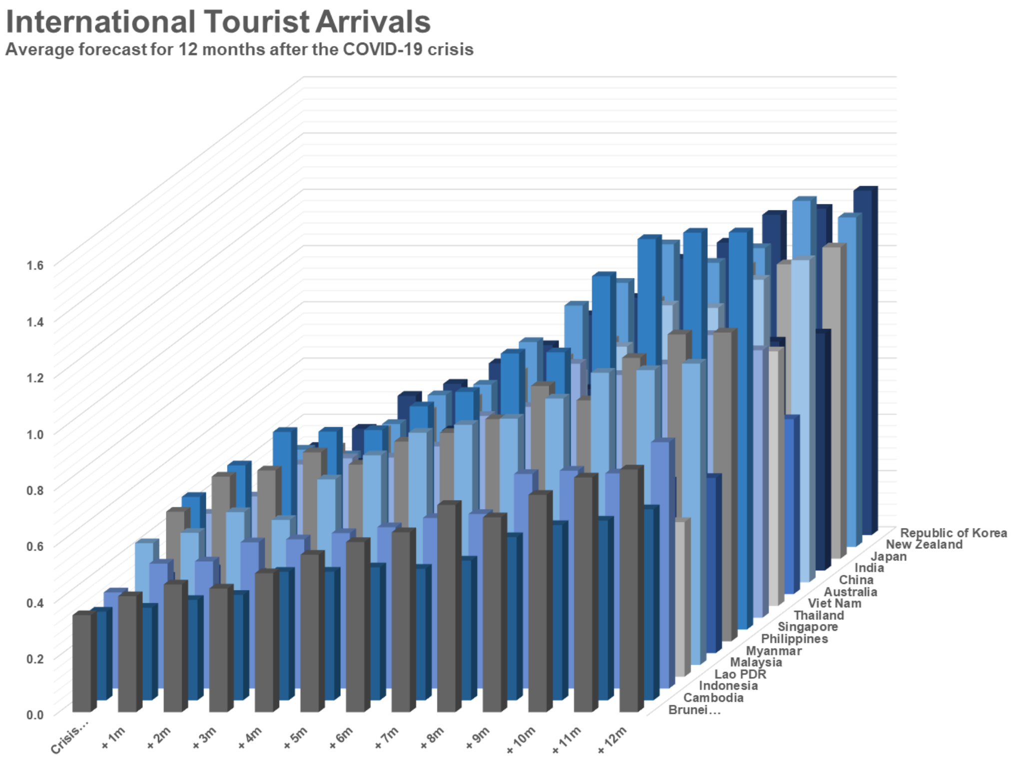
tourism revenue), GAM outperformed LSTM. Since our results will be presented as best- and worst-case scenarios (and not separately for each training set), we present the averages of the metrics across the five training sets used in Appendix II.

Figure 2. Average Forecasts for the Tourism Revenue Data Series



Lao PDR = Lao People’s Democratic Republic.
Source: Authors.

Figure 3. Average Forecasts for the International Tourist Arrivals Data Series



Lao PDR = Lao People's Democratic Republic.
Source: Authors.

We then proceed to showcase our summary outcomes. Tables 2 and 3 show the average expected change in the two data series for each country. We record the drop in the series 6 and 12 months from the end of the pandemic, after which it is not currently possible to make predictions (Collins-Kreiner and Ram, 2020). For each of the two points in time (6 and 12 months), we also present the best- and worst-case scenarios across all the different models implemented. This allows us to better understand the outcomes for each country, which is more useful in determining possible policy implications. We present graphs depicting month-by-month forecasts for each country in Figures 2 and 3.

The results of our forecasts yield some interesting findings. While most researchers (Lew et al., 2020; Polyzos et al., 2020; Gössling et al., 2020; Sigala, 2020; Škare et al., 2021) predicted recovery in the tourist sector in up to a year from the end of the pandemic, this is not true for all countries. Many countries in our sample demonstrate losses in the 12-month forecast, and this loss can be as high as

50% when compared to pre-crisis data. We note significant losses in both revenue and arrivals for Brunei Darussalam, Cambodia, Lao PDR, Myanmar, and Australia.

By contrast, some countries in the sample demonstrate significant post-COVID-19 increases in tourism, both in terms of revenue and in terms of arrivals. The champions here are Singapore, New Zealand, and Republic of Korea, which are notably countries with that have admittedly dealt with the pandemic in a more efficient manner. Other countries exhibit encouraging results, such as China, Japan, Philippines, and Malaysia. We also need to mention the forecasts of Viet Nam, which display a very small drop in both data series; this can be deemed the result of good performances in the previous crises (Dinh and Ho, 2020). We thus note that recovery in the region is asymmetric, which needs to be considered.

Another important observation is that both tourist arrivals and tourism revenue seem to transfer from less advanced to more advanced nations. The forerunners in recovery forecasts appear to be more advanced nations when compared to those who are lagging behind. There does not seem to be any indication that the share of tourism in the country's GDP plays any particular role in this outcome. However, it could be an indication that the lower per capita income of the trailing countries can hinder recovery efforts, especially after a deep crisis such as the current pandemic.

One further finding is that recovery in tourism revenue seems to be slower than tourist arrivals; this is true across all countries in the sample (with few exceptions), regardless of their performance or their post-crisis outcomes. We note that 12 months after the end of the pandemic, the losses in tourism revenue can be up to 25% higher than the corresponding losses in arrivals. This is particularly true for less-popular destinations such as Brunei Darussalam and Myanmar, but it is also true for countries like the Philippines, Indonesia and Malaysia. This finding suggests that recovery efforts are contingent on lower costs for tourists and this can have an important effect on the actual outcomes after the pandemic.

On the other hand, China, Japan, New Zealand, and Republic of Korea have demonstrated a quicker recovery of tourism revenue when compared to tourist arrivals. This suggests that, apart from attracting a higher number of tourists, they also attract tourists with higher income who are willing to spend more. This may also be due to these countries having exhibited better crisis management and thus being perceived as more trustworthy for higher-end tourists.

It is important to note here that these findings do not include any causality implications, based on our empirical approach. As mentioned earlier, the forecasts demonstrated here are based on the training samples alone and thus any data on the COVID-19 crisis and the management policies of each country are not taken into account. However, our models do predict better outcomes for the countries that have performed better in COVID-19 crisis management. This is not because the modelling methodology accounts for COVID-19 cases and deaths; rather, the performance of countries with better post-crisis outcomes is attributed to the better management of the previous crises in the training samples. It is this past performance that contributes to a positive outcome after the current pandemic.

5. Policy Implications and Suggestions

We have discussed the different scenarios for recovery in tourism revenue and tourist arrivals in the ASEAN and East Asian economies. By employing two distinct, versatile methodologies and five different training samples, we were able to create three scenarios regarding the post-crisis outcomes of these two data series 6 and 12 months after the end of the current pandemic. The implementation of machine learning methodologies has allowed forecasting the data series based on the countries' past performance on similar crises, while also accounting for the particulars of the current pandemic.

Our empirical work has yielded important outcomes. First, we have established that the recovery of the tourism industry is not symmetric in the region, since some countries may stay behind while others may even surpass pre-COVID-19 levels, in both data series. In addition, our forecasts suggest that tourist flows may shift to more advanced destinations, possibly to the perception that these destinations are safer. We believe that this effect will fade as we move further away from the pandemic. Second, we show that the expected recovery in tourism revenue seems to be far slower than tourist arrivals. This is true for most destinations in the sample and suggests that even if travel resumes, the economic uncertainty surrounding the crisis will result in reduced spending by tourists.

These findings suggest specific policy implications that are particularly interesting in the integrated context of the ASEAN and East Asian region. The asymmetric recovery patterns will need to be observed by policymakers since they can have two effects. First, given that the recovery forerunners are generally more advanced economies, the asymmetries can widen the gap between these countries and the rest of the countries in the region. Second, due to the strong integration ties of the region, the countries which are lagging behind may hinder the recovery efforts of weak economies, such as Viet Nam, Thailand, and Malaysia. Consequently, any centrally distributed aid from the ASEAN association needs to consider this effect.

Regarding the lag in tourism revenue recovery vis-à-vis tourist arrivals, it is evident that the tourism business profit models may need to be revised. If recovery is contingent on lower prices, then it is important the new business models consider the possibility of lower tourism revenue. If this is not achieved and the tourism sector is not able to offer a comparable level of services at lower prices, this can result in recovery efforts slowing down for both data series. This is particularly important in the context of the COVID-19 pandemic, where preventive measures (which are not expected to relax soon) have placed an increased strain on the cost models of the tourism industry. Safety measures notwithstanding, it could be a signal for policymakers that a cutback in costly preventive measures could be a top priority. As such, the importance of widespread vaccinations or the suggested vaccination passport has increased clout both in resuming tourist activities and in improving profitability in the industry. Modern information-sharing technologies, such as blockchain, can contribute to the distribution of vaccination information, while maintaining data integrity.

Finally, our results show how past performance in crisis management can result in improved outcomes in the current pandemic, with increased significance in the revenue data series. This confirms our expected findings that destinations that are perceived as safer not only attract a greater number of tourists, but also result in improved revenue flows. This suggests that policymakers need to ensure the perception of safety on the part of the incoming tourist in the destinations that they manage. To that effect, showcasing vaccination records amongst tourism employees can improve tourism revenue recovery.

Our research and outcomes come with certain limitations. First, given the nature of our data, we do not consider the possibility of local tourism, which can result in different recovery patterns in terms of total revenue. However, despite our data relating only to international tourism revenue, we could argue that the effects of local tourism may essentially be taken into account in the training subsamples. In addition, our approach does not consider the effects of the actual COVID-19 management efforts from government in the countries of our sample. Our forecasts are based only on the training samples and thus consider the past performance on crisis management. Hence, possible extensions of our work could take into account such data on the efficiency of the COVID-19 crisis management (e.g. number of cases, hospitalisations, death, or even vaccinations). Adding this information to a forecasting model would of course require a different modelling approach to account for the new information. However, such a methodology could help determine the extent to which crisis management can contribute to faster post-crisis recovery. It would also examine the validity of our assumptions on the causes of the performance of the recovery forerunners.

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Appendix I. Data Series and Sources

Country	International Tourist Arrivals	Tourism Revenue
Australia	1976+ monthly CEIC Data	2005+ quarterly CEIC Data
Brunei Darussalam	2004+ yearly CEIC Data	2001+ yearly CEIC Data
Cambodia	1995+ yearly World Bank	1995+ yearly CEIC Data
China	1997+ monthly National Bureau of Statistics, EIKON	1995+ monthly CEIC Data
India	1987+ monthly CEIC Data	2001+ monthly CEIC Data
Indonesia	1979+ monthly CEIC Data	1995+ yearly CEIC Data
Japan	1962+ monthly CEIC Data	1995+ yearly CEIC Data
Lao PDR	1995+ yearly CEIC Data	1991+ yearly CEIC Data
Malaysia	1989+ monthly CEIC Data	1981+ yearly CEIC Data
Myanmar	1995+ yearly CEIC Data	2006+ yearly CEIC Data
New Zealand	1978+ monthly CEIC Data	1998+ yearly CEIC Data
Philippines	1988+ monthly CEIC Data	1970+ yearly CEIC Data
Singapore	2014+ monthly CEIC Data	2007+ quarterly CEIC Data
Republic of Korea	1975+ monthly CEIC Data	1975+ monthly CEIC Data

Thailand	1997+ monthly office of Tourism Development, EIKON	1960+ yearly CEIC Data
Viet Nam	2001+ monthly CEIC Data	2000+ yearly CEIC Data

Lao PDR = Lao People’s Democratic Republic.

Appendix II. Accuracy Metrics

		MAPE			
		Tourist Arrivals		**Tourism Revenue**	
		GAM	**LSTM**	**GAM**	**LSTM**
ASEAN	**Brunei Darussalam**	10.7%	**8.6%**	9.7%	**8.9%**
	Cambodia	11.0%	**9.3%**	10.3%	**8.5%**
	Indonesia	9.9%	**9.3%**	11.0%	**8.5%**
	Lao PDR	**9.9%**	9.9%	**10.0%**	10.1%
	Malaysia	9.8%	**8.6%**	9.4%	**8.4%**
	Myanmar	9.5%	**9.0%**	9.9%	**9.1%**
	Philippines	9.3%	**9.2%**	9.7%	**8.6%**
	Singapore	9.2%	**9.1%**	11.1%	**9.5%**
	Thailand	11.2%	**9.9%**	11.1%	**9.9%**
	Viet Nam	9.5%	**8.5%**	11.1%	**9.5%**
Australia		9.5%	**8.3%**	10.1%	**9.1%**
China		10.4%	**8.4%**	10.1%	**9.1%**
India		9.9%	**8.4%**	**9.7%**	11.2%
Japan		10.1%	**8.3%**	9.9%	**9.5%**
New Zealand		10.4%	**9.0%**	10.8%	**8.4%**
Republic of Korea		10.6%	**9.5%**	10.1%	**8.6%**

		MAE			
		Tourist Arrivals		**Tourism Revenue**	
		GAM	**LSTM**	**GAM**	**LSTM**
ASEAN	**Brunei Darussalam**	0.00062	**0.00059**	0.00056	**0.00049**
	Cambodia	0.00060	**0.00050**	0.00059	**0.00059**
	Indonesia	0.00059	**0.00056**	0.00061	**0.00049**
	Lao PDR	0.00063	**0.00049**	**0.00054**	0.00055
	Malaysia	**0.00054**	0.00056	0.00062	**0.00051**
	Myanmar	0.00061	**0.00058**	**0.00056**	0.00060
	Philippines	0.00057	**0.00052**	**0.00053**	0.00055
	Singapore	0.00054	**0.00053**	0.00060	**0.00057**
	Thailand	0.00059	**0.00054**	0.00061	**0.00051**
	Viet Nam	0.00054	**0.00049**	0.00062	**0.00057**

Australia	**0.00059**	0.00059	**0.00053**	0.00056
China	0.00058	**0.00052**	0.00054	**0.00052**
India	0.00056	**0.00051**	0.00056	**0.00053**
Japan	0.00061	**0.00059**	0.00053	**0.00050**
New Zealand	0.00064	**0.00058**	0.00062	**0.00059**
Republic of Korea	0.00053	**0.00051**	0.00060	**0.00052**

		RMSE			
		Tourist Arrivals		**Tourism Revenue**	
		GAM	**LSTM**	**GAM**	**LSTM**
ASEAN	**Brunei Darussalam**	0.08109	**0.08037**	0.08953	**0.06899**
	Cambodia	0.08264	**0.07771**	0.08193	**0.07582**
	Indonesia	0.08447	**0.07430**	0.08784	**0.06824**
	Lao PDR	**0.07771**	0.08264	0.09291	**0.08188**
	Malaysia	0.09038	**0.07203**	**0.07940**	0.08037
	Myanmar	0.08109	**0.06899**	0.08784	**0.07051**
	Philippines	0.08953	**0.07127**	0.07940	**0.07582**
	Singapore	0.09038	**0.07809**	0.08193	**0.08037**
	Thailand	0.09122	**0.08112**	0.08447	**0.06975**
	Viet Nam	**0.08193**	0.08264	0.07855	**0.07658**
Australia		0.09291	**0.07506**	0.07940	**0.07127**
China		0.08869	**0.08264**	0.08109	**0.07203**
India		0.07855	**0.07506**	**0.07686**	0.07809
Japan		0.08447	**0.07203**	0.09038	**0.08264**
New Zealand		**0.08024**	0.08037	0.09291	**0.07127**
Republic of Korea		0.09207	**0.07203**	0.07686	**0.07430**

ASEAN = Association of Southeast Asian Nations, GAM = Generalized Additive Model, LSTM = Long Short Term Memory, Lao PDR = Lao People's Democratic Republic, MAE = Mean Absolute Error, MAPE = Mean Absolute Percentage Error, RMSE = Rooted Mean Square Error.
Source: Authors.

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